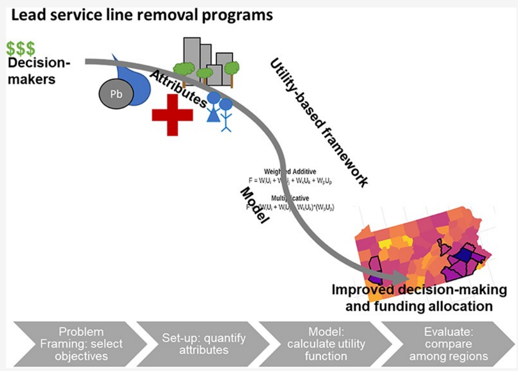
ACS ES&T Engineering
pubs.acs.org/estengg
Article

Improved Decision-Making: A Sociotechnical Utility-Based Framework for Drinking Water Investment

Sara E. Schwetschenau,* Alyssa Schubert, Richard J. Smith, Seth Guikema, Nancy G. Love, and Shawn P. McElmurry

Cite This: *ACS EST Engg.* 2022, 2, 1475−1490
Read Online

ABSTRACT: To achieve the goals of the Safe Drinking Water Act, state and local water authorities need to make decisions about where to direct limited funding for infrastructure improvements and currently do so in the absence of adequate evaluative metrics. We developed a framework grounded in utility theory that compares trade-offs explicitly and broadens the factors considered in prioritizing resource allocations. Relevant existing indices were reviewed to identify data applicable to drinking water decision-making. A utility-theory-based decision analysis framework was developed and applied to evaluate how different objectives affect funding decisions for lead service line replacement (LSLR) programs in Pennsylvania and Michigan, United States. The decision framework incorporates drinking water quality characteristics with community and environmental quality attributes. We compare additive and multiplicative model structures, different weights, and spatial scales. Our decision framework showed that the inclusion of additional data beyond what is usually considered in LSLR decisions could change the top 10 counties or public water systems prioritized. Further, the counties or water systems in the top 10 were influenced by the model structure and weights. Prioritization changed based on which data were included, and has implications for the use of evaluative metrics beyond traditional water system data.



KEYWORDS: *equity, environmental justice, drinking water, funding, policy*

1. INTRODUCTION

The investment gap between needed and available funds for the nation's drinking and wastewater infrastructure, driven by decades of underinvestment, is projected to grow to $136 billion by 2039.[1] Despite this gap, state primacy agencies and local utilities must make decisions on where and how to invest available funds, which may mean prioritizing some public water systems (PWSs) over others due in part to limited resources. Water infrastructure projects are notoriously expensive and politically complex; therefore, to assist in and standardize the allocation decisions, decision-making tools are critical. The 1974 Safe Drinking Water Act (SDWA), which sets national drinking water standards and enforceable regulatory requirements, was amended in 1996 to establish the Drinking Water State Revolving Fund (DWSRF). The DWSRF is the primary means through which states fund water system infrastructure improvements.[2] Currently, states have some flexibility in evaluating and ranking the project applications they receive, but the required primary objectives are to prioritize funding projects that are necessary to ensure compliance with SDWA, address the most serious risks to human health, and assist systems most in need according to affordability criteria.[3]

The number of violations accrued by a water system is the primary metric for compliance under SDWA; however, the methodology for obtaining and reporting a violation is unreliable. For example, a contaminant's maximum contaminant level (MCL) is set based on the concentration closest to the recommended level that is feasible to measure and achieve, which suggests that water users may be exposed to contaminant levels that are harmful to human health prior to triggering an MCL violation.[4,5] For instance, studies have observed an increased risk of adverse health effects from ingesting drinking water with nitrate concentrations below the MCL.[6] Further, studies have found significant under-reporting or inaccurate reporting of violation data in the Safe Drinking Water Information System (SDWIS).[7−9] For example, a 2009 audit of 14 states estimated that these states inaccurately reported or did not report 26% of health-based violations and 84% of monitoring violations.[10] This is important given that recent work has found relationships between the incidence of violations and community attributes, such as socioeconomic or

Received: January 8, 2022
Revised: April 14, 2022
Accepted: April 14, 2022
Published: May 5, 2022

demographic factors. The incidence of drinking water violations has been found to be higher among community water systems serving uninsured households, communities of color, and low-income communities.[7,11−13] Rural community water systems have been found to have more frequent violations.[8] This unreliability in reporting may result in mis-characterized or -contextualized relationships found between community attributes and violations, such as the under-predicting of violations[14] or the total exclusion of very small water systems from violation trend analyses due to their likelihood of having inadequate reporting practices.[8] Ultimately, incomplete or inaccurate data limit states' ability to identify and prioritize systems with the most serious compliance problems. Consequently, estimating the DWSRF's impact on compliance by looking at violation data alone is insufficient.

Prior work suggests that to accurately assess the risk to human health, consideration should be given to the individual, cumulative, and collective impact of contaminants and nonchemical stressors (e.g., economic, psychological, or nutritional) on certain communities.[15−19] For example, the frequency and intensity of exposure to environmental pollution, including drinking water contamination, have been found to be variable and associated with socioeconomic status, race, and location, including proximity to multiple exposure (multimodal) pathways.[11,20,21] A household's ability to cope financially and psychologically with the consequences of a drinking water violation has also been associated with race, ethnicity, and class.[12,22] In other words, drinking-water-related risk is not experienced independently from other socio-environmental attributes or alternative sources of risk, nor is it equitably distributed. To achieve equity in drinking water, more diverse data should be included in the decision-making process. Importantly, not all studies have found consistent relationships between these variables (e.g., Mueller and Gasteyer, Statman-Weil et al.),[21,23] indicating that these relationships may be place-based and influenced by the spatial scale at which the study was conducted (e.g., county, public water system, census tract).[18,21,23,24]

Despite growing evidence indicating the importance of community attribute data and place-based decision-making in the context of drinking water, the DWSRF, which is the primary tool used to allocate limited state funding for drinking water infrastructure, has not been updated to include them.[15] To create a more comprehensive tool, additional data sources need to be identified and included. Indeed, other federal programs, such as the Older Americans Act, require states to distribute funding to local jurisdictions based on a combination of the geographic distribution of older adults (e.g., rural residence) and the unmet need (e.g., income, disability status) of those adults.[25,26] In the context of drinking water, case studies in which community-specific, high-resolution data were collected have demonstrated the importance of including non-water system data in analyses to understand nuanced relationships with water quality.[11,22,27] It is also necessary to understand how to incorporate additional data. A possible solution is to use a cumulative metric in the form of an index. An index is composed of diverse data, or attributes, which result in a cumulative value or measurement when combined. For example, the United States air quality index combines information about five criteria pollutants to produce one measurement, or index value, which serves as an indicator of air quality.[28] Several indices exist that focus on environmental exposure through drinking water; they provide useful data and serve as indicators of exposure, vulnerability, or risk.[29−33] However, many are non-adaptable, meaning that they are highly specific to their objective, and tend to weight all the attributes within the index equally, which may not be an appropriate assumption. For example, a livelihood vulnerability index proposed by Hahn et al.[33] uses primary household data and weights all seven subcomponents of the index equally, implicitly assuming that an equal marginal change in the value of each attribute has the same effect on the community. While the use of household data is ideal for high-resolution analyses, it is not always possible to obtain these same data at a more granular level. Furthermore, it is impossible to know if equal weighting is a valid assumption without assessing how the estimations change as a function of weighting. Prior work with the Multidimensional Poverty Index, for example, showed how the resulting estimates are sensitive to a variety of weights, including expert opinion, frequency-based, and equal weighting schemes.[34]

An alternative to a cumulative metric such as the index is the use of utility functions, which allows stakeholders to select the model's functional forms and weights for each attribute to clearly align the valuations implied by the index system with the intended valuations of the decision-makers.[35−37] It also frames the decision-making via a method that is reproducible and adaptable for a variety of different stakeholders and objectives. For example, Guikema and Milke[38] used utility functions to integrate multistakeholder objectives to prioritize funding environmental conservation projects. Karner et al.[37] demonstrated how utility functions might be used to prioritize transportation planning decisions. Prior scholarship by Balazs and Ray[39] and Vanderslice[40] demonstrated that it is possible to assess disparities in environmental exposure based on community attributes using adaptable frameworks. Therefore, we propose a decision-making framework using utility functions to identify and integrate additional available data with current evaluation metrics in the context of drinking water.

To demonstrate how this framework might be applied, we take inspiration from the Infrastructure Investment and Jobs Act that was recently passed in the United States and will allocate an additional \$15 billion[41] for the replacement of lead service lines through the Drinking Water State Revolving Fund. With an estimated 6 to 10 million lead service lines[42] across the United States and an average replacement cost of \$4700 per line,[43] these additional federal funds still fall at least \$13 billion short.[44] As cities in Pennsylvania and Michigan have both experienced recent exceedance of the Lead and Copper Rule (LCR)[45,46] and are undertaking lead service line replacement (LSLR), these are relevant locations to which these funds may be directed and serve as exemplar states for demonstrating our framework. Lead is a contaminant with high regional variability for which the number and location of regulatory samples are often insufficient to identify all water systems with increased lead concentrations.[46,47] Not only might the LCR be an insufficient metric of community lead exposure, but the resulting harm is not uniform across communities.[7,20,39] Consequently, we apply the decision-making framework to demonstrate which counties and public water systems that Michigan and Pennsylvania could prioritize for replacement and how the prioritization changes with different data or weights. We review relevant indices to select appropriate data for the decision analysis.

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

With this proposed method, we strive to address how LSLR allocation decisions will change (1) with the inclusion of multimodal lead exposure data and community attribute data, such as susceptibility to lead exposure and ability to cope with the exposure consequences; (2) based on changes in the composite model form and weight selection; and (3) with spatial scale. Lastly, we evaluate the equity implications of different attribute and weighting assumptions by comparing demographics of regions prioritized. Further, the demographics of our model results are compared to current state DWSRF funding priority lists and locations with the highest frequency of LCR violations. We organize this paper by first reviewing the literature to select appropriate additional data and community attributes. Next, we select utility functions based on the additional data and community attribute structures. We then use the utility functions to calculate objective functions. Finally, we combine objective functions to calculate overall composite metrics, and evaluate the results at the county (Michigan and Pennsylvania) and PWS spatial scales (Pennsylvania).

2. BACKGROUND

2.1. Review of Relevant Indices and Attributes. One way to combine information for decision-making is to create an index and use the relative cumulative value of the index to prioritize the use of resources. Indices are utilized in a variety of disciplines to provide a standardized metric for measuring and comparing a bundle of community attributes, defined by geographical location, or time periods. Localized community attributes, such as measures of living conditions, resources, or attributes of populations, can be incorporated into an index to guide efforts in the improvement of living conditions and uncover areas of concern, allowing for a more directed distribution of resources.[48] To review the existing indices for applicability and to select the appropriate additional data for our analysis, we conducted a review of relevant indices and attributes in the risk management (e.g., susceptibility or vulnerability), poverty, environmental health, and water management literature.

