Optimizing Placement of Residential Shelters for Human Trafficking Survivors

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Abstract: Residential shelters play a critical role in the stabilization and eventual reintegration to society for trafficked persons and entail a large investment. In the United States, survivors of human trafficking live every state. However, in 2018 a majority of states lack dedicated residential shelters for trafficking survivors. Even in states with shelters, data suggests that demand greatly exceeds capacity, and significant disparity exists between states with respect to the legislative environment and provision of auxiliary services for survivors. We present an optimization approach to evaluate the societal impact of opening dedicated shelters for trafficking survivors at a regional level. Using concepts from health and social welfare economics, we develop an optimization model that allocates a budget for locating residential shelters in a manner that maximizes a measure of societal impact while respecting budgetary constraints. For our case study, we measure this impact via a societal value quantified by a combination of labor productivity gained, reduction in juvenile arrests, disability-adjusted life years averted, and legislative environment, adjusted for the demand for shelters and the current number of shelters available, less construction and operating costs. We illustrate the utility of the model via our case study that allocates a budget among a candidate set of residential shelters for female sex trafficking survivors in the United States. Via sensitivity analyses on a robust set of uncertain parameters, we present policy implications of shelter placements using an optimization approach to support this critical societal concern.

Key words**:** human trafficking; societal impact; integer optimization; budget allocation; facility location

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1. Introduction

Human trafficking is increasingly recognized as a prevalent and malicious human rights problem worldwide, including in the United States (U.S.) (Greenbaum 2014; President's Interagency Task Force to Monitor and Combat Trafficking in Persons 2014; Shelley 2010). The United Nations defines human trafficking as the recruitment, transportation, transfer, harboring or receipt of persons through force, fraud, coercion or other objectionable means for the purpose of exploitation (United Nations Office on Drugs and Crime, 2014). While human trafficking encompasses individuals exploited through forced labor or services, servitude, and the removal of organs, this manuscript specifically focuses on trafficking for commercial sexual exploitation within the U.S., which may include engaging a victim in prostitution, in a sex-oriented business, or in the production of sexual images.

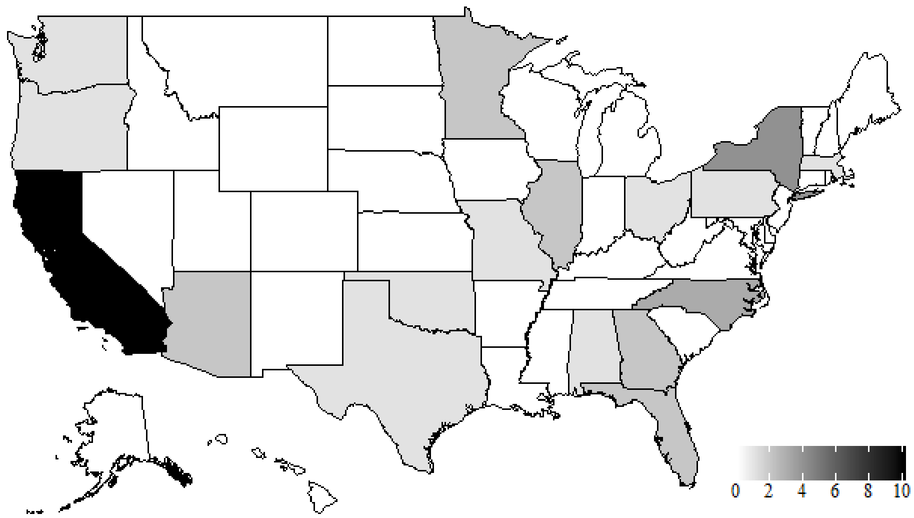
While numerous figures on the prevalence of trafficking have been suggested, such estimates vary widely and have been criticized for their lack of transparent methodology. Accurate estimates are difficult to obtain due to the illicit nature of the crime, lack of a standard method of reporting trafficking cases, inconsistent definitions and interpretations (e.g., what constitutes "coercion"), lack of recognition by authorities, and the tendency of survivors to underreport (Greenbaum 2017).

Physical and sexual violence are common among survivors of sex trafficking, as is profound psychological manipulation. Trafficked survivors may experience complex trauma from these ordeals, as well as from forced isolation, deprivation, psychological abuse, degradation, and threats made to themselves or others (Greenbaum 2014). Survivors are commonly diagnosed with depression, anxiety and post-traumatic stress disorder (PTSD), with one international study finding 80% of survivors had at least one mental disorder and more than half (57%) had comorbid depression, anxiety and PTSD (Hossain, Zimmerman, Abas, Light, & Watts, 2010). Such adverse consequences may have debilitating effects on survivors, exacerbated by the significant trauma sustained prior to being trafficked, due to family dysfunction, poverty, and other stressors.

Numerous studies underscore the critical gap in coordinated services to support the care of human trafficking survivors (Davy 2015; Institute of Medicine and National Research Council 2013). The myriad of needs extends beyond medical and psychological aspects to food, shelter, clothing, housing, education, job training, and financial stability. In a survey of law enforcement personnel familiar with sex trafficking cases, 65% identified shelter and housing as the most needed service for survivors (Clawson et al. 2006).

Current shelter options for human trafficking survivors include emergency, transitional, and long-term residential shelters, with lengths of stays ranging from a few days or months to a year or more. Despite the need, a number of reports indicate that housing for survivors of sex trafficking is limited, and in many parts of the country it is nonexistent (Clawson et al. 2009; Ferguson et al. 2009; Finklea et al. 2011; Gragg et al. 2007; Guarino et al. 2009). For example, a 2012 survey of 68 organizations providing shelter services found that 2,173 beds were available to human trafficking survivors in the U.S. for at least one overnight stay (Polaris Project, 2012). However, only 678 were shelter beds exclusively designated for survivors of human trafficking (labor or sexual trafficking), of which 529 were appropriated for survivors of sex trafficking. Reichert and Sylwestrzak (2013) provide another viewpoint during the same timeframe, identifying 37 facilities in the U.S. providing long-term residential housing services exclusively to human trafficking survivors, as depicted in *Figure 1*. These facilities provided a total of 682 beds in 17 states and the District of Columbia; 5 additional states were in the process of opening facilities, and 28 states had no residential programs for survivors of sex trafficking with no plans to open any.

Figure 1: Existing Residential Shelters for Human Trafficking Survivors, reproduced from Reichert and Sylwestrzak (2013)



In addition to dedicated human trafficking shelter beds, survivors of sex trafficking may be placed in a variety of settings, including residential treatment centers, shelters serving survivors of domestic violence and sexual assault, child protective services-funded group homes and foster care placements, and juvenile correction facilities (Clawson et al. 2009). Many survivors receive services from shelters for runaway and homeless youth or drop-in centers without being identified as a survivor of sex trafficking. This can result in trauma and related health problems being left untreated (Beck et al. 2015; Clawson and Grace 2007). Even if service providers are able to identify a client as a sex trafficking survivor, the restrictions on the maximum length of stay many homeless and domestic violence shelters impose may not provide sufficient time for the service provider to build trust with the survivor—a key component to effective service provision (Clawson and Grace 2007). Furthermore, the location of homeless shelters and drop-in centers not dedicated to trafficking are often public knowledge, and therefore also known to traffickers. This clearly poses a safety concern for survivors trying to separate themselves from their traffickers and can also be a concern for staff and other clients. In their 2007 study, Clawson and Grace indicate that several runaway/homeless youth shelters and drop-in centers "reported cases of traffickers recruiting girls outside the facilities or, in some cases, girls being sent into the shelters to recruit other girls." For these reasons and others, professionals continuously stress the importance and need for more residential programs uniquely tailored to the sex trafficking population. Encouragingly, the Reichert and Sylwestrzak (2013) study found that 27 programs plan to offer a total of 354 additional residential beds to adult and minor survivors of human trafficking in the future.

Furthermore, in addition to providing safe housing, dedicated residential programs typically provide services to address survivors' needs as they relate to social support, counseling, education, job skills, and life skills (Ide & Mather, 2018). As such, survivors receiving services at dedicated human trafficking residential shelters may experience improvements in their mental health, be better prepared to find employment opportunities, and avoid criminal justice charges in the future.

Broad consensus exists among professionals across various sectors serving survivors of sex trafficking that there are too few services available to meet current needs, and that existing services are unevenly distributed geographically, lack adequate resources, and vary in their ability to provide specialized care to survivors of these crimes (Institute of Medicine and National Research Council, 2013). At the same time, while public awareness of sex trafficking has increased substantially over the past 15 years and efforts to address this and other types of human trafficking are continuing at national, state, and local levels (Senate and House of Representatives of the United States of America in Congress, 2015; United States Department of State, 2016), quantitative research to inform public policy, prevention, and intervention efforts is relatively sparse (Institute of Medicine and National Research Council, 2013). Furthermore, a lack of funding poses additional challenges to providing services to survivors (Gragg et al., 2007; Jones & Lutze, 2016).

To address these needs, we introduce a mathematical framework to aid decision-makers in allocating a limited budget among various geographical locations to fund residential shelters designated specifically for survivors of sex trafficking in a manner that maximizes a measure of societal value. The model evaluates the tradeoff in the cost of opening and operating shelters in each location with the health benefits, labor productivity gained, reduction in criminal justice costs, and the associated legislative environment, seeking to identify one or more allocations of shelters to locations in an optimal manner.

The contribution of this paper to the operations research literature is threefold. First, this study represents one of the initial efforts to tackle a planning problem specific to the human trafficking context, namely that of locating residential shelters for trafficking survivors, with operations research methodologies. Specifically, we present a nonlinear integer optimization model to recommend the location of new shelters – how many, what type, and where – in a manner that maximizes a measure of societal impact. Second, the objective function of our proposed optimization model incorporates societal benefits of investing in long-term shelters for human trafficking survivors that are rarely considered in existing studies. We introduce methods that incorporate measures of the local legislative atmosphere regarding human trafficking as well as the health benefits, labor productivity gained and reduction in criminal justice costs associated with operating shelters. Third, in our case study we employ a unique variable definition that enables effective representation of the effect of decreasing marginal returns in societal benefits from placing multiple shelters in the same location, accomplished by a priori enumeration and computation of objective function coefficients.

This work also contributes to the human trafficking literature. It is the first to use an optimization approach to illustrate the benefit of evaluating multiple decision factors (e.g., cost, current number of shelters, demand) and facilitate increased efficiency of scarce anti-trafficking resources in a manner that maximizes a measure of societal impact. Moreover, this work represents a significant modeling effort in formulating an ill-defined operations research problem (Gralla et al. 2016).

The remainder of the paper is organized as follows. Section 2 positions our paper in the relevant literature. In Section 3 we develop a general integer optimization model that allocates a budget for a candidate set of residential shelters for human trafficking survivors in a manner that maximizes societal impact. We then introduce a case study which considers allocating the human trafficking shelter budget of a federal funding among the 50 U.S. states. Section 4 provides the corresponding detailed case study model formulation and Section 5 proposes methods for obtaining the necessary societal model parameters. Section 6 presents the results of the case study, including a discussion on sensitivity insights and a comparison of our framework to other prioritization schemes. Section 7 concludes the paper with a discussion on the implications of incorporating our model into the current budget allocation process.

2. Literature Review

The challenge of where to locate residential human trafficking shelters has not been studied in the literature. There is, however, a rich body of research in the somewhat related areas of facility location in disaster management and humanitarian relief.

Strategic planning regarding the location and selection of distribution centers, medical centers, shelters, and other facilities are an important approach in disaster management (Boonmee, Arimura, & Asada, 2017). In the humanitarian facility location area, studies can be categorized by how the location problem is framed: as minisum (e.g., Abounacer et al. 2014; Khayal et al. 2015); set covering (e.g., Dekle et al. 2005; Rosas et al. 2009); maximal covering (e.g., Murali et al. 2012), and minimax (e.g., Akgün et al. 2015). Common natural disaster investigations include earthquakes (e.g., Mete and Zabinsky 2010; Verma and Gaukler 2015), hurricanes (e.g., Rawls and Turnquist 2012), and floods (e.g., M.-S. Chang et al. 2007), while others consider epidemics (e.g., Murali et al. 2012) and optimization models for general disaster scenarios (e.g., Dekle et al. 2005; Duran et al. 2011; Salman & Yücel 2015).

While some studies such as Jia et al. (2007b, 2007a) and Dessouky et al. (2006) use core location decisions to formulate maximal covering location models with multiple quantity-of-coverage and quality-of-coverage requirements, other logistical challenges are also frequently studied. Some challenges include evacuation planning, stock pre-positioning, relief distribution, casualty transportation, and other operational issues

(Caunhye, Nie, & Pokharel, 2012). Further, Boonmee et al. (2017) survey the research regarding humanitarian facility location optimization models and classify each work based on the relevant objectives, conditions, disaster types (e.g. earthquake, flood), facility location types, and solution methods, concluding that new objectives focused on reliability and ease of access could be developed. Moreover, Boonmee et al. (2017) note that quantitative and qualitative measurements could be added to the parameters so as to include quality measurements in considering facility location problems such as availability, accessibility, functional ability and risk. Caunhye et al. (2012) conducted a more general literature survey of optimization models in emergency logistics, including facility location. They note that the literature is lacking when it comes to objectives other than responsiveness and cost-efficiency. Whether in the context of disaster management or human trafficking, there is a need to estimate intangible costs (He & Zhuang, 2016).