Myriad indices have been proposed to measure susceptibility or vulnerability.[24,49−53] Some indices have been created to answer a specific question or adapted from a previously established index for a particular community or condition. For example, indices have been developed to measure a community's vulnerability to climate change.[33,54] Several water-related indices have been defined in the last four decades, many of which provide some measurement of water scarcity, quality, or security,[30,32,55,56] and existing reviews of these indices provide a thorough overview.[29,31,57] In recent years, the associations between community attributes and their environmental health outcomes have been increasingly investigated.[18,20,23,39,40,58−61] While these works do not propose an index, they use attributes in a similar manner to examine or compare an outcome through time and space. Moreover, they emphasize that an entire population is not uniform and that different people and communities face varying likelihoods of negative health consequences following exposures. For example, age and nutrition affect one's susceptibility to negative health effects associated with lead exposure.[7,62] A detailed description of the attributes used in the works cited above is provided in Table S6.

While there are many indices that measure variability in the human ability to cope with exposure to a hazard, as well as indices related to water management or security, we found that such indices tend to be site-specific and nontransferable across location, community, or decision context. For example, the Falkenmark Water Stress Index (WSI), a measure of the amount of freshwater available per person annually, is heavily cited and widely used but is less suited for urban use.[56] Sullivan et al. established a Water Poverty Index[30,63] (WPI) designed to measure household and community water stress and included measures of access to water, water quantity, quality and variability, and capacity for water management, among others. While the WPI methodology has been applied to various other indices (e.g., Hahn et al.[33]), the primary focus of the WPI is on people in poverty and does not include other attributes, such as race or insurance status, which are relevant to capturing coping ability in the United States.[7,12] To capture the urban context, Jensen and Wu propose a set of Urban Water Security Indicators indicative of water stress, quality, and management capacity.[32] These attributes are designed to measure a city's water security score, and not all of the included attributes are relevant to funding decision-making. None of the relevant reviewed indices were applicable, as is, to the chosen decision-making scenario.

Notably, many of the indices reviewed were constructed using balanced weighted averages, meaning that all attributes are given the same weight or are balanced relative to the other attributes in a sub-index. Consequently, a 1% increase in attribute X is just as significant as a 1% increase in attribute Y, which may not be an appropriate assumption for some attributes. For example, a 1% increase in a proxy for lead exposure such as the number of homes built before 1978 is not equivalent to a measured 1% increase in lead load from paint to which a community is exposed. Additionally, many of these indices require data that are not publicly accessible or not widely collected. While tailored data collection can provide valuable insight into the association between community attributes and the index objective, the use of such data limits the applicability of such indices to other objectives.

2.2. Decision Analysis and Utility Theory Approaches. A decision analysis concept, utility functions, provides solutions to some of the critiques identified among existing indices and is a reproducible approach that supports complex decisions with multiple stakeholders.[36,38,64−67] Utility functions integrate quantitative and categorical data, or attributes, and explicitly represent and quantify trade-offs between attributes to create an overall score or index value. Utility functions take a functional form that relates attribute levels to the utility (i.e., degree of satisfaction) derived by stakeholders to better align available data with objectives. Selection of functional forms incorporates specific assumptions about the attributes into the model and should be considered in the model selection process.[38] For example, the functional form of a utility function can be additive, multiplicative, exponential, or some other mathematical form. Objective utility functions can be weighted and combined based on the overall objective and decision context, and trade-offs among objectives assessed. Selection of attribute or utility function weights is a current topic of debate in the literature.[68] To combine attributes or functional forms, different structures may be used. For example, the majority of the indices described in the section above use an additive structure when combining attributes. However, there are benefits to considering alternative forms and alternative weights, such as comparing how decision

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

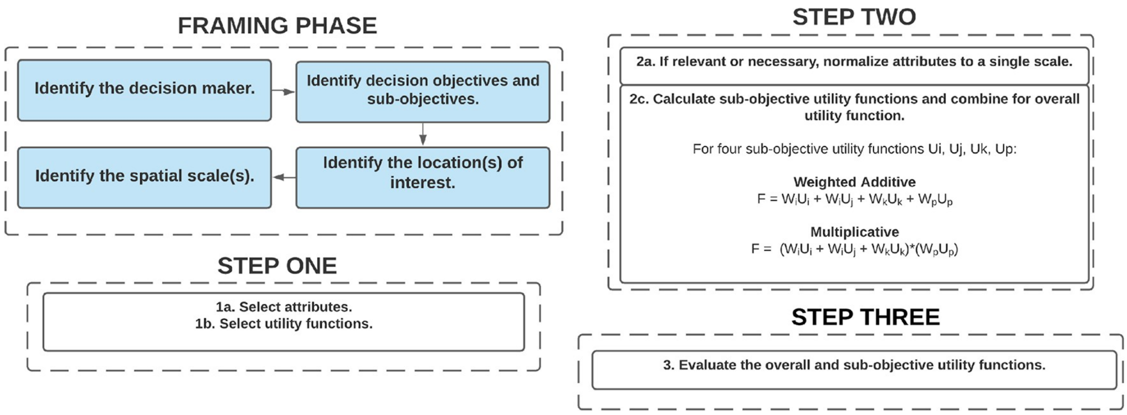


Figure 1. General decision framework used to build utility functions.

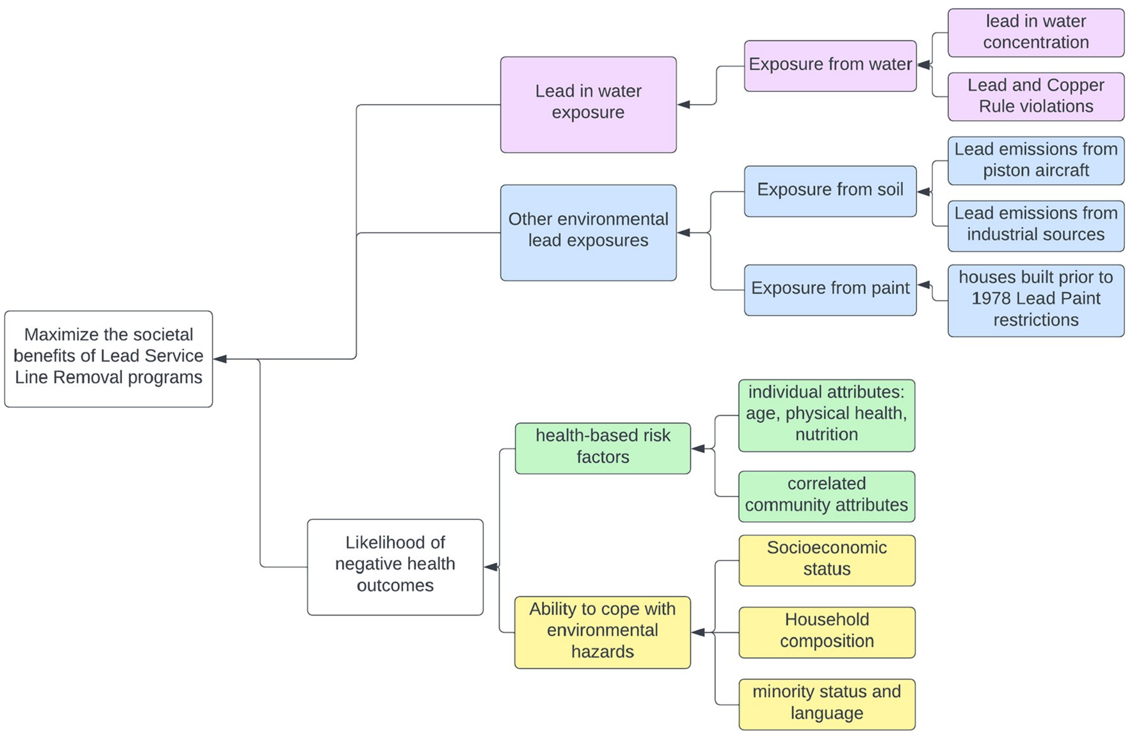


Figure 2. Objective hierarchy identifying overall objective, subsequent component objectives, and attributes used to define each objective. The color indicates the objectives specified in the model.

results change. In this work, we compare a weighted additive functional form to a multiplicative form.

3. METHODS

Utility theory-based decision analysis is a data-driven approach designed to help decision-makers identify their objectives and, in this case, apply those objectives consistently when prioritizing water systems for lead service line replacements. The framework proposed consists of four steps shown in Figure 1 and described below.

3.1. Frame the Decision. In decision analysis, the framing phase consists of identifying all stakeholders and decision-makers and determines the attributes included in the framework and the utility functions used.[38] More specifically, first, the primary decision-maker is identified (e.g., the state primacy agency authority). With stakeholder input, the decision-maker designs the problem space by selecting the decision objective (e.g., funding allocation for infrastructure improvements). Second, the decision-maker further defines the objective function through measurable objectives (e.g., reducing public health risk). Third, the location of interest is specified, and last, the spatial scale of analysis is defined (e.g., county or public water system). The selected objectives should be listed into a hierarchy representative of the order of priority. Often, objectives must be defined by their component parts. Typically, objectives lower in the hierarchy describe the highest objective and are defined such that they may be measured mathematically.

For the current scenario, the decision-maker is the state primacy agency, and the decision is where in Michigan and Pennsylvania to allocate DWSRF funding for LSLR. Michigan and Pennsylvania were selected as the locations of interest because they include both rural and urban regions, have a range of land uses, experienced the majority of their development prior to 1980 (prior to the existence of regulations restricting lead use in housing, plumbing, and

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

industrial processes), have public water systems of all sizes, and recently experienced lead-related violations. The decision objective is to maximize the societal benefits associated with LSLR. The relationship between this primary objective and the lower-level component objectives such as other source of lead exposure and risk factors associated with negative health outcomes following lead exposures is defined in Figure 2. The data sources and spatial resolution of each attribute are defined in Supporting Information S1 and Table S1.

Ideally, analysis would allow for a comparison among water systems, allowing primacy decision-makers to target funds to specific water systems. However, few states publish water system boundaries, making it challenging to associate community attributes to a specific water system. As a result, prior work examining disparities in water quality is often limited to county-level analysis.[40,69] Pennsylvania does publish the spatial boundaries for all community water systems, allowing for two spatial scales to be compared. Comparison of results by spatial scale (county versus public water system boundary) allows for an analysis of how the prioritized areas might shift and describes the importance of creating a national database of water system boundaries.

3.2. Step 1: Select Attributes and Utility Functions.

Based on the decision objectives, the decision-maker and relevant stakeholders select attributes to measure each defined objective. These attributes may be selected from the literature, local expert interviews, or stakeholder input.[36] Attributes should be normalized to a consistent scale, such as 0−1. In decision analysis, each attribute should be assigned a utility function to convert the attribute score to a utility score.[38] The decision-maker should select the utility functions based on the attribute characteristics and such that changes in attribute levels are reflective of changes in stakeholder preferences. For example, if an increase in an attribute value has an exponential effect (e.g., a hypothetical change from 1 to 2 units benefits the decision-maker less than a change from 2 to 3), an exponential utility function or similar should be selected to reflect the non-incremental change.

For the current scenario, the attributes that best describe each component objective are drawn from the literature. Then, the functional form for each objective's utility function is selected based on attribute data structure, distribution, and known associations from the literature. The first two objectives capture sources of lead exposure, and the second two objectives measure the likelihood of negative health outcomes following lead exposure.

3.2.1. Objective 1: Lead in Water Exposure. To maximize LSLR benefits, areas where the likelihood of exposure to lead via drinking water is the highest should be prioritized. Attributes indicative of these locations are identified based on a review of Lead and Copper Rule documentation[70] in addition to EPA and state-specific water quality data sets.[71−73] Attributes beyond the current regulatory trigger, an exceedance of the LCR action level, were selected to incorporate current knowledge of risks posed by lower lead concentrations.[100] The attributes selected include the following: the number of LCR violations is selected to capture locations with a history of lead exposure; the most recent 90th percentile lead concentration is selected to measure current exposure using the LCR metric triggering treatment changes; and the median concentration of lead samples is used as an attribute to capture low-level exposures that could still pose a risk to residents.[100]

3.2.2. Objective 2: Other Sources of Lead Exposure. To maximize LSLR benefits, areas where the likelihood of exposure to lead via alternative sources is the highest should be prioritized. Common sources of lead today include legacy lead-bearing building materials (e.g., lead paint in houses built prior to 1978), industrial pollution, and deposition from piston aircraft using leaded aviation gas.[74,75] Attributes describing these sources include US Census estimates of the proportion of housing stock built prior to 1978,[76] EPA Toxic Release Inventory records of lead released per year,[77] and National Emissions Inventory estimates of lead pollution from piston engine aircraft.[78]

3.2.3. Objective 3: Negative Health Effects. To maximize LSLR benefits, areas where the likelihood that exposure to lead will result in a negative health outcome is the highest should be prioritized. Certain community and health attributes can increase an individual's likelihood of experiencing negative health effects from lead exposure.[70] Such attributes include children in early development (under the age of 5 years), poor nutrition, and general poor health resulting in an increase in lead absorption. Past research has also found an association between poverty and minority communities having an increased risk of elevated blood lead levels.[74,79,80] Blood lead level data are not used as they are not publicly available and data are not collected evenly across a region or population;[81] therefore, they may not be representative of the health risks posed by lead exposure.

3.2.4. Objective 4: Ability to Cope with Environmental Hazards. To maximize LSLR benefits, areas where there is a reduced ability of a community to cope with a water-related emergency should be prioritized. Attributes descriptive of a community's ability to cope are identified from a review of the literature, and the CDC's social vulnerability index is used as a starting point. Selected attributes target measurement of coping ability via financial (disposable income for bottled water, point-of-use water filters, etc.), mental (stress management, ability to read and comprehend communications about drinking water quality or status), and physical (access to medical care, access to sanitary services) means. Further, CDC SVI attributes are removed if they are clearly unrelated to lead exposure or are captured in another objective (e.g., housing attributes are captured elsewhere, and transportation attributes are not deemed sufficiently relevant). Attributes found in the literature but not included in the CDC's SVI are then added (e.g., poor mental health). The selected set of attributes includes single-parent households,[24,82] school education or less,[24] speaking English less than well,[24] unemployed,[24] households without health insurance,[83] poor mental health,[84,85] and absence of complete plumbing facilities.[86]

Next, the utility function is selected based on an inspection of the structure and distribution of each attribute and known relationships from the literature. Tables S1 and S2 show more detailed information about each attribute's range, utility function, and objective structure. For attributes that are in units of lead concentration (mass/volume) or load (mass/time), the utility function is selected to be logarithmic because research has shown that a nonlinear relationship exists between lead exposure and health risk, indicating that there is a greater marginal increase in the negative health outcomes from lead exposure occurring at the lowest lead concentrations.[62] Other attributes presented as percentages (e.g., the percent of the population under the age of 5 years) are used without transformation. The numerical range covered by an attribute is

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

analyzed to assess the implicit valuation that may be incorporated into the model as a result of the difference in range among attributes to be combined (see Table S2).

These selected attributes are not descriptive of all possible sources of lead exposure or all variables that may contribute to negative health outcomes or reduced coping ability; rather, they are meant to represent major contributors with a documented relationship to the described objective. All selected attributes are from publicly available databases and available at the census tract scale unless otherwise stated. Public access to data is a requirement as it is the intention that any decision-maker should be able to apply these techniques. In other applications, decision-makers should use the best available data that describe the objectives of interest. For the county-level analysis, data sets defined at the same spatial units are combined by first calculating the intersection of each data set within the county boundaries and then calculating the weighted area average of each attribute for all intersected polygons within a county. When aggregating water system attributes to the county level, a population weighted average is used instead to reflect the population affected. The same area-weighting process is used to aggregate all data sets to the water system boundary spatial unit.

3.3. Step 2: Calculate the Utility Functions. Utility functions are used to combine attributes within each objective as well as the objectives into the overall objective function. Many functional forms of utility functions exist, each with assumptions.[36] If the decision-maker chooses to assign weight to the attributes or utility functions, the weights should be determined using expert opinion, attribute-level trade-off analysis, or references from the literature.[87] Weighting is also useful to reflect the hierarchical ranking of objectives from the framing phase.[38] Importantly, when weights are not specifically selected, any combination of attributes still implies a relative weighting, and this weighting may not be an accurate representation of decision-maker objectives. A sensitivity analysis should be performed to examine the overall effect of the selected weights on the objective values. Once the weights are defined, the objective functions may be calculated for the selected spatial unit (e.g., public water system, county) for the location of interest.

For the current scenario, all attributes are structured such that an increase in attribute value (e.g., increase in the median lead sample concentration) corresponds to an increase in the overall utility function. Attributes are grouped by objective and transformed as described in Table S1; transformed attributes are summed to compute the four objectives. Two functional forms—additive and multiplicative—combine objectives and are then compared. Given that the decision-maker in this scenario is a state primacy agency and the goal is to prioritize locations to receive DWSRF funds for LSLR, we begin by placing the most emphasis on the first objective, as it is a direct measure of lead exposure from a drinking water system. As such, in the additive objective function (eq 1), the highest weighting is applied to the lead in water objective. The prioritization among objectives and the associated selected weights may vary among decision-makers and is a source of uncertainty in the model. Weighting of individual attributes may be necessary if the direct combination of attributes is illogical due to a difference in scale or if decision-maker valuation of attributes necessitates it.[88] Given the number of attributes selected here, valuation of each attribute may be an onerous task; therefore, attributes were grouped or transformed such that unweighted combination could be used. Each decision-maker must make this calculation and decide the approach that's best for their decision.

In the multiplicative function (eq 2), the water lead exposure objective is multiplied by the sum of the other objective functions, and the other sources of lead exposure objective is given the greatest weighting, as a lead exposure must be present for any risk to occur. The last two objectives were given second and equal weight. Weights are intentionally selected within each function such that they add to one.

$$U_{\text{additive}} = 0.5U_{\text{WaterPb}} + 0.25U_{\text{AltPb}} + 0.125U_{\text{NegHealth}} + 0.125U_{\text{Cope}} \tag{1}$$

$$U_{\text{multiplicative}} = U_{\text{WaterPb}}(0.5U_{\text{AltPb}} + 0.25U_{\text{NegHealth}} + 0.25U_{\text{Cope}}) \tag{2}$$

Following the initial evaluation of the utility functions described in eqs 1 and 2, we parametrically vary the objective weights to assess how potential changes in weights will impact the analysis. As discussed above, this is done due to the subjective nature of weight selection. As weights are adjusted systematically between 0.1 and 1 in 0.1 increments, the overall objective function value is recalculated. Where weights did not add to 1, all objective weights are scaled such that they would sum to 1. The resulting set of objective function values of all weight combinations is characterized by calculating the fraction of iterations for which a specific county or water system has an objective function value ranked in the top quartile. If objective functions are not highly sensitive to weight, one would expect the rankings to remain mostly constant, with the same counties or water systems ranked highest across the vast majority of the simulation iterations.

3.4. Step 3: Evaluate the Utility Functions. The final step is evaluative. Decision-maker review of objective values and objective function rankings motivates discussion among stakeholders and helps ensure that decisions enacted reflect local values. The decision-maker may evaluate the change in objective values across the study area with the goal of maximizing the utility of the decision. Observing trends in objective function valuation and location rankings allows for trade-offs among objectives to be quantified. Further, decision-makers may consider the recommended project prioritization in context with trade-offs among objectives. Locations identified in rankings and the associated demographics of those locations are compared to Project Priority Lists (PPLs) published for each state and allow decision-makers to see the effect of this approach on project selection.[89,90] Decision-makers may also iterate on their selected attributes, functional forms, or weights. In this scenario, locations with the highest objective function value represent locations where the greatest benefits would result from water system investment. The evaluations for the scenario are elucidated in the following section.