Studies exist that capture notions of societal impact, particularly in the healthcare OR literature and humanitarian relief literature. Researchers have used proxies to capture human suffering (e.g., Sheu 2007; Yi and Özdamar 2007) leading to Holguín-Veras et al. (2013) arguing that welfare economic principles need to be explicitly considered in post-disaster humanitarian logistic models. The authors introduce the notion of *deprivation cost* as the economic valuation of the human suffering associated with a lack of access to a good or service. The notion of human suffering resulting from delivery delays are increasingly being considering in humanitarian logistics problems (e.g., Yu et al. 2018). While post-disaster humanitarian logistic models do incorporate notions of human suffering, such objectives tend to focus on the benefit to the recipient of the service rather than to society at large. In our model that aims to improve trafficking survivors' access to shelter services, we incorporate both recipient-focused benefits (e.g., disability-adjusted life years (DALYs) averted) as well as broader societal benefits.

Our study considers the primary decisions related to the location of shelters (quantity, size, and location), and introduces a novel objective function to measure not only the cost, but also the societal benefit of these decisions. By explicitly quantifying the functional ability of a shelter to rehabilitate survivors and considering objectives related to societal benefit, we address the research gaps identified by Caunhye et al. (2012) and Boonmee et al. (2017). Moreover, in contrast to many existing studies, our approach considers both the individual benefit to the recipient, in terms of the health benefits received by the survivor, as well as the societal benefit received by the community where the survivor was rehabilitated, in terms of labor productivity gained and healthcare costs avoided.

3. General Optimization Model Framework

We consider the situation in which a funding agency must determine how to allocate its budget (b) for shelters among a set of entities eligible to receive funding. Entities may request funding for shelters of different types ($t \in T$) based on characteristics such as the number of beds (n_t), whether the shelter is limited to a particular gender, or whether the shelter serves survivors of a specific age. We recognize that the consideration of which entities will receive funding depends on many factors—including the strength of the grant application—and assume that the funding agency has selected a group of candidate shelter locations (I) that meet its initial grant screening requirements. It is over this group of finalists that we optimize the budget allocation and decide how many shelters S_t of each type to fund in each location $i \in I$. Upper ($\overline{m}_{it}$) and lower ($\underline{m}_{it}$) bounds limit the number of shelters of each type at each location, while aggregate upper ($\overline{m}_i^{agg}$) and lower ($\underline{m}_i^{agg}$) bounds limit the total number of shelters *of any type* that can be established at each location.

Let x be a decision variable vector composed of elements x_{it}, each of which represents a nonnegative integer number of shelters of type t to place in location i. Moreover, suppose there exists a function of social welfare $f(x)$ that measures the societal value – that is, benefits $R(x)$ less costs $K(x)$ – of an allocation x of shelter types to locations. We assume costs $K(x)$ are approximately *linear* with respect to the shelters built and operated, as given the relatively few number of shelters in any location it is difficult to envision significant economies of scale. We assume the benefit function $R(x)$ is nondecreasing, but *not necessarily* *linear*, as funding additional units of shelters in the same location has the likely effect of decreasing returns to scale on the priority of establishing additional shelters in that location before establishing shelters in others. Objective functions with decreasing returns to scale are common in humanitarian operations (Gralla et al. 2014; Holguín-Veras et al. 2013).

With these elements, we formulate the residential shelter placement problem as:

$$\begin{aligned}
&\textit{Maximize} && f(x) = R(x) - K(x) && \\
&\textit{subject to} && K(x) \leq b, && \\
& && \underline{m}_{it} \leq x_{it} \leq \overline{m}_{it} && \forall\, i \in I, t \in T, \\
& && \underline{m}_i^{agg} \leq \textstyle\sum_{t \in T} x_{it} \leq \overline{m}_i^{agg} && \forall\, i \in I, \\
& && x_{it} \in \mathbb{Z}_+^n && \forall\, i \in I, t \in T.
\end{aligned}$$

The integer variables and the knapsack-like budget constraint cause the problem to be NP Hard, as with linear $f(x)$, $\underline{m}_{it} = 0\ \forall\, i \in I, t \in T$, $\overline{m}_{it} = 1\ \forall\, i \in I, t \in T$, $\underline{m}_i^{agg} = 0\ \forall\, i \in I$, and $\overline{m}_i^{agg} = M\ \forall\, i \in I$ for large enough M, we have an instance of the NP Hard binary integer knapsack problem.

4. Case Study: Optimization Model for the U.S. Context

Explicitly estimating the nonlinear $R(x)$ function would be very challenging even if widespread human trafficking shelter data and corresponding effects were readily available (they are not). To address this, we introduce an alternative variable definition that enables nonincreasing returns to scale to be represented in objective function coefficients, which—in conjunction with a weighting factor $a_i^{S_t}$, nonincreasing in S_t,—prioritizes certain locations for receiving shelters. As an example, prioritization weights could be a function of the number of shelters already located nearby or the unmet demand for shelters. *Table 1* contains the sets and parameters used in our optimization model.

We assume that each entity receiving funding will operate their shelters at full capacity (as demand greatly exceeds supply in the current U.S. human trafficking shelter context) and that three quantifiable benefits are obtained for each client-year the shelter is open: (1) an increase in the disability-adjusted life years (DALYs) averted (d_t); (2) a gain in labor productivity (p_{it}), and (3) a reduction in criminal justice costs associated with juvenile arrests (q_{it}). As no standardized assessment mechanism currently exists concerning the effectiveness of residential shelters for sex trafficking survivors in the U.S., program specific definitions of success are widely varied, and success rates range between 10% – 100% (Ide & Mather, 2018). To account for this variability in effectiveness, we multiply the d_t, p_{it}, and q_{it} benefits by δ_t^{DALYs}, δ_{it}^{LP}, and δ_{it}^{CJ}, respectively, which indicate the proportion of full (i.e., 100%) rehabilitation that is expected to occur in each area.

Additionally, since DALY units are in years, we convert them to monetary units by multiplying the DALYs averted by a location-dependent measure of societal willingness to pay (w_i) per DALY averted (see, e.g., Brandeau and Zaric 2009, Sassi 2006). The benefits are incorporated into our model, and are weighed against the annual capital (c_{it}^{build}) and operational (c_{it}^{bed}) costs to entities for providing such services.

We incorporate the following set of binary decision variables:

$$X_i^{[S_1,\ldots,S_{|T|}]} = \begin{cases} 1 & \text{if } [S_1, \ldots, S_{|T|}] \text{ shelters of type } t = 1, \ldots, |T| \text{ at } i \in I \text{ recieve funds to locate a shelter,} \\ 0 & \text{otherwise} \end{cases}$$

where the $[S_1, \ldots, S_{|T|}]$ vector has the following interpretation. Suppose that there are two shelter types: small and large; then $X_i^{[2,1]}$ would represent the decision to locate two small shelters, and one large shelter, in location i. This decision variable definition allows us to avoid nonlinearities in the objective function that would otherwise occur due to the priority for funding a certain number of shelters of a certain type $t \in T$ in a specific location $i \in I$, $a_{it}^{S_t}$, being dependent on the number of other types of shelters funded in other locations. For an example illustrating how the $a_{it}^{S_t}$ priority values can be calculated based on this definition, please see Appendix C.

Table 1: Sets and Parameters Used in the Optimization Model

Symbol	Definition
$\boldsymbol{I}$	*Set of candidate shelter locations, indexed by i*
$\boldsymbol{T}$	*Set of shelter types, indexed by t*
$\boldsymbol{a_i^{[S_1,\dots,S_{\lvert T\rvert}]}}$	*Priority score for adding* $[S_1, \dots, S_{\lvert T\rvert}]$ *shelters of their respective types at* $i \in I$
$\boldsymbol{a_{it}^{S_t}}$	*Component of priority score associated with adding* S_t *shelters of type* $t \in T$ *at* $i \in I$
$\boldsymbol{b}$	*Budget of funding agency for shelter funding*
$\boldsymbol{c_{it}^{build}}$	*Annual capital cost of shelter type* $t \in T$ *at* $i \in I$
$\boldsymbol{c_{it}^{bed}}$	*Annual cost per bed of shelter type* $t \in T$ *at* $i \in I$
$\boldsymbol{d_t}$	*DALYs averted per survivor fully rehabilitated at shelter of type* $t \in T$
$\boldsymbol{l_t}$	*Average length of stay (in days) at shelter of type* $t \in T$
$\boldsymbol{n_t}$	*Number of beds in shelter of type* $t \in T$
$\boldsymbol{p_{it}}$	*Labor productivity gained per survivor fully rehabilitated at shelter of type* $t \in T$ *at* $i \in I$
$\boldsymbol{q_{it}}$	*Criminal justice costs averted due to reduction in juvenile arrests per survivor fully rehabilitated at shelter of type* $t \in T$ *at* $i \in I$
$\boldsymbol{\delta_t^{DALYs}}$	*Proportion of 'DALYs averted' expected to occur at shelter of type* $t \in T$
$\boldsymbol{\delta_{it}^{LP}}$	*Proportion of 'labor productivity gained' expected to occur at shelter of type* $t \in T$ *at* $i \in I$
$\boldsymbol{\delta_{it}^{CJ}}$	*Proportion of 'criminal justice costs averted' expected to occur at shelter of type* $t \in T$ *at* $i \in I$
$\boldsymbol{S_t}$	Number of shelters funded of type $t \in T$ at a given location
$\boldsymbol{w_i}$	*Willingness to pay at location* $i \in I$ *per DALY averted*
$\boldsymbol{\overline{m}_{it}}$	*Maximum number of shelters of type* $t \in T$ *that can be funded at* $i \in I$
$\boldsymbol{\underline{m}_{it}}$	*Minimum number of shelters of type* $t \in T$ *that can be funded at* $i \in I$
$\boldsymbol{\overline{m}_i^{agg}}$	*Maximum number of shelters that can be funded at* $i \in I$*(aggregated across types)*
$\boldsymbol{\underline{m}_i^{agg}}$	*Minimum number of shelters that can be funded at* $i \in I$ *(aggregated across types)*

For a given location $i \in I$, there are $\prod_{t\in T}(\overline{m}_{it} + 1)$ possible combinations of values for the vector $[S_1, \dots, S_{|T|}]$; hence there are $\sum_{i\in I}\prod_{t\in T}(\overline{m}_{it} + 1)$ binary $X_i^{[S_1,\dots,S_{|T|}]}$ decision variables. For example, if $\underline{m}_{it} = 0$ and $\overline{m}_{it} = 3\ \forall\, i \in I, t \in T$, 16 decision variables are constructed for each location $i \in I$: $X_i^{[0,0]}$, $X_i^{[0,1]}$, $X_i^{[0,2]}$, $X_i^{[0,3]}$, $X_i^{[1,0]}$, $X_i^{[1,1]}$, $X_i^{[1,2]}$, $X_i^{[1,3]}$, $X_i^{[2,0]}$, $X_i^{[2,1]}$, $X_i^{[2,2]}$, $X_i^{[2,3]}$, $X_i^{[3,0]}$, $X_i^{[3,1]}$, $X_i^{[3,2]}$, $X_i^{[3,3]}$. By definition, each variable represents an allocation of zero or more shelters of each type $t \in T$, for a given location $i \in I$. If $\overline{m}_{it}$ is identical across all $t \in T$ and $i \in I$, the number of decision variables may also be written as $|I|(\overline{m}_{it} + 1)^{|T|}$.

Without loss of generality, let us reference each of the $\prod_{t\in T}(\overline{m}_{it}+1)$ unique combinations by $[S_{1j},\dots,S_{|T|j}]$, with $j\in\{1,2,\dots,\prod_{t\in T}(\overline{m}_{it}+1)\}$. Then the associated priority-weighted annual cost of opening $[S_{1j},\dots,S_{|T|j}]$ shelters at location $i\in I$ is:

$$\kappa_i^{[S_{1j},\dots,S_{|T|j}]}=\sum_{t\in T}S_{tj}a_{it}^{S_{tj}}\left(c_{it}^{bed}n_t+c_{it}^{build}\right),$$

whereas the strictly financial cost is similarly:

$$\bar{\kappa}_i^{[S_{1j},\dots,S_{|T|j}]}=\sum_{t\in T}S_{tj}\left(c_{it}^{bed}n_t+c_{it}^{build}\right).$$

We then express an overall societal value of shelter combination $[S_{1j},\dots,S_{|T|j}]$ by subtracting its associated priority-weighted cost $\kappa_i^{[S_{1j},\dots,S_{|T|j}]}$ from an aggregate priority-weighted societal benefit:

$$\gamma_i^{[S_{1j},\dots,S_{|T|j}]}=\sum_{t\in T}S_{tj}a_{it}^{S_{tj}}\left(\left(w_i\delta_t^{DALYs}d_t+\delta_{it}^{LP}p_{it}+\delta_{it}^{CJ}q_{it}\right)n_t\frac{365}{l_t}\right)-\kappa_i^{[S_{1j},\dots,S_{|T|j}]}.$$

Here $n_t\frac{365}{l_t}$ represents the number of clients a shelter of type $t\in T$ can serve each year.

With this notation, we formulate the optimization model as follows:

$$\textit{Maximize}\quad \sum_{i\in I}\sum_{j=1}^{\prod_{t\in T}(\overline{m}_{it}+1)}\gamma_i^{[S_{1j},\dots,S_{|T|j}]}X_i^{[S_{1j},\dots,S_{|T|j}]} \tag{1}$$

$$\textit{subject to}\quad \sum_{i\in I}\sum_{j=1}^{\prod_{t\in T}(\overline{m}_{it}+1)}\bar{\kappa}_i^{[S_{1j},\dots,S_{|T|j}]}X_i^{[S_{1j},\dots,S_{|T|j}]}\le b, \tag{2}$$

$$\sum_{j=1}^{\prod_{t\in T}(\overline{m}_{it}+1)}X_i^{[S_{1j},\dots,S_{|T|j}]}\le 1 \qquad \forall\, i\in I, \tag{3}$$

$$\underline{m}_{it}\le\sum_{j=1}^{\prod_{t'\in T}(\overline{m}_{it'}+1)}S_{tj}X_i^{[S_{1j},\dots,S_{|T|j}]}\le\ \overline{m}_{it} \qquad \forall\, i\in I,t\in T, \tag{4}$$

$$\underline{m}_i^{agg}\le\sum_{j=1}^{\prod_{t'\in T}(\overline{m}_{it'}+1)}\sum_{t\in T}S_{tj}X_i^{[S_{1j},\dots,S_{|T|j}]}\le\ \overline{m}_i^{agg} \qquad \forall\, i\in I, \tag{5}$$

$$X_i^{[S_{1j},\dots,S_{|T|j}]}\in\{0,1\} \qquad \forall\, i\in I,j\in\{1,2,\dots,\prod_{t\in T}(\overline{m}_{it}+1)\}. \tag{6}$$

Objective function (1) maximizes our measure of societal value, that is, the priority-weighted difference between the monetized societal benefits and the cost of locating shelters. For each survivor that receives services at the shelter, a societal benefit is incurred that includes the monetary benefit of averting future health concerns and juvenile arrests, as well as the contributions to gains in labor productivity. These benefits are weighed against the annual capital and operating costs of the shelter. Constraint (2) ensures that the total financial cost does not exceed the budget. Constraints (3) require the model to choose at most one combination of shelter types to establish at each location. Constraints (4) and (5) impose bounds on the number of shelters of each type and the total number of shelters that can be established in each location, respectively. Variable domains are expressed in (6).

5. Case Study: Obtaining Optimization Model Parameters

Formulation (1) – (6) can be used to assess a set of specific potential shelter locations. We now present a specific case study of a federal funding agency that dedicates a portion of its budget to opening new residential shelters for sex trafficking survivors in the U.S. We assume that the funding agency allocates the budget among the 50 states (I), and any state receiving funding will use auxiliary means to determine the specific shelter location(s). However, our model could also be employed at a state or regional jurisdiction, provided input parameters are available at such a granular level. This underscores a common challenge in conducting accurate quantitative analyses concerning human trafficking – there is a general lack of consistent, comprehensive data available. Because of this, we conduct extensive sensitivity analyses by varying five key model parameters to analyze the sensitivity of societal value with respect to these variations (these are summarized in *Table 2* of Section 4.1). We chose 2014 as the reference year because it is the most recent year with reliable and consistent availability across many of our data estimates.

We assume states can open small (6 beds) or large (14 beds) shelters, or a combination of both[1]. Thus, set T has two elements. To promote distributing the budget to multiple locations, we limit the number of

[1] Shelter bed capacity was determined by averaging the bed capacity of the small and large shelters listed in the Reichert and Sylwestrzak (2013) study of U.S. residential programs for survivors of sex trafficking for which we could also find 2013-2015 990 tax forms specifying their operating costs. Shelters with 10 or fewer beds were classified as small shelters; shelters with more than 10 beds were categorized as large.

shelters that can be added to a state in this budget cycle to be between $\underline{m}_i^{agg} = 0$ and $\overline{m}_i^{agg} = 3 \ \forall\, i \in I$, and do not place any further restrictions on the number of shelters of each type added per state (i.e., $\underline{m}_{it} = 0$ and $\overline{m}_{it} = 3 \ \ \forall\, i \in I, t \in T$). The average length of stay is assumed to be the same for large and small shelters (i.e., $l_1 = l_2$); sensitivity values of 12, 18, and 24 months are considered, which is pursuant to the assessment of service providers concerning the length of time needed to build trust, provide necessary treatment, and develop a long-term plan for rehabilitation (Clawson and Grace 2007). To account for variability in shelter effectiveness, we explore the effect of varying δ_t^{DALYs} across the values of 0, 0.25, 0.5, 0.75, and 1. We set $\delta_t^{LP} = \delta_t^{CJ} = 1$.

Multiple U.S. governmental agencies fund anti-human trafficking initiatives, earmarking a proportion of the funds for victim-centered services. According to the Trafficking in Persons report, the Department of Health and Human Services and Department of Justice together budgeted at least 31.7M USD for victim-centered services in FY 2016[2] (United States Department of State, 2017). We solve the optimization model under the assumption that a small fraction (no more than 10%) of this budget is dedicated toward funding long-term residential shelters (specifically: 1M, 2M, and 3M USD).

In the remainder of this section, we describe how the remaining model parameters are calculated. The resulting state-dependent values can be found in Appendix A.

[2] The Department of Health and Human Services granted 3.4M USD for coordinated victim-centered services. The Department of Justice granted 19.7M USD for 33 victim service providers offering specialized and comprehensive services, a portion of 6M USD for American Indian and Alaska Native trafficking victim services, and 2.6M USD for U.S. citizen and legal permanent resident child sex trafficking victim services (p. 417).

5.1 Shelter Costs

The cost of acquiring and operating a long-term residential shelter for human trafficking survivors can vary greatly depending on the number of beds, variety of survivor services that the shelter coordinates, and the geographic location.

5.1.1 Annual Capital Costs

Capital funds are required to secure a facility and prepare it for operation as a residential shelter which may include new construction or facility renovations, as well as obtaining staff and facility licensures. In a 2012 national survey of domestic minor sex trafficking shelter providers, respondents indicated that capital fundraising costs ranged from 250,000 USD for a 1-year pilot to 2.5M USD when responding to the question "How much capital did you initially raise to create your program / facility?" (ECPATUSA, Shared Hope International, The Protection Project, & John Hopkins University, 2013). The variation appears related to the number of beds in the shelter; shelters with more than 10 beds tended to have larger capital costs.

We classified each shelter that responded to the capital cost question on the 2012 ECPAT USA national survey as small or large, based on the number of beds dedicated to human trafficking survivors (Reichert & Sylwestrzak, 2013). We then averaged the 2012 capital cost for each category and converted to 2014 USD by multiplying by the ratio of the 2014 to 2012 Consumer Price Index (CPI) value (United States Bureau of Labor Statistics, 2018). To account for housing affordability variation across states, we calculated the ratio of the 2014 Median Monthly Housing Cost (MMHC) for each state to the average 2014 MMHC across all 50 states (United States Census Bureau, 2018), and multiplied the state ratios by the average cost. This provided a capital cost for each size shelter in each state. Lastly, we annuitized the capital cost using a 20-year loan structure with no fees and 10% annual interest rate to obtain an annual capital cost.

5.1.2 Annual Per Bed Operating Cost

In addition to capital costs, shelters also incur operating costs. We estimated the 2014 annual per bed operating cost in each of the 50 states as follows. For each shelter listed in the Reichert and Sylwestrzak (2013) study of U.S. residential programs for sex trafficking survivors that specified operating costs in Internal Revenue Service (IRS) Form 990 (in any of the years 2013 through 2016) found via an internet search of public records, we divided their operating cost by the number of beds listed in Reichert and Sylwestrzak (2013). As operating costs can vary greatly by organization due to shelter size and auxiliary services, we focused our cost calculations on shelters that operate 10 or fewer beds to obtain the per bed cost of small shelters; in the next paragraph we detail how we extrapolated the cost of a large shelter bed relative to the cost of a small shelter bed. To account for inflation, all costs were converted to 2014 USD by multiplying the cost per bed at each shelter by the ratio of the 2014 to the IRS Form 990 year (i.e., 2013 – 2016) CPI value. An average annual cost per bed for small shelters was derived via these 2014 costs.

As with the capital costs, we adjusted for variation in costs among states by using the ratio of the 2014 MMHC for each state to the average 2014 MMHC across all 50 states and multiplied the average cost per bed at a small shelter by this ratio. Compared to bed operating costs at small shelters, beds at large shelters may either reflect economies of scale, or be more costly because of additional services and outreach events. Thus, we assumed the cost per bed at large shelters is a multiple of the bed operating costs at small shelters – namely, 0.5, 0.75, 1, 1.25, and 1.5. The variation in the total annual cost of opening a shelter across states is illustrated in *Figure 2*.

Figure 2: Total Annual Shelter Cost

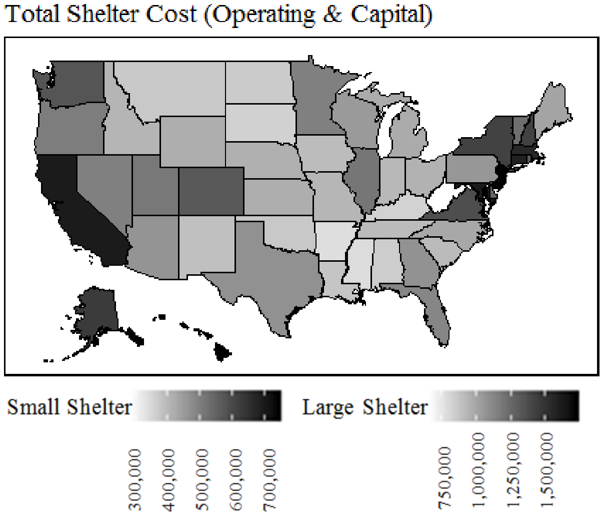
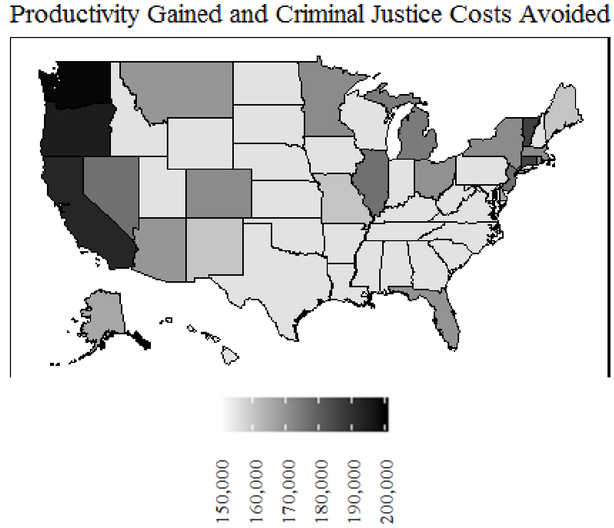


Figure 3: Labor Productivity Gained and Criminal Justice Costs Avoided



5.2 Shelter Benefits

Shelters provide a variety of benefits for both the survivors they serve, as well as the surrounding community. In this manuscript, we incorporate three key benefits: labor productivity gained, criminal justice costs avoided, and DALYS averted.

5.2.1 Labor Productivity Gained and Criminal Justice Costs Avoided

From a related study concerning non-fatal child maltreatment (Fang, Brown, Florence, & Mercy, 2012), we obtain estimates for lifetime labor productivity gained (144,360 in 2010 USD) and criminal justice costs avoided per survivor (6,747 in 2010 USD), and subsequently convert them to 2014 costs (respectively, 156,502 USD and 7,314 USD). Similar to our method for calculating state-dependent shelter costs, we subsequently weight the labor productivity and criminal justice values by the ratio of the 2014 minimum wage of each state to the average 2014 minimum wage among the 50 states to obtain state-dependent labor productivity and criminal justice values, which are visually depicted in *Figure 3* (National Employment Law Project via CNN, 2018).

5.2.2 DALYs Averted

In addition to providing a place of refuge, shelters dedicated to serving human trafficking survivors help ensure proper healthcare and support services are provided. Common psychological and behavioral health issues associated with human trafficking that linger even after the trafficking has ceased include depression, anxiety, post-traumatic stress disorder (PTSD), and alcohol and substance abuse (Hossain et al., 2010; Lederer & Wetzel, 2014; Smith, Vardaman, & Snow, 2009; Varma, Gillespie, McCracken, & Greenbaum, 2015). These health concerns can manifest singularly or as comorbid conditions. In fact, one study found that over half of the sex trafficked women and girls participating in the study had comorbid depression, anxiety, and PTSD (Hossain et al., 2010).

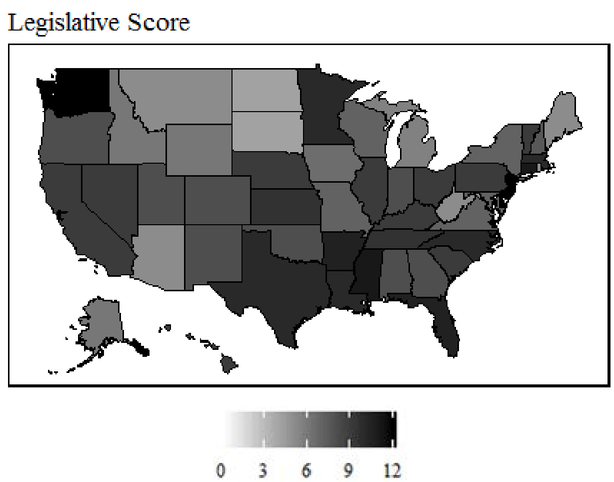
We account for the improvement in human trafficking survivors' health by calculating the DALYs averted by treating their depression, substance abuse, and PTSD while receiving shelter services – DALY is a measure of burden arising from a disease or health condition that incorporates the impact of living with a health issue at different ages (Fox-Rushby & Hanson, 2001; Murray & Lopez, 1996a). Under the assumptions that 1) the health issues are untreated when the survivor begins receiving shelter services, 2) while receiving shelter services, the health issues are identified and treated according to the standard of practice, and 3) the survivors the shelter serves would not have received treatment for these health concerns had the shelter not existed, up to $d_t =$11.02 DALYs may be averted per survivor as a result of receiving shelter services (calculated via the methods in Appendix B). However, to account for the reality that survivors may have physical and mental health concerns that persist even after receiving treatment through the shelter and that the health concerns of survivors differ, we moderate d_t by $\delta_t \in [0,1]$ to represent that only a proportion of the 11.02 DALYs may be averted.