4. RESULTS AND DISCUSSION

4.1. How Will LSLR Allocation Decisions Change with Each Objective Function and the Associated Changes in the Attributes? For both Michigan and Pennsylvania, each selected objective prioritizes different regions within the state (see Figure 3). This indicates that the inclusion of lead

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

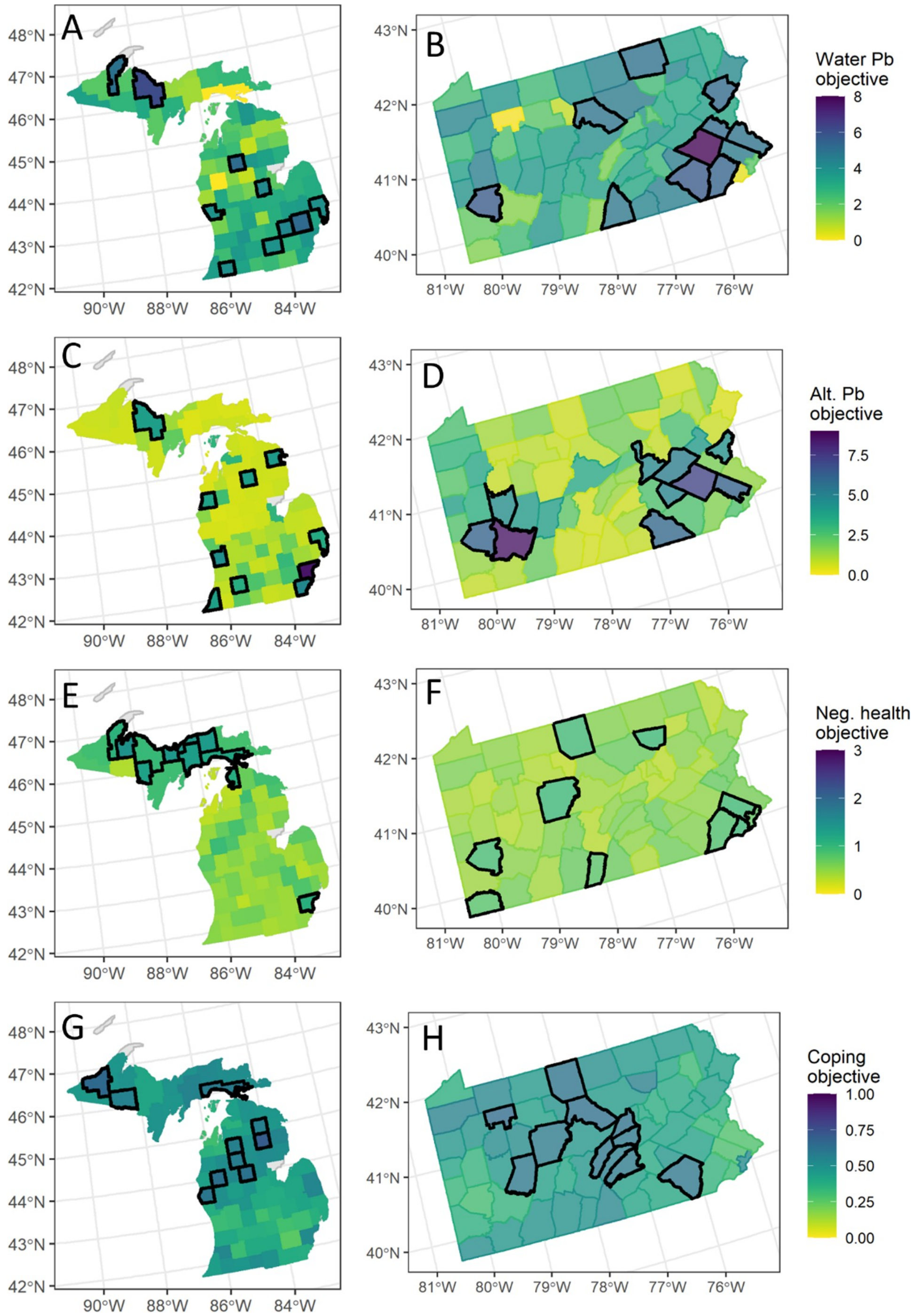


Figure 3. County-level objective and overall objective utility results for Michigan (left) and Pennsylvania (right). Darker shades indicate higher values. Top row (A and B) objective results indicate counties where the likelihood of exposure to lead via drinking water is highest. Second row (C and D) objective indicates areas where the likelihood of exposure to lead via alternative sources is highest. Third row (E and F) objective identifies areas where the likelihood that exposure to lead will result in a negative health outcome is highest, and the bottom row (G and H) identifies areas where there is a reduced ability of a community to cope with a water-related emergency. Top 10 highest-ranked counties are outlined in black.

exposure data from sources other than drinking water and attributes that make a community more susceptible to lead exposure will result in a change of how available LSLR funds are prioritized. The lead in water exposure objective, shown in Figure 3A,B, combines three different drinking water lead metrics (the number of LCR violations, median of lead sample concentrations, and 90th percentile of lead sample concentrations) and provides a more complete picture of lead exposure via drinking water in each state. LCR violations are designed to capture the historical compliance of a region, measured as 10% of samples being greater than 15 ppb. Depending on the underlying causes of elevated drinking water lead levels, the median lead sample concentration provides additional information. The ranked order of counties based on the lead in water objective is not equivalent to the ranked order of counties based on the number of LCR violations. More specifically, 4 of the top 10 and 6 of the top 25 counties in Pennsylvania and 4 of the top 10 and 8 of the top 25 counties

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

Table 1. Distribution of Demographics for Locations Identified by Each Objective and Current Project Priority List and Frequency of LCR Violations

	percent Black				percent poverty			
	min	median	mean	max	min	median	mean	max
Michigan counties								
all Michigan counties	0.35%	1.36%	2.75%	28%	5.50%	12.30%	12.80%	32.10%
current PPL	0.6%	6.4%	8.9%	28.1%	7.4%	12.0%	11.5%	17.2%
LCR violations	0.6%	3.2%	4.0%	8.6%	5.6%	9.6%	9.7%	12.6%
lead in water objective	0.5%	1.1%	2.8%	8.6%	5.6%	10.8%	10.5%	16.3%
alternative sources of lead objective	0.3%	2.0%	5.1%	28.1%	6.0%	10.8%	11.3%	17.2%
negative health effects objective	0.5%	2.1%	5.8%	28.1%	9.1%	12.5%	13.1%	17.2%
coping objective	0.5%	1.0%	1.7%	7.2%	11.2%	16.5%	17.4%	23.1%
Pennsylvania counties								
all Pennsylvania counties	0.4%	1.8%	3.1%	31.0%	4.7%	10.2%	10.2%	18.8%
current PPL	0.7%	2.5%	2.8%	4.8%	5.2%	12.2%	12.0%	19.6%
LCR violations	1.1%	2.2%	3.8%	14.1%	4.7%	8.1%	8.5%	11.9%
lead in water objective	1.1%	2.7%	4.2%	14.1%	4.9%	7.7%	8.6%	15.4%
alternative sources of lead objective	0.9%	2.9%	3.3%	7.7%	4.7%	7.3%	7.6%	10.4%
negative health effects objective	0.9%	3.8%	7.1%	31.0%	4.7%	11.4%	11.0%	18.8%
coping objective	0.9%	1.7%	3.5%	20.9%	7.8%	13.1%	12.6%	15.8%

in Michigan change when additional drinking water lead data are included in the decision process (see Table S3 and S4).

Similar geographic trends are seen for lead in water and alternative sources of lead exposure and include a combination of urban and rural counties. Alternative sources of lead exposure describe deposition from aviation gasoline, regulated industrial lead releases, and a higher frequency of old housing stock, which is more likely to include lead paint (Figure 3C,D), and geographic trends reinforce that lead exposure is not an exclusively urban risk. Pearson's rank correlation coefficients were calculated to compare the two lead exposure objectives and were positively correlated for Pennsylvania (corr = 0.3, $p < 0.05$) but not significant for Michigan (see Supporting Information Section S2). Lead exposure occurs at the local scale; for example, households may have lead paint or plumbing, and neighborhoods may contain lead polluting industries. Aggregation to the county scale results in a loss of spatial specificity, reduces the sample size of the analysis, and can lead to inconclusive results. This motivates the spatial scale analysis conducted in Section 4.5 and the need for an improved collection of household-level lead exposure data.

When the objective is to identify communities with attributes associated with negative health effects due to lead exposure, Michigan's Detroit region and rural areas, specifically Upper Peninsula counties, are prioritized (Figure 3E). In contrast, urban and peri-urban southeast and southwest counties dominate the Pennsylvania rankings (Figure 3F). When the objective is to identify communities with attributes associated with a reduced ability to cope with a water-related emergency, central Pennsylvania rural counties have the highest ranking (Figure 3H), and results are uncorrelated with the negative health effects objective. In Michigan, rural counties are still prioritized (Figure 3G) but in different locations than under the negative health effects objective (corr = 0.3, $p < 0.05$).

In Michigan and Pennsylvania, the change in county rankings indicates that if additional drinking water lead concentration data are combined with LCR violation data, then LSLR funds will be disbursed differently. Further, comparison with the alternative sources of lead objective shows that the inclusion of multimodal lead sources would identify different target locations for LSLR programs. Lead is not a unique contaminant in having multiple modes of exposure; more broadly, index systems allow for exposure indicators at different spatial scales or units of measure to be aggregated such that the way people experience pollution across sources—drinking water, housing, air, or food—and throughout their daily lives— home, work, or, school—is better reflected in decision-making tools. When considering community susceptibility objectives, regions with different characteristics than the lead exposure objectives are identified. This indicates that locations where any type of lead exposure is more likely highest are not necessarily the locations with the populations that are most susceptible to experiencing a negative health outcome or are less able to cope with such exposures. Reinforcing this point, the negative health effects and coping objectives are negatively correlated or uncorrelated with lead exposure objectives (Figures S7 and S8).

These results suggest that, in the case of drinking water, it is critical to include additional data because SDWA violations are not consistently reported[69] and consideration of community attributes is critical to capture what communities are exposed to and also how susceptible they are to such exposures. Further, the LCR is not structured to measure drinking water lead exposure equally across a service area.[91] More specifically, Allaire et al[8] and McDonald and Jones[7] showed that violations are more likely to occur in low-income or rural regions and in smaller water systems; Marcillo and Krometis[92] identified increased rates of monitoring and reporting violations in small water systems, a possible indicator of under-reporting of other violations and water quality concerns. This observation is supported by our result showing that a higher incidence of LCR violations is associated with locations that have a lower proportion of both Black residents and residents below the poverty threshold (see Table 1). Is the number of LCR violations increased in larger, whiter, richer, and more urban water systems (1) because lead risk is truly higher in these locations or (2) because smaller, poorer, minority, and rural systems lack reliable reporting and accurate data? We cannot clearly answer these questions without a better drinking water lead monitoring across all water systems; however, our results do show that the number of violations is an insufficient metric