5.3 Willingness to Pay

Within the past few years there has been an increased societal awareness of human trafficking. Such a shift may suggest a corresponding increase in the societal willingness to pay for residential shelters and similar services that empower trafficking survivors to recover, and ideally thrive, post-trafficking. As legislation is often a reflection of societal perceptions of an issue, we base the willingness to pay of each state on the presence or absence of "10 categories of laws that are significant to a basic legal framework that combats human trafficking, punishes traffickers, and supports survivors" as reported in Polaris (2014), where higher scores, on a scale of 0 to 12, are preferable (*Figure 4*).[3]

This was achieved by normalizing the legislative score r_i^{Leg} of each state $i \in I$ relative to the average legislative score of all 50 states (r_{avg}^{Leg}). The normalized score was subsequently multiplied by a base willingness to pay, ω^{Leg}, to obtain the state dependent willingness to pay (i.e., $w_i = \omega^{Leg}(r_i^{Leg}/r_{avg}^{Leg})$). A conservative base willingness to pay of ω^{Leg}=20,000 USD was used (Brandeau & Zaric, 2009; Owens, 1998).

Figure 4: State Legislative Score



[3] For the purposes of this study, a state's legislative environment is deemed supportive if it has laws that are critical to the basic legal framework to combat trafficking, punish traffickers and support survivors. Examples of such state statutes include posting a human trafficking hotline, training on human trafficking for law enforcement, providing survivors with the ability to seek civil damages, victim assistance statues which mandates the creation of a victim services plan or funds programs to help survivors. (Polaris, 2014).

5.4 Prioritization Framework

While each state would certainly benefit from receiving federal funding for shelter services, the reality of a limited budget necessitates prioritizing states that would benefit the most from receiving these funds. We associate a priority score for each state based on the prevalence of human trafficking and the current number of dedicated human trafficking shelters per million residents within the state. Of the states with a similar number of shelters, states with a high prevalence of human trafficking will be prioritized to receive funding over states with a low prevalence. Similarly, we prioritize states that have fewer shelters per million residents among states with the same prevalence. Thus, states with a high prevalence of trafficking that do not currently have any dedicated residential shelters for human trafficking survivors receive the highest priority for funding, while states with a lower prevalence of trafficking and more shelters per million residents than other states receive the lowest priority for funding assistance.

As accurate estimates of the prevalence of sex trafficking within each of the 50 United States do not exist (Fedina & DeForge, 2017; Nawyn, Birdal, & Glogower, 2013; Weitzer, 2014), we assume that the number of sex trafficking cases per million residents reported to the National Human Trafficking Hotline (NHTH) in 2015 is positively correlated with the number sex trafficking survivors seeking shelter services in each state (Polaris, 2018). Population data were based on recent estimated resident populations for each state (United States Census Bureau, 2015). We also used census data and the National Survey of Residential Programs for Victims of Sex Trafficking to obtain the number of shelters per million residents in each state (Reichert & Sylwestrzak, 2013). *Figures 5* and *6*, respectively, display a comparison of the sex trafficking prevalence and shelters per million residents across states, and *Figure 7* illustrates how these two components are combined to produce a prioritization score for locating an additional human trafficking shelter in each state. Darker states in *Figure 5* (i.e., greater prevalence) and lighter states in *Figure 6* (i.e., fewer current shelters) are prioritized (i.e., darker states) in *Figure 7*. We refer to Appendix C for more information on priority score calculations and resulting state priority scores.

The implementation of this prioritization framework into the objective function was enabled by our choice of using binary decision variables $X_i^{[S_1,\ldots,S_{|T|}]}$; doing so offered the advantage of a priori estimation of the objective contributions for each representation of $[S_1, \ldots, S_{|T|}]$ shelters. While this results in a somewhat larger number of variables, for realistic $\overline{m}_{it}$ and $\overline{m}_i^{agg}$ values this turned out to be reasonable from a computational perspective.

Figure 5: State Sex Trafficking Prevalence

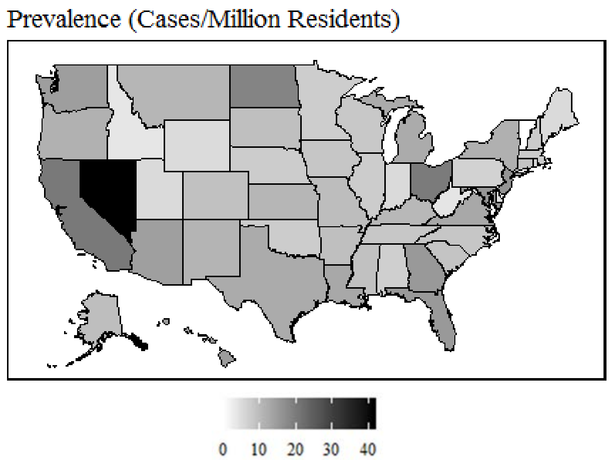


Figure 6: Shelters per Million Residents

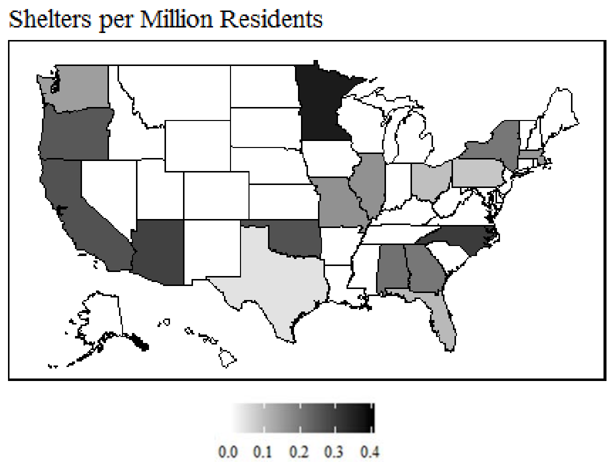
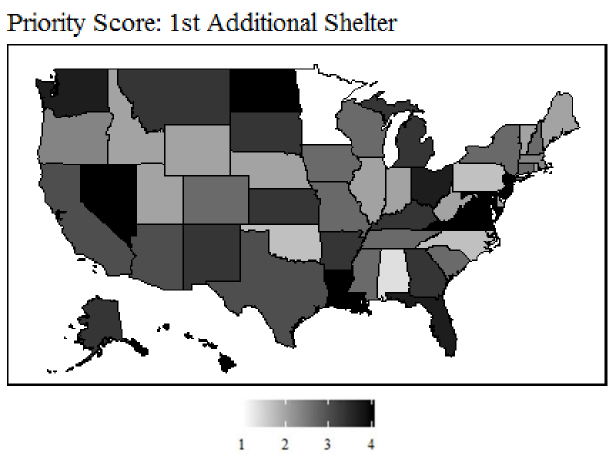


Figure 7: State Priority Score for Adding 1 Additional Shelter



6. Case Study: Results and Insights

We now present the results of our case study, a discussion on insights from varying model parameters, and a comparison of the outcomes of our optimization framework versus those of other prioritization schemes.

6.1 Summary of Sensitivity Parameters and Computational Environment

Because of the uncertainty regarding human trafficking data, we performed extensive sensitivity analyses around several key model parameters to determine their effect on the optimal budget allocation for shelter locations. *Table 2* summarizes the ranges of values used in our sensitivity analysis.

Table 2: Values of Parameters Varied in Sensitivity Analysis

Parameter	**Values Used in Sensitivity Analysis**
Budget	1M, 2M, 3M USD
Bed cost multiplier for large shelters	0.5, 0.75, 1, 1.25, 1.5
Length of stay (months)	12, 18, 24
Willingness to pay	20,000 USD
Proportion of DALYs Averted	0, 0.25, 0.5, 0.75, 1

This permutation of values resulted in 225 test instances of model (1) – (6). We used the Gurobi Optimizer (Gurobi, 2018) with Python 2.7 interface for the optimization modeling and solving. Each instance was generated and solved to global optimality within approximately 20 seconds.

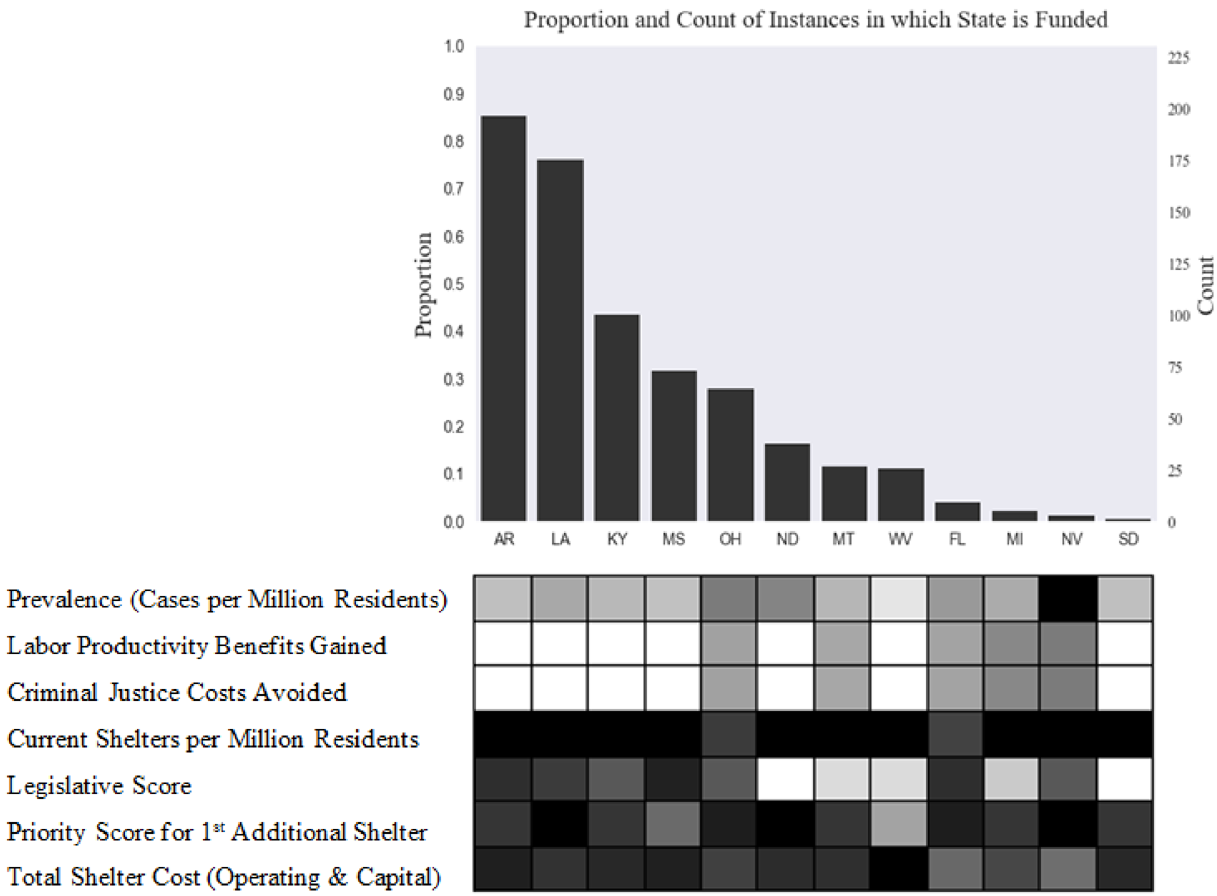
6.2 Sensitivity Analysis Insights

We now discuss sensitivity analysis insights, including the proportion of instances in which it is optimal to locate at least one shelter in state $i \in I$, how the optimal number and locations of shelters change as the parameters vary, and the effect of budget reductions on the optimal shelter locations.

6.2.1 States Appearing in Any Solution

Twelve unique states appear among the 225 optimal solutions. *Figure 8* illustrates the proportion of instances for which these unique states have at least one shelter (of any type) in the optimal solution. The heat map below the bar chart in *Figure 8* depicts various factors of the objective function – the darker the color, the more favorable that factor is for locating a shelter. For example, 192 out of the 225 instances located at least one shelter of any type in Arkansas. As indicated by the corresponding heat map gradations, Arkansas is a particularly desirable state in which to fund a shelter, as it currently does not have any shelters yet has a medium level of trafficking prevalence, low costs and an attractive legislative score.

Figure 8 Sensitivity Analysis Results; Darker Shades in the Heat Map Indicate Factors That are More Favorable for Locating Shelters



6.2.2 Comparison across Solution Instances (3D Plot Analysis)

Figures 9a–c correspond to low, medium, and high budget values (1M, 2M and 3M USD), respectively, and depict the space of optimal solutions by varying the length of stay, the large bed cost multiplier, and the product of willingness to pay and the proportion of DALYS averted through shelter services. This results in 75 solution instances for each figure. Solutions are described by the state abbreviation followed by the number of small and large shelters located. For example, “MS 1S, 0L | AR 1S, 0L” corresponds to locating one small shelter in Mississippi and one small shelter in Arkansas.

These figures illustrate that the optimal solution is very sensitive to the bed cost multiplier, and moderately sensitive to length of stay. The optimal solution tends to be especially sensitive to length of stay at lower values of the product of willingness to pay and proportion of DALYs averted, while stabilizing for higher values. Moreover, for fixed values of the large bed cost multiplier, there is stability when the product of willingness to pay and the proportion of DALYs averted varies from 5,000 to 20,000 USD, and across most values of length of stay.

There are 60 unique solutions among the 225 instances considered. When a unique solution appears more than once, it always appears in a contiguous manner – that is, adjacent to other appearances of that solution. While only 12 unique states appear among the 225 instances, no solution is optimal across all three of the budget levels. That said, the solution of locating one large shelter in Arkansas, and one of each type of shelter in Louisiana is common between the medium and high budget levels.

It is insightful to examine the least favorable scenario – having the lowest budget, highest length of stay, highest bed costs for large shelters, and no contribution to societal benefit for the product of willingness to pay and proportion of DALYs averted. Even in such a case, there is positive societal value in locating at least one shelter, as evidenced by the optimal solution of one large shelter in West Virginia (WV 0S, 1L). Stated another way, while the solution to “Do Nothing” is always feasible, *the societal benefits outweigh the costs when locating residential shelters even under the least favorable scenario* – resulting primarily from the favorable cost setting of West Virginia.

Figure 9a: Plot of Solutions as Parameter Values Vary for a 1M USD Budget

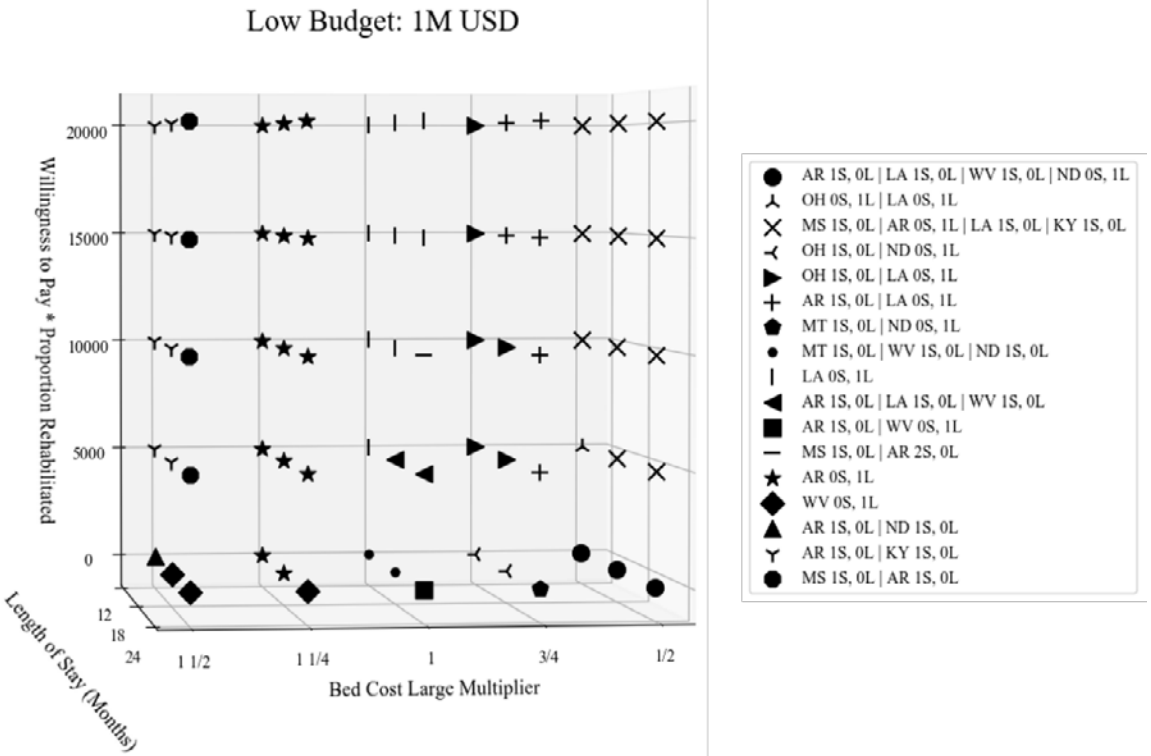


Figure 9b: Plot of Solutions as Parameter Values Vary for a 2M USD Budget

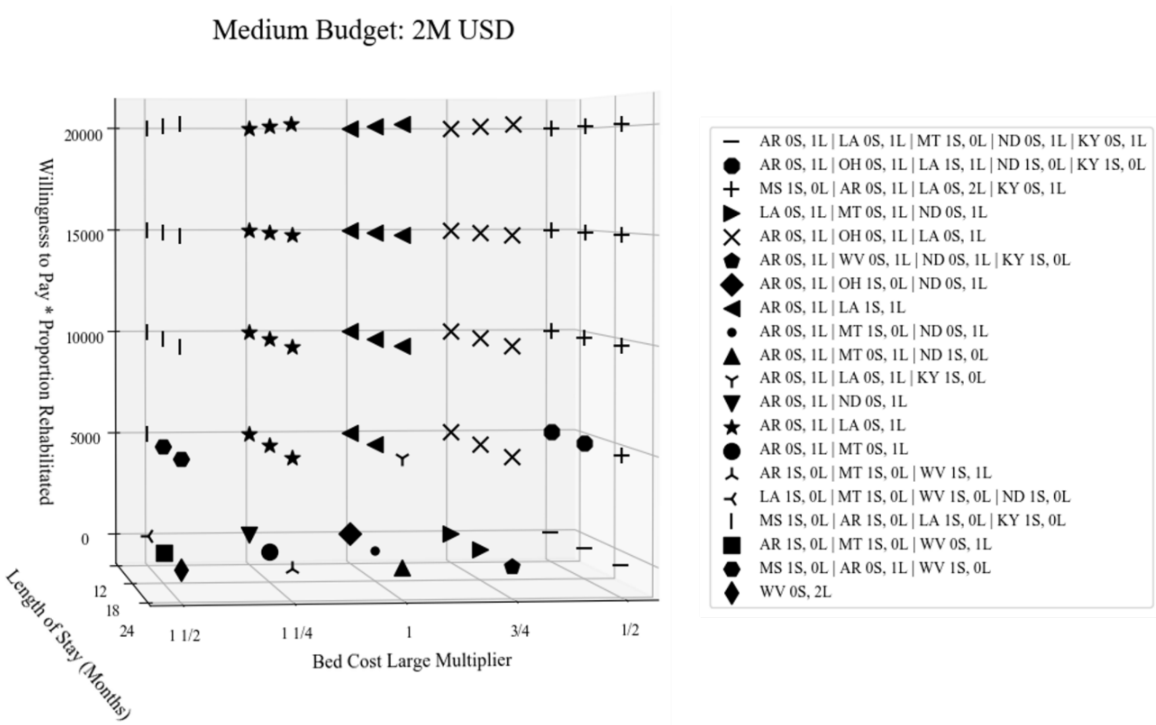
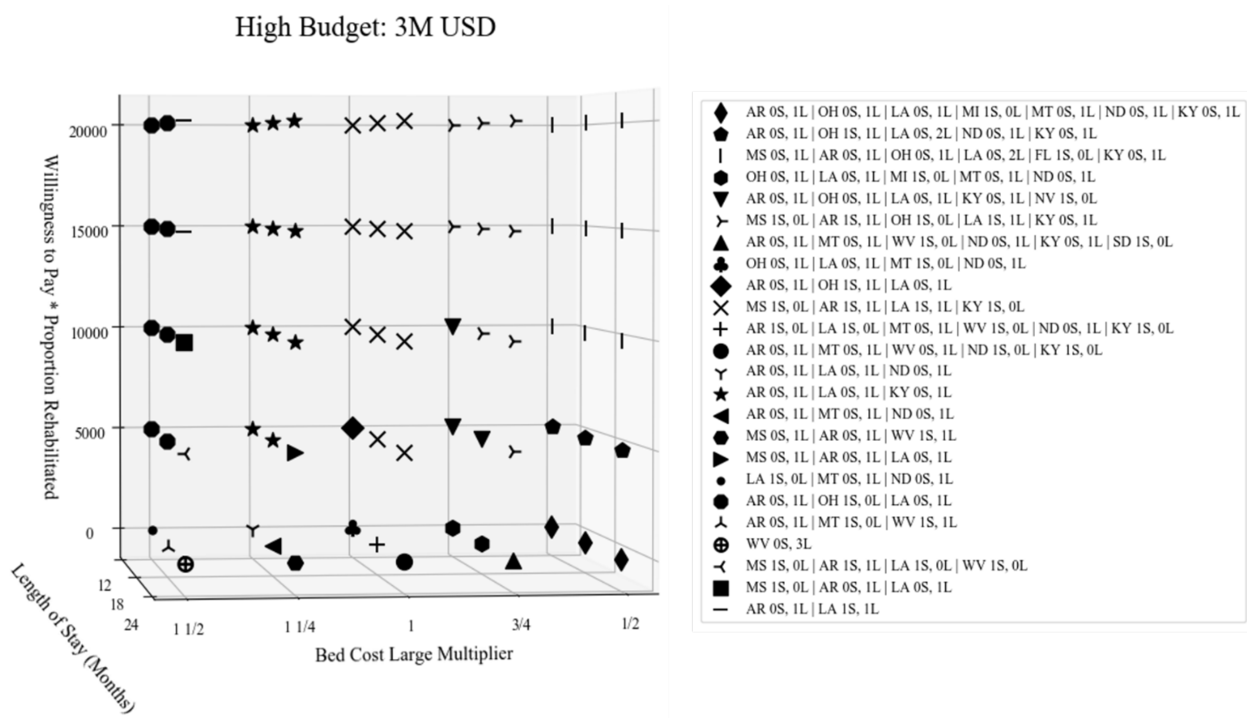


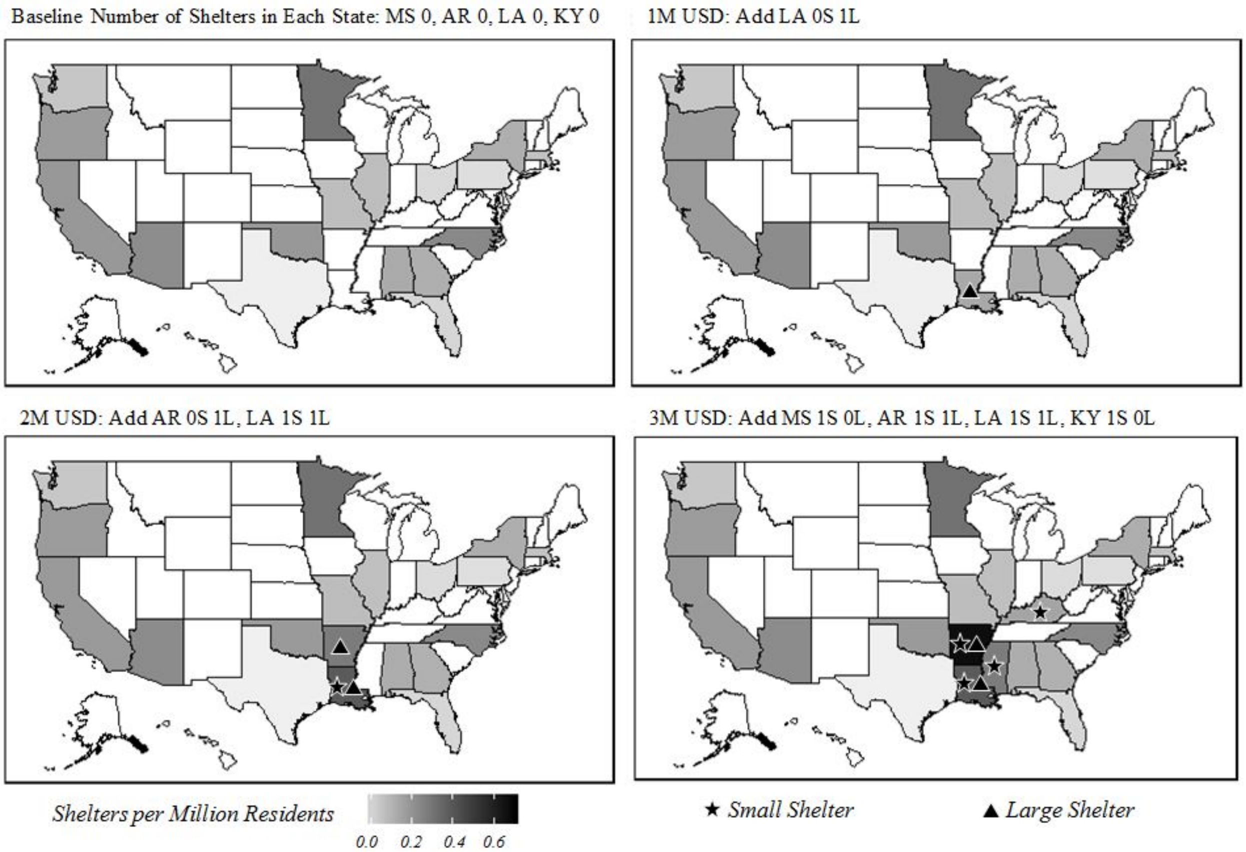
Figure 9c: Plot of Solutions as Parameter Values Vary for a 3M USD Budget



6.2.3 Effect of Budget Changes on Optimal Solutions

Of all the parameters considered in our sensitivity analysis, the optimal solution was the most sensitive to changes in the budget; regardless of other parameter values, increasing the budget across the 1M, 2M, and 3M USD budget values tends to expand upon the set of selected shelters.