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

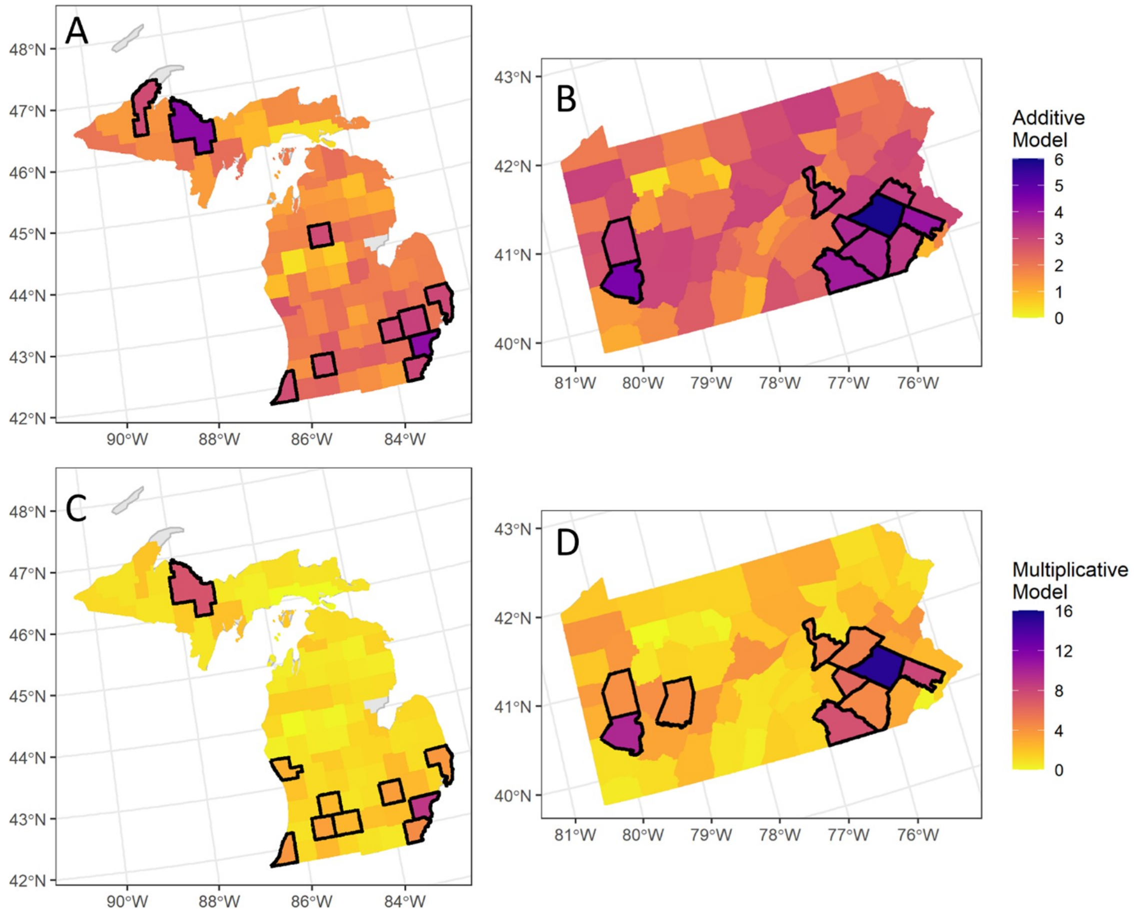


Figure 4. Overall objective functions for (A and C) Michigan and (B and D) Pennsylvania. The additive model is shown in panels A and B, and the multiplicative form is shown in panels C and D. The top 10 counties are outlined in black in each panel.

to identify communities and water systems in need of infrastructure investment. Frameworks such as what we are introducing provide a more complete picture of where water system improvements will result in the greatest benefit, not just the greatest reduction in number of violations.

4.2. How Do the Demographics of Prioritized Locations Change Based on the Objective and Compared to Decision Criteria Such as Current Project Priority Lists and LCR Violations? When the demographics represented by the lead in water objective are compared to the demographics of other objectives, the need to include attributes other than water system data if equity is a specific priority project selection priority is highlighted. Further, each selected objective prioritizes different locations than were selected by each state's current selection process, represented by their respective DWSRF PPLs (see Tables S3–S5). The current DWSRF PPL funds water system needs beyond lead. As a result, criteria beyond those selected here are likely included; therefore, the specific water systems and their associated counties would be expected to differ from our results. However, comparing the demographic characteristics of DWSRF PPLs, the locations identified by our objectives, and the overall state statistics does allow us to assess how well equity goals are incorporated into decision-making processes. Table 1 shows the range, mean, and median statistics across the set of prioritized projects selected by each of our objectives, locations with the greatest number of LCR violations, and the DWSRF PPLs. Demographics for the locations with the greatest number of LCR violations are shown for comparison because these would be current priority locations for LSLR projects. Where the PPL included multiple projects in the same county, duplicates were removed.

Prioritized county-level demographics changed with the objectives selected in our model. For Michigan, the top 10 counties based on the lead in water objective have similar demographics to the counties identified using LCR violation rankings alone in that the population of those counties has a lower proportion of Black residents and residents in poverty than PPL locations. For Michigan, the alternative sources of lead and negative health effects objectives selected counties with the highest mean proportion of the Black residents, 5.1 and 5.8%, respectively, but still lower than the current PPL locations. In contrast, the coping objective selected counties with the highest proportions of residents below the poverty threshold, 13.1% of the population on average, higher than the statewide average and the current priority list (8.9%). In Pennsylvania, the negative health effects objective selected counties with the highest average proportion of Black residents (7.1%), and the coping objective selected counties with the highest proportion of residents below the poverty threshold (12.6%). For both objectives, representation was higher than the demographic statistics for the current priority list (2.8% average percent Black and 12.0% average percent below poverty threshold) and state-wide demographics (3.1% average percent Black and 10.2% average percent below poverty threshold).

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

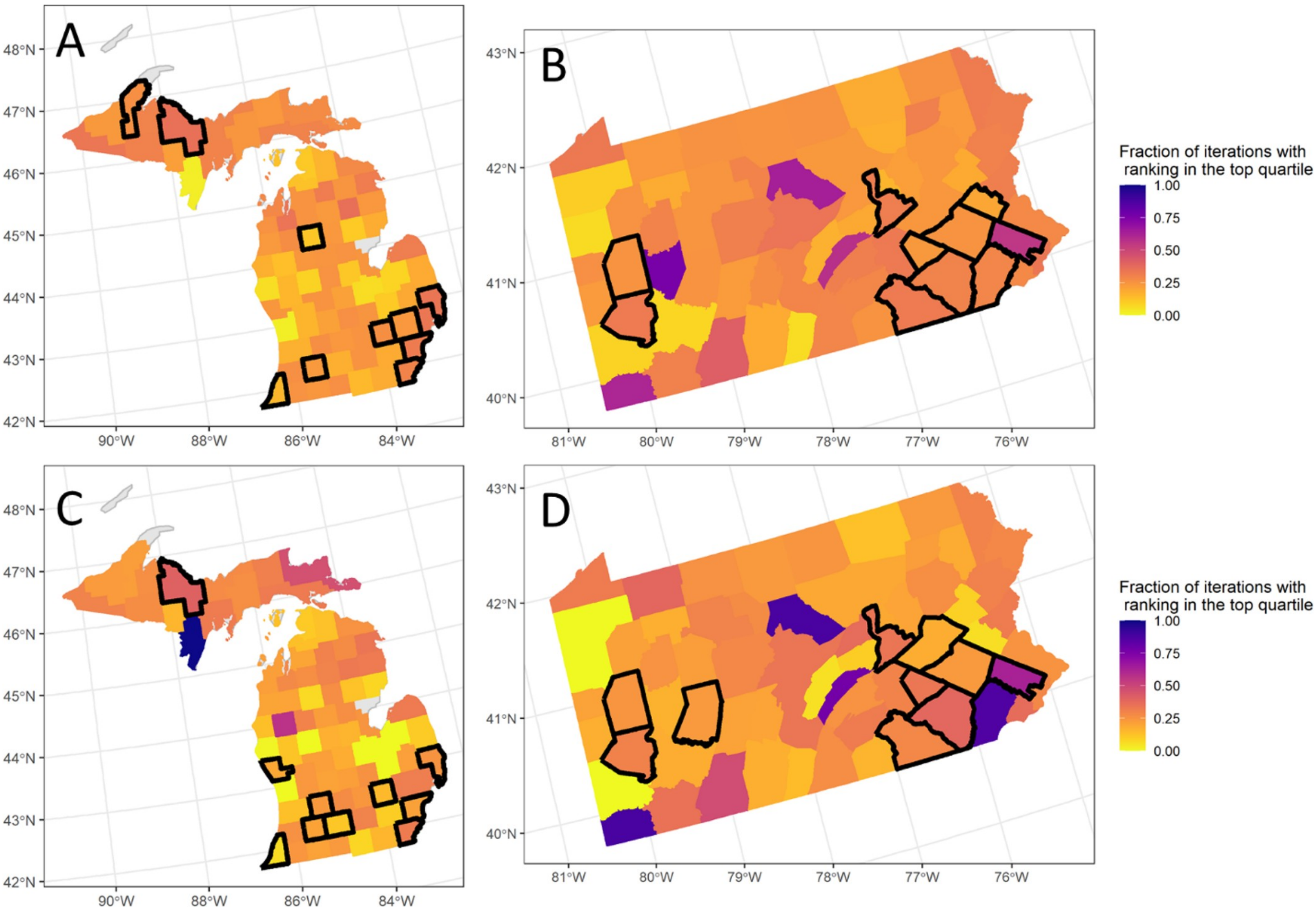


Figure 5. Sensitivity analysis varying objective function weights: fraction of iterations for which a county was ranked in the top quartile. Counties outlined in black were ranked top 10 using selected weights shown in Figure 3. Results from (A and B) the additive function and (C and D) the multiplicative function.

The prior section showed divergence among locations prioritized by each objective function and clarifies the different types of communities that would be prioritized for LSLR funding when lead exposure versus health and coping attributes are considered in decision-making. These results are important because, similar to the approach of the EPA's EJSCREEN,[93] prioritizing environmental justice in infrastructure decisions requires metrics that combine community attributes with indicators of exposure. This drove the inclusion of demographic attributes, such as the proportion of the population that identifies as Black and the proportion in poverty, which are included in a subset of objective functions. This demographic analysis also shows how community composition changes with the selected objective and confirms that the inclusion of these variables within the negative health and coping objectives changes priority rankings. Comparison of results with the current PPL demographics suggests that the inclusion of equity consideration is used in the current PPL selection process. However, the current specific selection criteria are incorporated into the project weighting process and do not allow for tradeoffs to be assessed. The method presented is transparent and allows for this type of tradeoff assessment to be conducted—valuable information for decision-makers.