Figure 10: Effect of Varying Budget on Optimal Solution (Large Bed Cost Multiplier $= \mathbf{1}$; $\forall \boldsymbol{t} \in \boldsymbol{T}$ $\boldsymbol{\delta_t}$*=0.5,* $\boldsymbol{l_t}$*=18,* $\boldsymbol{\omega^{Leg}}$*=20,000 USD)*



For example, while there are currently no shelters located in Mississippi, Arkansas, Louisiana, or Kentucky, it is optimal to locate at least one shelter in each of these states under a 3M USD budget (assuming a large bed cost multiplier, proportion of DALYs averted, length of stay, and base willingness to pay equal to 1, 0.5, 18 months, and 20,000 USD respectively; see *Figure 10)*. Six shelters are supported in this instance: Arkansas and Louisiana both receive one large and one small shelter, while Mississippi and Kentucky both receive one small shelter. If the budget is reduced to 2M USD, the small shelters in Arkansas, Mississippi, and Louisiana are forgone. Further budget reductions to 1M USD result in only a single large shelter being funded in Louisiana.

6.2.4 Policy Insights

To underscore the impact that optimization makes on determining the best budget allocation, we now compare an optimized outcome using the model presented in Section 3 versus the best solution that could be obtained by manual analysis according to a set of reasonable policies. In particular, we consider the manual policies specified in Table 3, which were identified in consultation with representatives from a non-profit that operates residential shelters for human trafficking survivors. When there is not enough room remaining in the budget for including an additional shelter in the state with the highest priority according to the respective manual policy, we allow for the next such state that fits within the budget to receive the shelter.

For the baseline scenario of 2M USD budget, length of stay of 18 months, large bed cost multiplier of 1 for large shelters, and product of willingness to pay and proportion of DALYs averted equaling 10,000 USD, we compute the solutions according to the policies specified in *Table 3*. We then evaluate the policy solutions by comparing their performance to the optimized solution from the model presented in Section 3 (top row of *Table 3*), which locates a single large shelter in Arkansas and both a large and small shelter in Louisiana, having an annual cost of 1,985,310 USD and a priority-weighted societal value of 16,737,762 USD.

Table 3: Comparing Societal Value of Optimized Solution versus Nine Manual Policy Solutions

Policy Framework	**Policy Solution**	**Societal Value (USD)**	**Loss in Societal Value (USD)**
Optimized Solution	***1L in AR, LA; 1S in LA***	***16.7M***	--
Lowest Cost Shelters	3S in WV, AR	9.4M	7.4M (44%)
Highest Prevalence, Small Shelters	3S in NV; 1S in OH	9.9M	6.9M (41%)
Highest Prevalence, Large Shelters	1L in NV, ND	11.1M	5.6M (34%)
Most Cases, Small Shelters	2S in CA; 1S in TX	5.5M	11.2M (67%)
Most Cases, Large Shelters	1L in CA	4M	12.7M (76%)
Highest Legislative Score, Small Shelters	3S in DE; 1S in MS	5.5M	11.3M (67%)
Highest Legislative Score, Large Shelters	1L in DE, WV	6.5M	10.2M (61%)
Highest Labor Productivity + Criminal Justice Costs Avoided, Small Shelters	3S in WA	8.5M	8.2M (49%)
Highest Labor Productivity + Criminal Justice Costs Avoided, Large Shelters	1L in WA, WV	10.4M	6.3M (38%)

Table 3 details the optimized solution from the model presented in Section 3 in the first row, followed by the best solution according to each of the nine policy frameworks. The associated societal values of these solutions are presented, as well as the absolute and percent loss in societal value when compared with the

optimized solution from the model presented in Section 3. While all manual policy solutions resulted in at least 34% less societal value, in some cases, more than 75% of the societal value is lost with a manual policy solution. This represents a great deal of unrealized societal value that decision-makers can access via optimization.

7. Concluding Remarks

The rapidly evolving space of combatting human trafficking is ripe for applications of operations research. However, we are not aware of other studies that use such techniques for allocating a budget to locate residential shelters for human trafficking survivors. To address this gap, we represent the challenge of determining where to locate additional shelters as a nonlinear integer optimization model. In the context of locating shelters in the United States, we define a measure of societal benefit that integrates disparate factors such as trafficking prevalence, available bed supply, annual capital and operating costs, labor productivity gained, criminal justice costs averted, and the societal willingness to pay for health benefits. Through a careful variable definition, we allow a priori computing of the societal value for each combination of shelters funded at each location. This approach allows for locating residential shelters in states in a manner that both respects budgets and maximizes societal value. While we use a case study aimed at allocating a federal funding agency's budget to serve as an illustration, the same model could be employed from the perspective of national non-profit organizations that operate multiple shelters across the country. Overall, our study represents an innovative use of optimization to address a budget allocation problem with a broader societal impact, and we show that significant additional societal value can be realized in this severely resource-constrained environment.

Through a sensitivity analysis on key model parameters, we demonstrate that, even in the least favorable scenario, there is inherent societal value in actively placing at least one shelter. Moreover, it is worthwhile to consider the assumptions made in our case study underlying the societal willingness to pay. It has been suggested that "programs in the U.S. that cost less than 50,000 USD per QALY gained are usually considered cost effective; programs that cost 50,000 to 100,000 USD per QALY gained are sometimes considered cost effective; and programs that cost more than 100,000 USD per QALY gained are not usually considered cost effective" (Brandeau & Zaric, 2009; Owens, 1998). Moreover, a *rough* conversion from QALY to DALY is DALY / 1.5 = QALY (Sassi, 2006). This implies that programs costing less than 75,000 USD, between 75,000 – 150,000 USD, and more than 150,000 USD per DALY are, respectively, usually, sometimes, and not usually considered cost effective. Thus, even with the fairly modest 20,000 USD willingness to pay per DALY averted used in this study, there exists a compelling case that our optimization approach creates significant societal value.

However, there are limitations to using the aforementioned sources as proxy values. Notably, the number of cases reported to the NHTH is likely a factor of how widely disseminated the hotline number is and individuals' willingness to call. It is therefore not intended to represent the full scope of human trafficking. Additionally, each case reported to the NHTH may involve multiple survivors, and a single survivor may call the hotline multiple times.

Residential shelters also differ from one another in a variety of ways, such as the extent of service provided, shelter capacity, maximum length of stay, and survivor eligibility criteria. Our model does not account for these differences at a detailed level, largely due to challenges obtaining robust, complete, and timely data, a phenomenon which has been previously described in the human trafficking literature (Konrad et al. 2017). Although we have attempted to compile the most recent list of residential shelters for human trafficking survivors, it is likely that our list is not exhaustive. Furthermore, a number of human trafficking shelters do not openly disclose their location as a safeguard to prevent traffickers from finding the location of survivors.

Certainly, entities operating human trafficking shelters consider additional factors that are not included in our modeling approach – such as the presence of a network of auxiliary service providers specializing in caring for human trafficking survivors, the availability of in-kind building donations, and the number of dedicated human trafficking shelter beds (rather than the number of shelters) in a region – when deciding where to locate a shelter. Given the data-scarce context, we believe that the factors represented in our model represent a realistic effort toward accurately characterizing the relative need for shelter services across the 50 states. As stated before, the results of and sensitivity analysis surrounding our model are not intended to serve as the final decision regarding the optimal allocation of shelters; rather, they are recommendations that can augment the decision-making process for entities involved in shelter location decisions.

While this project focuses specifically on locating residential shelters for survivors of sex trafficking within the United States, it could be tailored to shelters in other countries to incorporate geographical and cultural nuances provided the necessary data inputs are available. Another obvious extension would be to consider the location of other types of entities which incur capital and operating costs, yet provide difficult-to-quantify societal benefit, such as shelters for individuals seeking asylum and survivors of labor trafficking or domestic violence. The model and solution approach could also be adapted to support decision-making for location analysis problems in which there is benefit to society at large, despite aspects of the facility that are undesirable to the immediate neighborhood—such as prisons or addiction treatment facilities. While we have yet to do so, our optimization approach could be embedded in a decision-support tool to further facilitate the decision-making process.

In conclusion, this study provides preliminary evidence for the value of incorporating additional metrics of societal benefit into humanitarian operations research problems and proposes a deeper analysis of preferences and societal benefits as possible extensions to this work. Our approach also provides value to governmental and nonprofit decision-makers, as it offers a means to effectively allocate scarce resources, and enables sensitivity analyses to examine the effect of small changes in the budget on the optimal allocation of shelters.

Acknowledgements

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Appendix A: State Dependent Parameters

Table AI: State-dependent Costs and Benefits (USD)

State	Annual Capital Costs: Small Shelter	Annual Capital Costs: Large Shelter	Annual Cost Per Bed (Small Shelter)	Labor Productivity Gained + Criminal Justice Costs Avoided	Willingness to Pay
Alabama	38,173	82,058	3,848	154,976	19,632
Alaska	66,145	142,189	93,308	165,664	14,724
Arizona	48,531	104,325	68,460	168,870	12,270
Arkansas	35,386	76,068	49,917	154,976	25,767
California	73,559	158,126	103,766	192,383	22,086
Colorado	59,994	128,965	84,630	171,008	19,632
Connecticut	72,087	154,961	101,689	185,971	26,994
Delaware	57,470	123,540	81,069	165,664	29,448
Florida	51,108	109,863	72,095	169,511	25,767
Georgia	48,952	105,229	69,054	154,976	19,632
Hawaii	78,291	168,299	110,441	154,976	22,086
Idaho	42,432	91,214	59,856	154,976	14,724
Illinois	54,210	116,532	76,471	176,351	22,086
Indiana	42,011	90,309	59,263	154,976	19,632
Iowa	41,170	88,501	58,076	154,976	15,951
Kansas	43,694	93,926	61,636	154,976	23,313
Kentucky	37,437	80,476	52,810	154,976	22,086
Louisiana	39,698	85,336	55,999	154,976	24,540
Maine	45,482	97,769	64,158	160,320	12,270
Maryland	73,875	158,804	104,211	154,976	17,178
Massachusetts	70,562	151,684	99,538	171,008	24,540
Michigan	44,325	95,283	62,526	174,214	13,497
Minnesota	52,264	112,350	73,726	171,008	24,540
Mississippi	35,649	76,633	50,288	154,976	26,994
Missouri	42,379	91,101	59,782	160,320	17,178
Montana	39,119	84,093	55,183	168,870	12,270
Nebraska	43,378	93,248	61,191	154,976	22,086
Nevada	52,264	112,350	73,726	176,351	22,086
New Hampshire	64,621	138,911	91,157	154,976	18,405
New Jersey	77,923	167,507	109,922	176,351	29,448
New Mexico	40,539	87,145	57,186	160,320	19,632
New York	64,673	139,024	91,231	171,008	17,178
North Carolina	44,745	96,187	63,120	154,976	24,540
North Dakota	38,541	82,850	54,368	154,976	9,816
Ohio	42,958	92,344	60,598	169,939	22,086
Oklahoma	39,119	84,093	55,183	154,976	19,632
Oregon	52,895	113,706	74,616	194,521	19,632
Pennsylvania	47,953	103,082	67,644	154,976	22,086
Rhode Island	59,100	127,043	83,369	171,008	12,270
South Carolina	41,486	89,179	58,521	154,976	22,086
South Dakota	37,489	80,589	52,884	154,976	9,816
Tennessee	41,486	89,179	58,521	154,976	23,313
Texas	49,057	105,455	69,202	154,976	24,540
Utah	53,842	115,741	75,951	154,976	19,632
Vermont	55,629	119,584	78,473	186,612	22,086
Virginia	62,255	133,825	87,819	154,976	17,178
Washington	60,782	130,660	85,742	199,224	29,448
West Virginia	29,708	63,861	41,907	154,976	12,270
Wisconsin	47,374	101,838	66,828	154,976	17,178
Wyoming	43,694	93,926	61,636	154,976	14,724

Table AII: State Factors

State	Population	Cases[α]	Prevalence	Current Shelters	Current Shelters per Million Residents	Polaris Legislative Score
Alabama	4,858,979	34	7.00	1	0.21	8
Alaska	738,432	7	9.48	0	0.00	6
Arizona	6,828,065	97	14.21	2	0.29	5
Arkansas	2,978,204	28	9.40	0	0.00	10.5
California	39,144,818	792	20.23	10	0.26	9
Colorado	5,456,574	49	8.98	0	0.00	8
Connecticut	3,590,886	31	8.63	0	0.00	11
Delaware	945,934	4	4.23	0	0.00	12
Florida	20,271,272	308	15.19	2	0.10	10.5
Georgia	10,214,860	154	15.08	2	0.20	8
Hawaii	1,431,603	21	14.67	0	0.00	9
Idaho	1,654,930	6	3.63	0	0.00	6
Illinois	12,859,995	95	7.39	2	0.16	9
Indiana	6,619,680	35	5.29	0	0.00	8
Iowa	3,123,899	26	8.32	0	0.00	6.5
Kansas	2,911,641	31	10.65	0	0.00	9.5
Kentucky	4,425,092	46	10.40	0	0.00	9
Louisiana	4,670,724	60	12.85	0	0.00	10
Maine	1,329,328	7	5.27	0	0.00	5
Maryland	6,006,401	94	15.65	0	0.00	7
Massachusetts	6,794,422	51	7.51	1	0.15	10
Michigan	9,922,576	123	12.40	0	0.00	5.5
Minnesota	5,489,594	40	7.29	2	0.36	10
Mississippi	2,992,333	27	9.02	0	0.00	11
Missouri	6,083,672	59	9.70	1	0.16	7
Montana	1,032,949	11	10.65	0	0.00	5
Nebraska	1,896,190	14	7.38	0	0.00	9
Nevada	2,890,845	119	41.16	0	0.00	9
New Hampshire	1,330,608	10	7.52	0	0.00	7.5
New Jersey	8,958,013	142	15.85	0	0.00	12
New Mexico	2,085,109	23	11.03	0	0.00	8
New York	19,795,791	229	11.57	4	0.20	7
North Carolina	10,042,802	83	8.26	3	0.30	10
North Dakota	756,927	14	18.50	0	0.00	4
Ohio	11,613,423	232	19.98	1	0.09	9
Oklahoma	3,911,338	29	7.41	1	0.26	8
Oregon	4,028,977	46	11.42	1	0.25	8
Pennsylvania	12,802,503	83	6.48	1	0.08	9
Rhode Island	1,056,298	6	5.68	0	0.00	5
South Carolina	4,896,146	42	8.58	0	0.00	9
South Dakota	858,469	8	9.32	0	0.00	4
Tennessee	6,600,299	54	8.18	0	0.00	9.5
Texas	27,469,114	338	12.30	1	0.04	10
Utah	2,995,919	16	5.34	0	0.00	8
Vermont	626,042	0	0.00	0	0.00	9
Virginia	8,382,993	107	12.76	0	0.00	7
Washington	7,170,351	103	14.36	1	0.14	12
West Virginia	1,844,128	7	3.80	0	0.00	5
Wisconsin	5,771,337	46	7.97	0	0.00	7
Wyoming	586,107	3	5.12	0	0.00	6

[α] 2015 calls to the National Human Trafficking Hotline evaluated as potential cases of human sex trafficking

Appendix B: DALYs Averted Calculation

For each health condition, we calculate DALYs according to the method proposed by Murray and Lopez (1996a), where we first calculate YLD followed by YLL. Let y represent the number of years a trafficking survivor would be expected to live with the health condition, a^{onset} represent the age of onset of the health condition, and d represent the disability weight associated with the health condition. Additionally, let parameters $r = 0.03$, k =1, $\beta = 0.04$, and c =0.1658 represent the recommended base case values for the discount rate, age-weighting factor, parameter from the age weighting function, and constant, respectively (Murray & Lopez, 1996b, 1996a). With this notation, the YLD is calculated using the equation:

$$YLD = d\left(\frac{kce^{ra^{onset}}}{(r+\beta)^2}\left(e^{-(r+\beta)(y+a^{onset})}(-(r+\beta)(y+a^{onset})-1)\right.\right.$$
$$\left.\left.-e^{-(r+\beta)a^{onset}}(-(r+\beta)a^{onset}-1)\right)+\frac{1-k}{r}(1-e^{-ry})\right)$$

While the YDL focuses on the time from onset to death with the health condition, the YLL calculation considers the time from the health condition-induced death to the age at which the survivor would have been expected to live if the health condition was not present. Letting $a = y + a^{onset}$ denote the expected age of death with the health condition and l_a represent the non-disease burdened life expectancy at a, YLL is calculated by substituting l_a for y and a for a^{onset}in the YLD formula and dividing by d:

$$YLL = \left(\frac{kce^{ra}}{(r+\beta)^2}\left(e^{-(r+\beta)(l_a+a)}(-(r+\beta)(l_a+a)-1)-e^{-(r+\beta)a}(-(r+\beta)a-1)\right)\right.$$
$$\left.+\frac{1-k}{r}\left(1-e^{-rl_a}\right)\right)$$

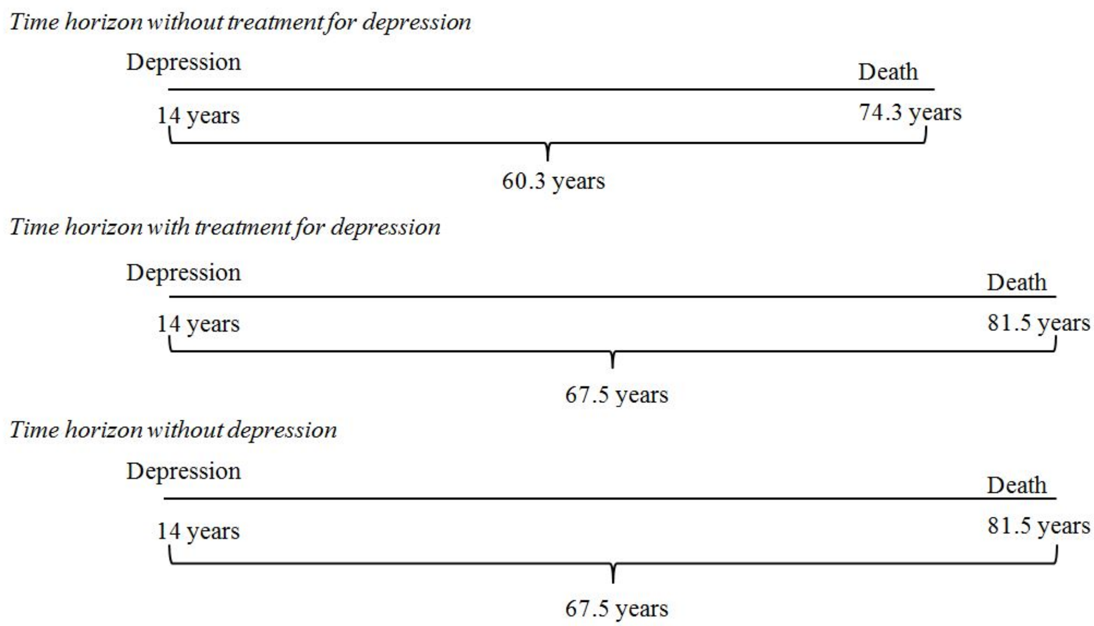
Although there is no definitive scholarly evidence regarding the average age of entry into sex trafficking in the U.S., many studies suggest the average age is 14 years old (Martin et al. 2010; Martin and Lotspeich 2014). Thus, to illustrate the calculations for the amount of DALYs averted by providing trafficking survivors access to healthcare services while in a shelter, suppose a trafficking survivor developed depression (i.e., major depressive disorder, moderate episode) at age 14.

Studies estimate that females who do not receive treatment for moderate episodic major depressive disorder have a decreased life expectancy of 7.2 years compared to the general population[4] (C. K. Chang et al., 2011). However, mild episodic major depressive disorder has no elevated risk of mortality compared to the general population (Ferrari et al., 2013). Thus, treating depression to at least the level of mild episodes results in a life expectancy of 67.5 additional years at the age of 14 (Arias, 2014). The expected time horizons for this trafficking survivor are shown in *Figure A1*.

We use three steps to calculate the total DALYs averted by treating the depression of a survivor while receiving shelter services. We begin by calculating the total DALYS lost due to untreated depression and then calculate the total DALYs lost due to treated depression. The difference in these two values signifies the DALYs averted by treating the depression.

[4] The study reports a decrease of 7.2 years in life expectancy from birth as compared to the general female United Kingdom population. While the DALY calculation would ideally incorporate the age-adjusted decrease in life expectancy, we assume the decrease in life expectancy at age 14 due to moderate episodic major depressive disorder is also 7.2 years due to limited age-adjusted data.

Figure B1: Illustrative Example of Time Horizon for Survivor with Depression



<u>Step 1: DALYs Lost Due to Untreated Depression</u>

The YLD calculation considers the 60.3 years the survivor lives with moderate episodic major depressive disorder if no treatment is provided (years 14 to 74.3). Using the values a^{onset} =14, y =60.3, and $d =$ 0.396 (major depressive disorder, moderate episode; Global Burden of Disease Study 2015 (2016)), along with $r =$ 0.03, k =1, $\beta =$ 0.04, and c =0.1658 as previously stated, we calculate $YLD(14) =$ 14.46.

YLL considers the years between the expected age of death without treatment to the age at which the survivor would have been expected to live without having experienced depression (years 74.3 to 81.5). As the survivor would have been expected to live to the age of 81.5, the remaining life expectancy at age a =74.3 is l_a =7.2. Thus, $YLL(74.3) =$ 3.73 from age 74.3 onward.

Next, we need to convert the YLL to the age of onset so that YLL and YDL have a common reference age when added together. Fox-Rushby and Hanson (2001) provide

$$YLL(a^{onset}) = YLL(a)e^{-r(a-a^{onset})}$$

as a conversion which gives YLL(14)=0.61. Thus, the total number of DALYs lost due to untreated depression is $DALYs^{Untreated} = YLL^{Untreated}\,(14) + YDL^{Untreated}\,(14) = 15.07$.

Step 2: DALYs Lost Due to Treated Depression

Now suppose the trafficking survivor received treatment for moderate episodic major depressive disorder at age 14 (the time of onset), and instead of dying at age 74.3, lives for the expected 81.5 year lifespan of someone who has received treatment. If we assume that the shelter provides treatment for the depression to the extent that it reduces its severity from a moderate (d =0.396) to mild (d =0.145; Global Burden of Disease Study 2015 (2016)) episode of major depressive disorder, the YLD calculation with $a^{onset} = 14, d = 0.145,$ and $y = 67.5$ gives $YLD^{Treated}(14)=5.38$. As mild episodic major depressive disorder does not reduce life expectancy as compared to the general population, $DALYs^{Treated} = YLD^{Treated}(14) = 5.38$

Step 3: DALYs Averted by Treating Depression

Thus, the number of DALYs averted by providing treatment for the depression is $DALYs^{Untreated} - DALYs^{Treated} = 15.07 - 5.38 = 9.69$.

Other Health Concerns

In addition to depression, human trafficking survivors can also experience a number of health concerns, including substance abuse, anxiety and PTSD (Abas et al., 2013; Lederer & Wetzel, 2014; Oram, Stöckl, Busza, Howard, & Zimmerman, 2012). These health concerns can manifest singularly or as comorbid conditions. In fact, one study found that over half of the sex trafficked women and girls participating in the study had comorbid depression, anxiety, and PTSD (Hossain et al., 2010). However, PTSD is commonly assumed to be contained within anxiety-related disability weights and DALY calculations due to the high prevalence of comorbidity and similarity to other anxiety related health concerns (Begg et al., 2007; Hossain et al., 2010). Thus, we seek to determine the DALYs averted for a survivor with comorbid depression, substance abuse, and anxiety.

As the 2015 Global Burden of Disease disability weights represent singular health conditions, we estimate disability weights for individuals with n multiple conditions using the approach described in Mathers et al., (2017):

$$d_{1:n} = 1 - (1 - d_1) * (1 - d_2) \cdots (1 - d_n).$$

The total decreased life expectancy for comorbid conditions was taken to be the maximum of the life expectancy reductions across the individual comorbid conditions. For example, as untreated depression or anxiety is associated with an expected 7.2 year reduction in life expectancy and untreated substance abuse is associated with an expected 14.7 year reduction (C.-K. Chang et al., 2011; Saarni et al., 2007), we assume comorbid untreated depression, anxiety, and substance abuse results in an expected 14.7 year reduction in life expectancy (*Table AI*).

Using the standard $r = 0.03$, $k = 1$, $\beta = 0.04$, $c = 0.1658$, and non-disease burdened age-adjusted life expectancies for females in the U.S. (Arias, 2014), treating a 14 year old survivor for comorbid depression, anxiety, and substance abuse will avert d_t =11.02 DALYs.

However, to account for the reality that survivors may have physical and mental health concerns that persist even after receiving treatment through the shelter and that the health concerns of survivors differ, we moderate d_t by $\delta_t^{DALYs} \in [0,1]$, resulting in only a proportion of the 11.02 DALYs may be averted.

Table BI: Life Expectancy Reductions and Disability Weights for Common Trafficking Related Health

Conditions

Health Condition	Decreased Life Expectancy (Years)		Disability Weight[5]		Description of Disability Weight	
	Untreated	Treated	Untreated	Treated	Untreated	Treated
Depression	7.2[6]	0.0[7]	0.396	0.145	Major depressive disorder, moderate episode	Major depressive disorder, mild episode
Substance Abuse[8]	14.7[9]	13.3[10]	0.373	0.235	Alcohol use disorder, moderate	Alcohol use disorder, mild
Anxiety	7.2[11]	0.0	0.133	0.030	Anxiety disorders, moderate	Anxiety disorders, mild
Depression, Substance Abuse, & Anxiety	14.7	13.3	0.672	0.273	---	---

[5] Disability weights for singular health conditions are reported directly from Institute for Health Metrics and Evaluation (2016) and are used to calculate comorbid disability weights

[6] Chang et al. (2011)

[7] Ferrari et al. (2013)

[8] As there are no disability weights associated with the collective "substance abuse" health condition, we assume the untreated and treated states correspond to moderate and very mild alcohol use disorders, respectively. While disability weights for amphetamine dependence and opioid dependence can also be classified under the "substance abuse" category, their disability weights are, respectively, less than and greater than the disability weights for alcohol use disorders. We therefore use the alcohol use disorder disability weights as an approximation.