4.3. How Will LSLR Allocation Decisions Change if We Integrate All Additional Data into Composite Models?

Selecting a prioritization objective function depends on how specific decision-makers value each objective relative to the others. If the primary goal of any program targeting a reduction of lead exposure is a reduction in health risks, then data beyond lead exposures must be considered.[15,18,19] Given that there is little alignment among county rankings and county demographics across objectives, an integrated model is critical to evaluate the implications of all objectives together. For both the additive and multiplicative composite models shown in Figure 4, counties in southern Michigan (see Figure 4A,C) and the southwest and southeast corners of Pennsylvania (see Figure 4B,D) would be prioritized for LSLR. Both composite functions have the highest correlation with the lead exposure measures lead in water and other sources of lead (corr = 0.7−0.9, $p < 0.05$ for PA and corr = 0.6−0.9, $p < 0.05$ for MI). This is likely due to the higher median objective function value (see Table S2) and higher weights applied, and to some extent, this is intentional since LSLR by definition must occur in locations where lead exposures exist. However, despite similar regional trends, the scenario that awards funding to only the top 10 counties selects a different set of counties among the two composite metrics when compared to using the lead in water objective alone (Figures 3 and 4). For Michigan, there was an overlap of six counties between the overall additive composite model and the lead in water objective; for Pennsylvania, there was an overlap of five. Michigan had an overlap of four counties between the overall multiplicative composite model

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

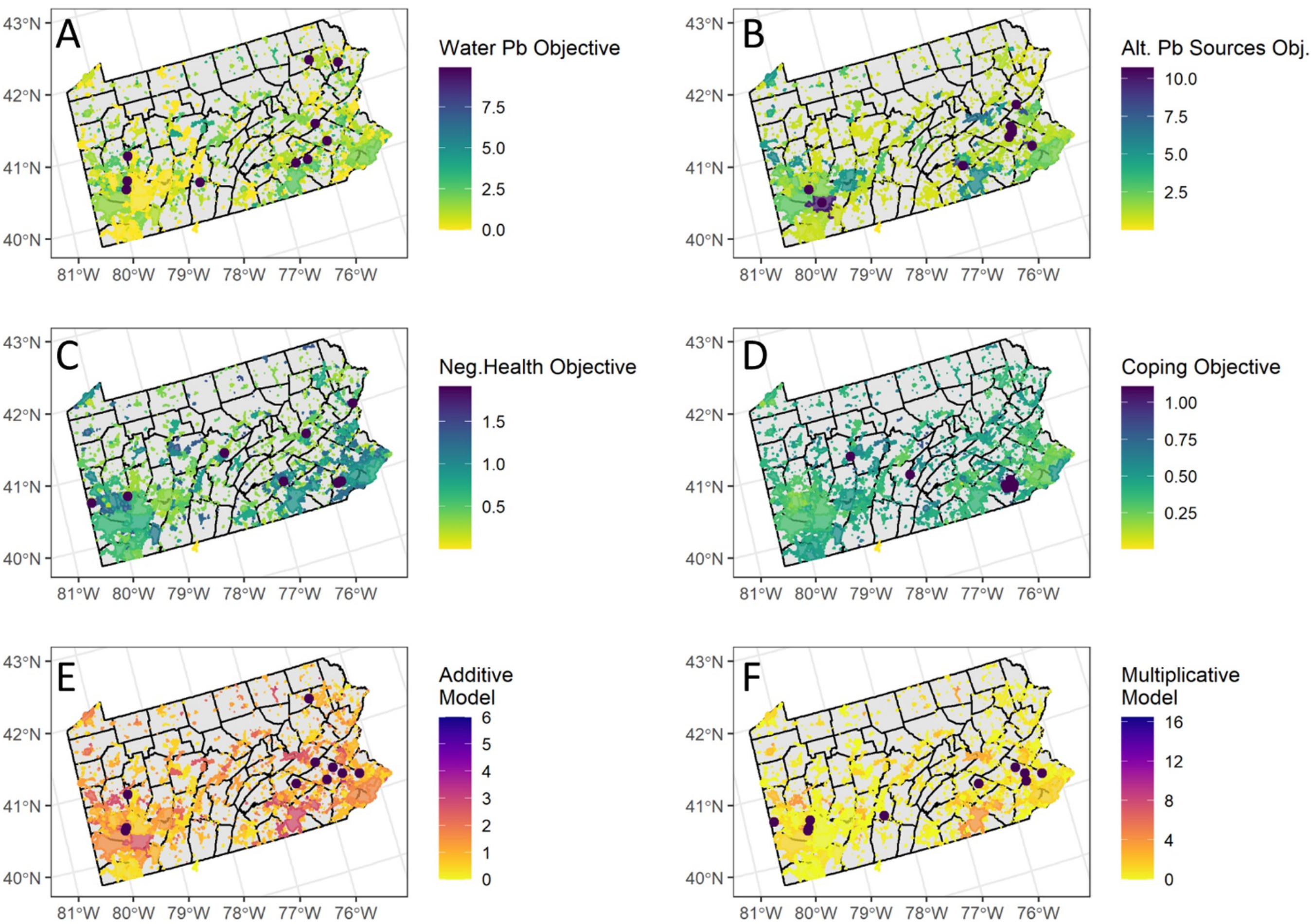


Figure 6. Water system level results calculated for Pennsylvania. The top row (A and B) shows the results of the lead exposure objectives. The middle row (C and D) shows the community susceptibility objectives. The additive overall objective function is shown in the bottom left (E), and the multiplicative form is in the bottom right (F). The top 10 counties for each are indicated with black dots in each panel. County boundaries are shown to illustrate how water system level objective function values can vary within county boundaries.

and the lead in water objective; for Pennsylvania, three counties overlapped.

Three counties in Michigan and two in Pennsylvania, identified by both cumulative models, were also listed in the current PPLs. Oakland County, MI, where the highest proportion of Black residents is located, was identified in each model and the current PPL. Across the top 10 counties in Michigan, the average proportion of Black residents is 5.4% and the average proportion of the population below the poverty threshold is 10.8%, lower than the PPL demographic statistics (8.9 and 11.5%, respectively, see Table 1). In Pennsylvania, the top 10 counties selected have an average of 3.4% Black residents and 7.5% of the population are below the poverty threshold, below current PPL averages of 2.8 and 12%, respectively. The availability of water-system-specific data in Pennsylvania allows us to consider how demographics change with improved spatial granularity. In both cumulative models, communities with higher proportions of Black residents (17%) and communities in poverty (14%) are identified, which emphasize the value of more accurate spatial data when making infrastructure investment decisions (see Section 4.5 for a more detailed PA water system scale analysis). To put these results in context, composite indices that combine environmental and community attributes are gaining in popularity (e.g., the Social Vulnerability Index);[24] thus, this work is a critical step to translating these concepts into water system decisions. Finally, if equity is a key objective, it should be defined explicitly and included in the model.

4.4. What Is the Effect of Weight Selection on LSLR Allocation Decisions? We have compared the prioritized regions based on two functional forms of composite models (additive and multiplicative). While Figure 4 shows that some variation exists between functional forms, the selection of weights introduces a high level of uncertainty. Figure 5 shows the sensitivity of results to changing objective function weighting: the additive and multiplicative functional forms for Michigan in Figure 5A,C and for Pennsylvania in Figure 5B,D. When selecting weights, the numerical range of each attribute and overall objectives must also be considered. Table S2 shows the range, median, and average statistics for each attribute and objective function. The lead exposure objectives (i.e., lead in water and other sources of lead) cover the largest range and have average values up to six times higher than the average negative health effect objective value: 2.75 vs 0.64 for Michigan counties, 3.4 vs 0.55 for Pennsylvania counties, and 1.22 vs 1.6 for Pennsylvania water systems. This difference in range exacerbates the effect of the higher weights selected for the lead exposure objectives. The sensitivity analysis conducted is designed to quantify the effect of objective function weights on overall compositive model rankings. To accurately assess

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

the effect of weight on prioritization separate from the effects of numerical range, objective values were normalized such that they all have the same range (from 0 to 10) in the sensitivity analysis.

Across all simulated weighting schemes, most counties are ranked in the top quartile in at least 25% of simulations, indicating the importance of weight selection. If results did not vary with weight selection, we would expect to see most counties never ranked in the top quartile and a consistent subset of counties ranked in the top quartile under the vast majority of weighting schemes. Of the top 10 list of counties from the original weighting (see Figure 4), only Montgomery County in southeastern Pennsylvania was ranked in the top quartile in greater than 50% of the simulated weighting schemes, indicating that a different weighting would likely change the counties selected for LSLR funding. Weight selection is a critical step in a decision-making process, yet many metrics combine diverse data including indices and weight data equally. As shown here, weight selection can have an effect on the decision outcome; here, the allocation of limited resources differs depending on weight.

4.5. How Will LSLR Allocation Decisions Change with Spatial Scale? Many counties in Michigan and Pennsylvania have multiple water systems; however, in Michigan, the smallest geography at which water systems are matched is the county. Therefore, the county is the smallest scale at which community attributes can be matched to water systems and subsequent analyses can be conducted. However, making LSLR decisions at the county scale ignores the physical reality that water systems do not follow county boundaries. Many water systems can exist within a single county, and many people within a county may not be served by public water systems but rather by private wells. The effect is that communities with the most to gain from LSLR may not be identified, particularly if the system is small or if water systems that do not have increased lead exposures are proximate to others with elevated lead exposures.

A high regional variability requires a more resolved spatial resolution to be used in data analysis.[94] We test the effect of using higher resolution data from Pennsylvania, where water system boundaries are published, on our data analysis method by comparing objective function results at the county scale (Figures 3 and 4) and the water system scale (Figure 6). The results indicate that refining the spatial scale would allow for a more targeted allocation of funds. In other words, specific water systems with an increased number of LCR violations or lead in water objective values are surrounded by systems with no violations and lead in water objectives values of zero within the same county (Figure 6A). Similarly, there is variability within counties for the other sources of lead, population susceptibility, and coping objectives (Figure 6B−D). These findings carry through to the combined objective functions (Figure 6E,F) and demonstrate that county-level resolution is not sufficient for the efficient allocation of DWSRF resources within LSLR programs. In fact, it is likely that improved allocation could be further achieved by resolution at the neighborhood scale, as lead service lines, elevated water lead levels, and community attributes associated with the negative health effects of lead are not uniform within water system boundaries either. However, insufficient data existed to test this hypothesis.

4.6. Implications for Decision-Makers. Decision-makers are the stakeholders who are responsible for allocating funds to water systems and identifying the types of projects to fund. In this case, the primacy agency, which is responsible for selecting the water systems and projects to award state revolving loan funds, is the decision-maker.

Consequently, to prioritize societal benefits, decision-makers must consider locations where exposures and populations susceptible to negative health outcomes or less able to cope with those exposures exist. Key findings for Michigan and Pennsylvania indicate that communities at an increased likelihood of lead in drinking water are not necessarily experiencing an increased likelihood of other compounding stressors. This analysis found that these locations will not likely be identified without explicit consideration of water quality data *and* additional relevant community attribute data. As a result, decision-making processes need to be altered to incorporate relevant community information.