[9] Calculated from point estimate for substance use disorder life expectancy reported in Chang et al. (2011)

[10] Calculated form upper limit on the 95% confidence interval for substance use disorder life expectancy reported in Chang et al. (2011)

[11]The 2013 review by Ferrari et al. indicates a lack of mortality data for anxiety disorders. Additionally, Saarni et al. (2007) finds that the burden of anxiety disorders is close to the burden of depressive disorders. As such, we estimate the decreased life expectancy attributable to anxiety disorders to be the same as that of depression.

***Appendix C*: Calculating State Priority Score**

We assign the prioritization score of each state based on a ranking system of its human trafficking prevalence and number of shelters per million residents. The prevalence of each state was ranked using quartiles (*Table BIII*). However, because our optimization model allows multiple shelters of various types to be funded per state, additional steps are needed when calculating the score for the number of shelters per state.

We begin by calculating the number of shelters per million residents that would be located in state $i \in I$ if $S_{Large} \in \{\underline{m}_{i,Large}, \dots, \overline{m}_{i,Large}\}$ additional large shelters were to be funded, given the total number of shelters currently located in state i (regardless of size). For each additional shelter $s \in \{0, \dots, S_{Large}\}$, we subsequently assign a ranking based on the number of shelters that would be present per million residents once the s^{th} additional large shelter is funded (*Table BIII*). Because approximately two-thirds of states did not have any shelters in 2014, we assign the highest shelter priority score to states with no shelters, and ranked the remaining states according to the nonzero tertiles of the current number of shelters per million residents.

Let r_i^{Prev} represent the prioritization ranking of the prevalence category for state $i \in I$. Also, let $r_{is}^{Shelter}$ represent the ranking of the number of shelters per million residents prior to the s^{th} additional large shelter being funded in state i. Parameters ω^{Prev} and $\omega^{Shelter}$, such that $\omega^{Prev} + \omega^{Shelter} = 1$, represent the respective prioritization weights of the factors. We then aggregate these two factors to generate a marginal weighted priority score for funding the s^{th} additional large shelter in state i:

$$a_i^s = \omega^{Prev} r_i^{Prev} + \omega^{Shelter} r_{is}^{Shelter}.$$

We sum these individual scores to obtain the total weighted priority score of funding S_{Large} additional large shelters in state i:

$$a_{i,Large}^{S_{Large}} = \sum_{s=0}^{S_{Large}} a_i^s.$$

A similar approach is used to calculate the weighted priority score for small shelters. However, whereas the calculation for the large shelters disregarded the number of additional small shelters funded in each state, the calculation for the small shelters accounts for the number of additional large shelters funded. This is because the total weighted priority score is a nonincreasing function in the number of shelters per million residents, and we assume that large shelters contribute a higher priority score than small shelters.

Hence, we calculate the number of shelters per million residents that would be located in state $i \in I$ if $S_{Small} \in \{\underline{m}_{i,Small}, \dots, \overline{m}_{i,Small}\}$ additional small shelters were to be funded in state i, given S_{Large} additional large shelters would also be funded in i. The corresponding total weighted priority score for funding S_{Small} small additional shelters at i is:

$$a_{i,Small}^{S_{Small}} = \begin{cases} 0 & if \;\; S_{Small} = 0 \\ \sum_{s=S_{Large}+1}^{S_{Large}+S_{Small}} a_i^s & if \;\; S_{Small} \geq 1 \end{cases}$$

Then, $a_i^{[S_{Small}, S_{Large}]} = a_{i,Small}^{S_{Small}} + a_{i,Large}^{S_{Large}}$.

Table BIII: Prevalence and Number of Shelters Categorizations

Prevalence (# of Hotline Cases per Million Residents)		**Shelters per Million Residents**	
Quartile	Ranking (r_i^{Prev})	Quartile	Ranking ($r_{is}^{Shelter}$)
[0,7.38)	1	[0, 0]	4
[7.38,9.17)	2	(0,0.15)	3
[9.17,12.67)	3	[0.15,0.23)	2
[12.67,41.16]	4	[0.23,0.36]	1

Using priority weights $\{\omega^{Prev}, \omega^{Shelter}\} = \{0.67, 0.33\}$ we obtain the aggregated state priority scores of locating $[S_{Small}, S_{Large}]$ additional shelters. As an example, suppose we wish to calculate the aggregated priority scores corresponding to locating 2 large shelters and 1 small shelter in Florida. Florida had 15.19 cases of sex trafficking per million residents reported to the hotline and 2 shelters (which corresponds to 0.10 shelters per million residents). The prevalence corresponds to $r_{FL}^{Prev} = 4$, while the first additional large shelter receives a rank of $r_{FL,1}^{Shelter} = 3$ because the state currently has 0.10 shelters per million residents. After funding the first additional shelter, the total number of shelters in the state increases to $3 \,/\, 20.271272 = 0.148$ shelters per million residents. Thus, the second additional large shelter also receives a rank of $r_{FL,2}^{Shelter} = 3$ and increases the total number of shelters in the state to $4 \,/\, 20.271272 = 0.20$ shelters per million residents. As a result, the additional small shelter (which is the third additional shelter considered) receives a rank of $r_{FL,3}^{Shelter} = 2$.

Hence,

$$a_{FL}^1 = 0.67 * 4 + 0.33 * 3 = 3.67, \qquad a_{FL}^2 = 0.67 * 4 + 0.33 * 3 = 3.67,$$

$$a_{FL}^3 = 0.67 * 4 + 0.33 * 2 = 3.34$$

and

$$a_{FL,Large}^2 = a_{FL}^1 + a_{FL}^2 = 3.67 + 3.67 = 7.34, \qquad a_{FL,Small}^1 = a_{FL}^3 = 3.34$$

which results in $a_{FL}^{[1,2]} = 7.34 + 3.34 = 10.68$.

Figure C1: Individual and cumulative state priority scores for funding 1 – 3 additional shelters

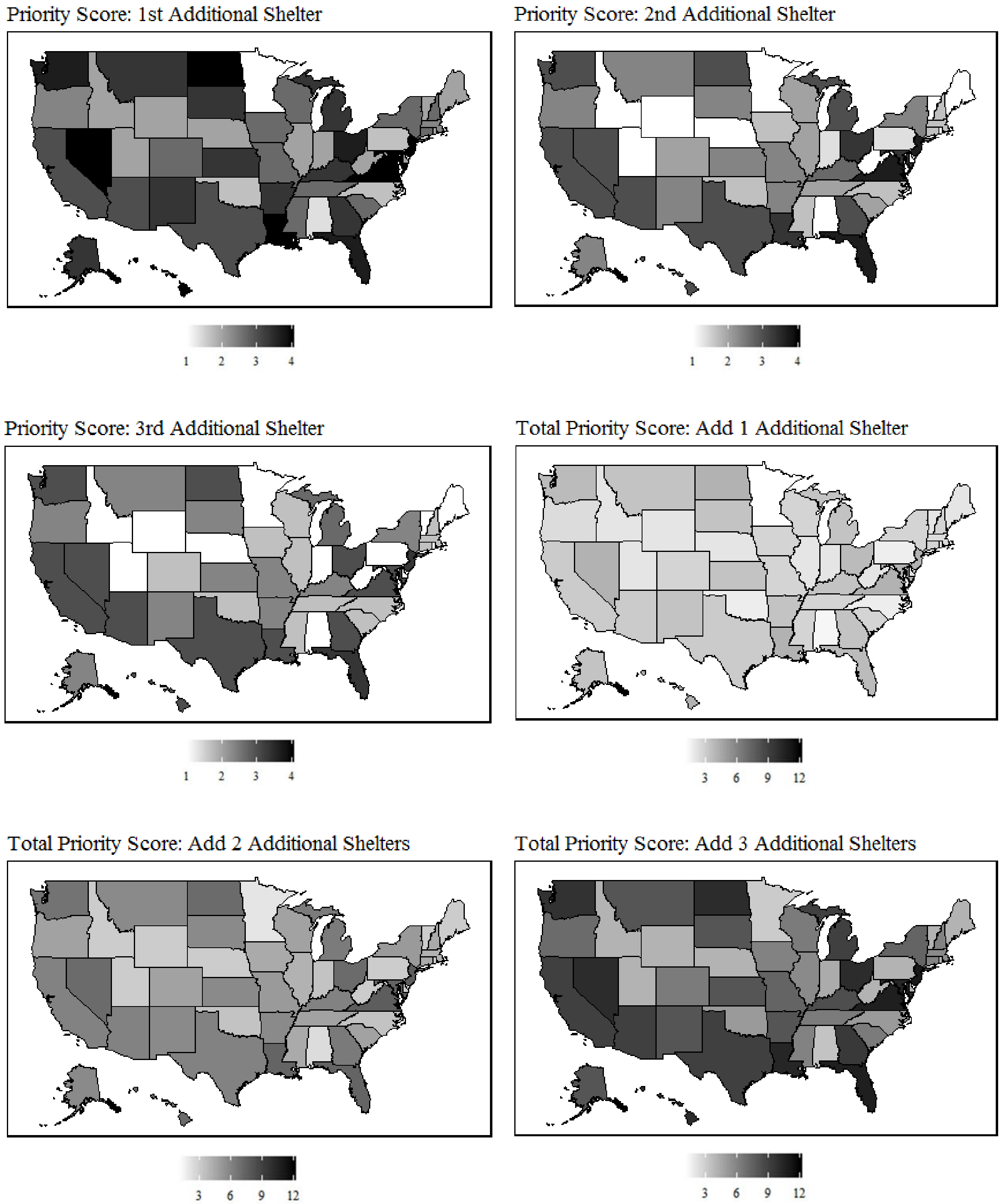


Table CI: Priority Score a_i^s of Funding the s^{th} Additional Shelter in State $i \in I$; {0.67,0.33}

State	a_i^1	a_i^2	a_i^3	a_i^4	a_i^5	a_i^6	a_i^7
Alabama	1.33	1.00	1.00	1.00	1.00	1.00	1.00
Alaska	3.33	2.33	2.33	2.33	2.33	2.33	2.33
Arizona	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Arkansas	3.33	2.33	2.33	2.33	2.33	2.33	2.33
California	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Colorado	2.67	2.00	1.67	1.67	1.67	1.67	1.67
Connecticut	2.67	1.67	1.67	1.67	1.67	1.67	1.67
Delaware	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Florida	3.67	3.67	3.33	3.00	3.00	3.00	3.00
Georgia	3.33	3.00	3.00	3.00	3.00	3.00	3.00
Hawaii	4.00	3.00	3.00	3.00	3.00	3.00	3.00
Idaho	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Illinois	2.00	2.00	1.67	1.67	1.67	1.67	1.67
Indiana	2.00	1.33	1.00	1.00	1.00	1.00	1.00
Iowa	2.67	1.67	1.67	1.67	1.67	1.67	1.67
Kansas	3.33	2.33	2.33	2.33	2.33	2.33	2.33
Kentucky	3.33	2.67	2.33	2.33	2.33	2.33	2.33
Louisiana	4.00	3.33	3.00	3.00	3.00	3.00	3.00
Maine	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Maryland	4.00	3.33	3.00	3.00	3.00	3.00	3.00
Massachusetts	2.33	1.67	1.67	1.67	1.67	1.67	1.67
Michigan	3.33	3.00	2.67	2.33	2.33	2.33	2.33
Minnesota	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mississippi	2.67	1.67	1.67	1.67	1.67	1.67	1.67
Missouri	2.67	2.33	2.33	2.33	2.33	2.33	2.33
Montana	3.33	2.33	2.33	2.33	2.33	2.33	2.33
Nebraska	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Nevada	4.00	3.00	3.00	3.00	3.00	3.00	3.00
New Hampshire	2.67	1.67	1.67	1.67	1.67	1.67	1.67
New Jersey	4.00	3.67	3.33	3.00	3.00	3.00	3.00
New Mexico	3.33	2.33	2.33	2.33	2.33	2.33	2.33
New York	2.67	2.33	2.33	2.33	2.33	2.33	2.33
North Carolina	1.67	1.67	1.67	1.67	1.67	1.67	1.67
North Dakota	4.00	3.00	3.00	3.00	3.00	3.00	3.00
Ohio	3.67	3.33	3.00	3.00	3.00	3.00	3.00
Oklahoma	1.67	1.67	1.67	1.67	1.67	1.67	1.67
Oregon	2.33	2.33	2.33	2.33	2.33	2.33	2.33
Pennsylvania	1.67	1.33	1.00	1.00	1.00	1.00	1.00
Rhode Island	2.00	1.00	1.00	1.00	1.00	1.00	1.00
South Carolina	2.67	2.00	1.67	1.67	1.67	1.67	1.67
South Dakota	3.33	2.33	2.33	2.33	2.33	2.33	2.33
Tennessee	2.67	2.00	1.67	1.67	1.67	1.67	1.67
Texas	3.00	3.00	3.00	3.00	2.67	2.67	2.33
Utah	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Vermont	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Virginia	4.00	3.67	3.00	3.00	3.00	3.00	3.00
Washington	3.67	3.00	3.00	3.00	3.00	3.00	3.00
West Virginia	2.00	1.00	1.00	1.00	1.00	1.00	1.00
Wisconsin	2.67	2.00	1.67	1.67	1.67	1.67	1.67
Wyoming	2.00	1.00	1.00	1.00	1.00	1.00	1.00