Work by social epidemiologists[39,40,95] has demonstrated how to integrate water-system-specific data, such as infrastructure status, with other community attributes. We found lead exposure objectives to be uncorrelated or negatively correlated with community susceptibility to lead exposure objectives and demonstrated the value of considering community characteristics and why such techniques should be applied to water system decision-making. Studies that have extensively collected household-level data[51,63] have demonstrated the importance of characterizing the relationships between people, housing, and environmental pollution, such as drinking water contamination. However, when comparing across hundreds or thousands of water systems within a state, household-specific data collection is not feasible, and such household-level studies do not always explore ways to use proxy variables to resolve a lack of household attributes in other communities. For example, can census tract-level data be used where household data are not attainable? Two examples of the use of census tract-level data are the social vulnerability index[24] and the municipal vulnerability index.[54] While imperfect, these metrics as well as the index introduced in this study allow for the inclusion of critical community characteristics in comparison across states. Yet, additional work is needed to better describe how proxy variables should be used in place of community-specific data. For example, previous work has shown that the commonly used method of evaluating household water affordability as a percentage of median household income is flawed.[96,97] However, as was done here, the percent of the population in poverty is used as a measure of community affordability or ability to cope financially may be a reasonable proxy.

A major contribution of this work is the explicit quantification of the effect of weight selection on decision outcomes. A limitation of the existing environmental health and vulnerability indices reviewed includes equal weighting of all attributes and the singular focus on use of an additive model.[24,54,63] While many discuss the importance of weight selection, the effects of the equal weighting selected are not tested. Our results (1) demonstrated the significant effect of attribute weighting on location-based priority rankings, raising concerns about the equal weighting used in most water risk indices, and (2) identified weight selection as a critical step in the decision-making process. However, in this paper, weights were only applied when combining objectives and were not applied to individual attributes. Future work should include evaluating the effect of weighting individual attributes through additional sensitivity analysis.

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

We have shown that a utility-theory-based framework provides flexibility, transparency, and adaptability to new stakeholders, and identifies new water system priorities, reducing the likelihood of non-optimal resource allocation. Within this framework, decision-makers should first determine the key objectives that need to be considered based on discussions with key local stakeholders (e.g., residents, community development groups, public health experts, water utility operators, etc.). Based on the objectives selected, the required attributes, model forms, and weight are then considered. Weighting may be complex depending on the decision objectives, stakeholders, and decision-makers involved, and this complexity should be considered when selecting an elicitation method. Guidance for selecting attributes and weights, structuring, and combining objectives is provided in Keeney's work (*Value-Focused Thinking*).[88] We consider two models, additive and multiplicative, to combine exposure and community attributes. Comparing the results and changes in locations ranked top 10 for each functional form highlighted the importance of function form on decision-making. Selecting the correct functional form can be difficult even for experts, and comparison of results across multiple forms is one approach to analyzing the importance and the effects of this assumption. With these models, we conducted a sensitivity analysis to quantify the effect of objective weighting on the rankings of counties or water systems selected for limited LSLR program funds and provide a template for decision-makers to follow. However, we do not consider the effect of weight on individual attributes. While this can be onerous when many attributes are used, the effect of this assumption should be assessed in future work. Additionally, future work should include an analysis of how this method supports drinking water stakeholders who are assessing the tradeoffs of allocating resources to address different contaminants beyond lead. Further, this method can also be applied within a single utility's service area to assess the neighborhoods for prioritized LSLR projects or improved monitoring.

A drawback of this type of utility theory approach is that validating results can be difficult, and decision-makers should consider how to validate their results. We recommend that decision-makers should, when possible, choose attributes from indices or studies that have already validated the attributes' relationship to or correlation with the outcome of interest. A sensitivity analysis should be completed to check the outcome's robustness to spatial scale and weight. Lastly, decision-makers should check their results against empirical evidence when available. Evidence used in prior works to validate index results includes expert opinion,[30] prior studies relating an attribute to an outcome,[54] and post-event statistics,[49] if attempting to reconcile an index projection with an actual event.

4.7. Implications for Policy Makers. Policy makers are stakeholders who are responsible for setting drinking water regulatory requirements and funding guidelines. The U.S. government has recognized the need for local water systems to remove lead service lines with the recent allocation of $15 billion toward this end under the Infrastructure Investment and Jobs Act.[41] While significant, the cost to remove all lead service lines in the United States is estimated to cost between $28 and $47 billion.[44] In this case, policy makers (primarily the federal EPA) have the mandate for setting requirements and priorities for the Infrastructure Investment and Jobs Act.

At the state level, state regulatory agencies will be responsible for prioritizing the distribution of available funds to water systems across their states with federal guidelines. For lead, which has many exposure routes, determining where to allocate LSLR program funds is a complex decision. Decision tools such as the one we have introduced can help policy makers identify the implications and tradeoffs among different regulations or funding guidelines ahead of rulemaking by clarifying where the greatest benefits can be realized. Furthermore, this method allows policy writers to better understand the sensitivity of funding allocation decisions around community attributes beyond drinking water lead levels and the weighting (i.e., prioritization) of both attributes and objectives within an overall composite model.

Proactive analysis of the equity and public health implications of rulemaking is critical, particularly with lead. Examples from Flint, MI, and Washington, DC, highlight the importance of such proactivity because, while significant funding for LSLR programs has been allocated, this occurred only after the communities suffered significant exposure to lead.[98,99] In these examples, the approach to LSLR was reactionary and is unacceptable for contaminants such as lead, which has irreversible health outcomes.[100,101] A benefit of the method developed here is that it allows policy makers to identify communities that have an increased *likelihood* of lead exposure and that are at the greatest risk of negative health effects or have a reduced ability to cope as a consequence of exposure. Yet, these results are not exact, and future work should include a quantification of the sources of uncertainty and the effects of both sampling and model uncertainty on prioritization recommendations for LSLR. For example, the lead in water exposure objective used here was created based on the best available data, LCR violations, and the median and 90th percentile of lead concentrations in water samples collected for each water system. However, the LCR requires only 100 samples for community water systems serving greater than 100,000 people[70] or 0.1% of houses served. This is insufficient for proper characterization of lead exposure in drinking water across an entire service area, and as a result, lead in drinking water exposure is uncertain.[46] Further, most water systems lack the resources to consistently sample a representative number of locations, and therefore, a policy change is required to allow for a more accurate characterization of drinking water lead exposure across all public water systems. Future work should include a comparison of how prioritization changes if policy changes are made that require improved data collection of lead exposures.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestengg.2c00008.

> Additional details describing the preparation of data sets and execution of the method presented; descriptive statistics of all model attributes; distribution functions; correlation coefficients and top 10 county ranking tables for each objective function; additional results of the sensitivity analysis; and literature review summary prepared in support of Section 2 (PDF)

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

AUTHOR INFORMATION

Corresponding Author

Sara E. Schwetschenau − *Department of Civil and Environmental Engineering, Wayne State University, Detroit, Michigan 48202, United States;* Present Address: Columbia Water Center, Columbia University, New York, NY 10027, United States; orcid.org/0000-0002-0606-8706; Email: saraschwetschenau@gmail.com

Authors

Alyssa Schubert − *Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, Michigan 48109, United States;* orcid.org/0000-0001-9884-2289

Richard J. Smith − *School of Social Work, Wayne State University, Detroit, Michigan 48202, United States*

Seth Guikema − *Department of Industrial & Operations Engineering and Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, Michigan 48109, United States*

Nancy G. Love − *Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, Michigan 48109, United States;* orcid.org/0000-0002-9184-2451

Shawn P. McElmurry − *Department of Civil and Environmental Engineering, Wayne State University, Detroit, Michigan 48202, United States;* orcid.org/0000-0001-7398-431X

Complete contact information is available at: https://pubs.acs.org/10.1021/acsestengg.2c00008

Author Contributions

The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript.

Funding

This work was conducted as part of the Water and Health Infrastructure, Resilience and Learning (WHIRL) Project supported by the National Science Foundation (NSF) under Grants CBET-1832591 and CBET-1832692. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NSF. Additional funding was provided by the Wayne State University Office of the Vice President of Research.

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This work was completed with assistance from the Environmental Working Group, which provided access to water in lead concentration data for Michigan and provided comments on the manuscript. The authors also benefited from early feedback from their Water and Health Infrastructure, Resilience and Learning Project team collaborators at Wayne State University, University of Michigan, and Indiana University.

REFERENCES

(1) The American Society of Civil Engineers. *The Economic Benefits of Investing in Water Infrastructure: How a Failure to Act Would Affect the US Economic Recovery*. 2020, 1−40.

(2) The United States Environmental Protection Agency. *EPA State Revolving Funds and WIFIA Available to Water and Wastewater Utilities*. https://www.epa.gov/fedfunds/epa-state-revolving-funds-and-wifia-available-water-and-wastewater-utilities (accessed January 2022).

(3) The United States Environmental Protection Agency. *Drinking Water State Revolving Fund Eligibility Handbook 2017*; Office of Groundwater and Drinking Water: Washington, D.C., 2017.

(4) Humphreys, E. *Regulating Contaminants Under the Safe Drinking Water Act (SDWA)*; The Congressional Research Service: Washington, D.C., 2021.

(5) Belzer, R. B. Achieving Economically Feasible Drinking Water Regulation. *J. Benefit-Cost Anal.* **2020**, *11*, 294−318.

(6) Ward, M.; Jones, R.; Brender, J.; de Kok, T.; Weyer, P.; Nolan, B.; Villanueva, C.; van Breda, S. Drinking Water Nitrate and Human Health: An Updated Review. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1−31.

(7) McDonald, Y. J.; Jones, N. E. Drinking Water Violations and Environmental Justice in the United States, 2011-2015. *American Journal of Public Health.* **2018**, 1401.

(8) Allaire, M.; Wu, H.; Lall, U. National Trends in Drinking Water Quality Violations. *Proc. Natl. Acad. Sci. U. S. A.* **2018**, *115*, 2078−2083.

(9) Foster, S. A.; Pennino, M. J.; Compton, J. E.; Leibowitz, S. G.; Molly, L. Arsenic Drinking Water Violations Decreased across the United States Following Revision of the Maximum Contaminant Level. *Environ. Sci. Technol.* **2019**, *53*, 11478−11485.

(10) U.S. Government Accountability Office (GAO). Drinking Water: Unreliable State Data Limit EPA 's Ability to Target Enforcement Priorities and Communicate Water Systems' Performance. *Water* **2011**, 1−74.

(11) Balazs, C.; Morello-Frosch, R.; Hubbard, A.; Ray, I. Social Disparities in Nitrate-Contaminated Drinking Water in California's San Joaquin Valley. *Environ. Health Perspect.* **2011**, *119*, 1272−1278.

(12) Switzer, D.; Teodoro, M. P. The Color of Drinking Water: Class, Race, Ethnicity, and Safe Drinking Water Act Compliance. *J.-Am. Water Works Assoc.* **2017**, *109*, 40−45.

(13) de Fur, P. L.; Evans, G. W.; Hubal, E. A. C.; Kyle, A. D.; Morello-Frosch, R. A.; Williams, D. R. Vulnerability as a Function of Individual and Group Resources in Cumulative Risk Assessment. *Environ. Health Perspect.* **2007**, *115*, 817−824.

(14) Pennino, M. J.; Compton, J. E.; Leibowitz, S. G. Trends in Drinking Water Nitrate Violations Across the United States. *Environ. Sci. Technol.* **2017**, *51*, 13450−13460.

(15) Sprinkle, R. H.; Payne-Sturges, D. C. Mixture Toxicity, Cumulative Risk, and Environmental Justice in United States Federal Policy, 1980−2016: Why, with Much Known, Was Little Done? *Environ. Heal. A Glob. Access Sci. Source* **2021**, *20*, 1−25.

(16) Fox, M.; Brewer, L.; Martin, L. An Overview of Literature Topics Related to Current Concepts, Methods, Tools, and Applications for Cumulative Risk Assessment (2007-2016). *Int. J. Environ. Res. Public Health* **2017**, *14* (), DOI: 10.3390/ijerph14040389.

(17) Villanueva, C. M.; Kogevinas, M.; Cordier, S.; Templeton, M. R.; Vermeulen, R.; Nuckols, J. R.; Nieuwenhuijsen, M. J.; Levallois, P. Assessing Exposure and Health Consequences of Chemicals in Drinking Water: Current State of Knowledge and Research Needs. *Environmental Health Perspectives*. Public Health Services, US Dept of Health and Human Services 2014, pp. 213−221, DOI: 10.1289/ehp.1206229.

(18) Gee, G. C.; Payne-Sturges, D. C. Environmental Health Disparities: A Framework Integrating Psychosocial and Environmental Concepts. *Environ. Health Perspect.* **2004**, *112*, 1645−1653.

(19) Payne-Sturges, D.; Zenick, H.; Wells, C.; Sanders, W. We Cannot Do It Alone: Building a Multi-Systems Approach for Assessing and Eliminating Environmental Health Disparities. *Environ. Res.* **2006**, *102*, 141−145.

(20) Delpla, I.; Benmarhnia, T.; Lebel, A.; Levallois, P.; Rodriguez, M. J. Investigating Social Inequalities in Exposure to Drinking Water Contaminants in Rural Areas. *Environ. Pollut.* **2015**, 88.

(21) Mueller, J. T.; Gasteyer, S. The Widespread and Unjust Drinking Water and Clean Water Crisis in the United States. *Nat. Commun.* **2021**, *12*, 3544.

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490

(22) Gaber, N.; Silva, A.; Lewis-Patrick, M.; Kutil, E.; Taylor, D.; Bouier, R. Water Insecurity and Psychosocial Distress: Case Study of the Detroit Water Shutoffs. *J. Public Health* **2021**, 839.
(23) Statman-Weil, Z.; Nanus, L.; Wilkinson, N. Disparities in Community Water System Compliance with the Safe Drinking Water Act. *Appl. Geogr.* **2020**, *121*, No. 102264.
(24) Flanagan, B. E.; Gregory, E. W.; Hallisey, E. J.; Heitgerd, J. L.; Lewis, B. A Social Vulnerability Index for Disaster Management. *J. Homel. Secur. Emerg. Manag.* **2020**, *8*, 1792.
(25) Colello, K. J. Older Americans Act: Funding Formulas. *Congr. Res. Serv.* **2019**, *37*.
(26) *Older Americans Act: Options to Better Target Need and Improve Equity*; GAO 13−74; U.S. Government Accountability Office, Washington, D.C., 2012.
(27) Okpara, U. T.; Stringer, L. C.; Dougill, A. J. Using a Novel Climate−Water Conflict Vulnerability Index to Capture Double Exposures in Lake Chad. *Reg. Environ. Chang.* **2017**, *17*, 351−366.
(28) The United States Environmental Protection Agency. *Air Now*. https://www.airnow.gov (accessed March 2022).
(29) Gitau, M. W.; Chen, J.; Ma, Z. Water Quality Indices as Tools for Decision Making and Management. *Water Resour. Manag.* **2016**, *30*, 2591−2610.
(30) Sullivan, C. A.; Meigh, J. R.; Giacomello, A. M.; Fediw, T.; Lawrence, P.; Samad, M.; Mlote, S.; Hutton, C.; Allan, J. A.; Schulze, R. E.; Dlamini, D. J. M.; Cosgrove, W.; Delli Priscoli, J.; Gleick, P.; Smout, I.; Cobbing, J.; Calow, R.; Hunt, C.; Hussain, A.; Acreman, M. C.; King, J.; Malomo, S.; Tate, E. L.; O'Regan, D.; Milner, S.; Steyl, I. The Water Poverty Index: Development and Application at the Community Scale. *Nat. Resour. Forum* **2003**, 189.
(31) Pedro-Monzonís, M.; Solera, A.; Ferrer, J.; Estrela, T.; Paredes-Arquiola, J. A Review of Water Scarcity and Drought Indexes in Water Resources Planning and Management. *J. Hydrol.* **2015**, *527*, 482−493.
(32) Jensen, O.; Wu, H. Urban Water Security Indicators: Development and Pilot. *Environ. Sci. Policy* **2018**, 33.
(33) Hahn, M. B.; Riederer, A. M.; Foster, S. O. The Livelihood Vulnerability Index: A Pragmatic Approach to Assessing Risks from Climate Variability and Change-A Case Study in Mozambique. *Glob. Environ. Chang.* **2009**, *19*, 74−88.
(34) Khan, F. N.; Akram, S. Sensitivity of Multidimensional Poverty Index in Pakistan. *Pakistan J. Soc. Issues* **2018**, *8*, 98−108.
(35) Huang, J. J.; Mcbean, E. A.; James, W. Multi-Objective Optimization for Monitoring Sensor Placement in Water Distribution Systems. *Water Distribution Systems Analysis Symposium*; American Society of Civil Engineers 2006.
(36) Keeney, R. L. Utility Functions for Multiattributed Consequences. *Manage. Sci.* **1972**, *18*, 276−287.
(37) Karner, A.; London, J.; Rowangould, D.; Manaugh, K. From Transportation Equity to Transportation Justice: Within, Through, and Beyond the State. *J. Plan. Lit.* **2020**, *35*, 440−459.
(38) Guikema, S.; Milke, M. Quantitative Decision Tools for Conservation Programme Planning: Practice, Theory and Potential. *Environ. Conserv.* **1999**, *26*, 179−189.
(39) Balazs, C. L.; Ray, I. The Drinking Water Disparities Framework: On the Origins and Persistence of Inequities in Exposure. *Am. J. Public Health* **2014**, 603.
(40) VanDerslice, J. Drinking Water Infrastructure and Environmental Disparities: Evidence and Methodological Considerations. *Am. J. Public Health* **2011**, *101*, S109.
(41) The United States Environmental Protection Agency *FACT SHEET: EPA & The Bipartisan Infrastructure Law*. https://www.epa.gov/newsreleases/fact-sheet-epa-bipartisan-infrastructure-law (accessed October 2021).
(42) The United States Environmental Protection Agency *Lead Service Line Replacement*. https://www.epa.gov/ground-water-and-drinking-water/lead-service-line-replacement (accessed October 2021).
(43) United States Environmental Protection Agency. *Strategies to Achieve Full Lead Service Line Replacement*. https://www.epa.gov/ground-water-and-drinking-water/strategies-achieve-full-lead-service-line-replacement(accessed October 2022).
(44) Campbell, S.; Wessel, D. *What would it cost to replace all the nation's lead water pipes?*. https://www.brookings.edu/blog/up-front/2021/05/13/what-would-it-cost-to-replace-all-the-nations-lead-water-pipes/ (accessed October 2021).
(45) Hanna-Attisha, M.; LaChance, J.; Sadler, R. C.; Champney Schnepp, A. Elevated Blood Lead Levels in Children Associated With the Flint Drinking Water Crisis: A Spatial Analysis of Risk and Public Health Response. *Am. J. Public Health* **2016**, *106*, 283−290.
(46) Schwetschenau, S. E.; Small, M. J.; Vanbriesen, J. M. Using Compliance Data to Understand Uncertainty in Drinking Water Lead Levels in Southwestern Pennsylvania. *Environ. Sci. Technol.* **2020**, *54*, 8857−8867.
(47) Katner, A.; Pieper, K. J.; Lambrinidou, Y.; Brown, K.; Hu, C. Y.; Mielke, H. W.; Edwards, M. A. Weaknesses in Federal Drinking Water Regulations and Public Health Policies That Impede Lead Poisoning Prevention and Environmental Justice. *Environ. Justice* **2016**, *9*, 109−117.
(48) Kingsley, G., Thomas, C., Claudia, J., Pettit, K. L. S. *Strengthening Communities with Neighborhood Data*; Urban Institute 2014.
(49) Cutter, S. L.; Finch, C. Temporal and Spatial Changes in Social Vulnerability to Natural Hazards; *Planning for Climate Change*, Routledge 2018, *105* (7), 129−137, DOI: 10.4324/9781351201117-16.
(50) Alkire, S.; Santos, M. E. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. *World Dev.* **2014**, *59*, 251−274.
(51) Pampalon, R.; Hamel, D.; Gamache, P.; Philibert, M. D.; Raymond, G.; Simpson, A. An Area-Based Material and Social Deprivation Index for Public Health in Québec and Canada. *Can. J. Public Heal.* **2012**, *103* (), DOI: 10.1007/bf03403824.
(52) Mayer, S. E.; Jencks, C. Poverty and the Distribution of Material Hardship. *J. Hum. Resour.* **1989**, *24*, 88.
(53) Federal Emergency Management Agency *National Risk Index Primer*; Washington: D.C., 2020.
(54) Menezes, J. A.; Confalonieri, U.; Madureira, A. P.; De Brito Duval, I.; Dos Santos, R. B.; Margonari, C. *Mapping Human Vulnerability to Climate Change in the Brazilian Amazon: The Construction of a Municipal Vulnerability Index*; *PloS one* 2018; Vol. *13*, DOI: 10.1371/journal.pone.0190808.
(55) Ohlsson, L. Water Conflicts and Social Resource Scarcity. *Phys. Chem. Earth, Part B Hydrol. Ocean. Atmos.* **2000**, *25*, 213−220.
(56) Falkenmark, M.; Lundqvist, J.; Widstrand, C. Macro-scale Water Scarcity Requires Micro-scale Approaches: Aspects of Vulnerability in Semi-arid Development. *Nat. Resour. Forum* **1989**, *13*, 258−267.
(57) Rijsberman, F. R. Water Scarcity: Fact or Fiction? *Agric. Water Manag.* **2006**, *80*, 17.
(58) York, A.; Tuccillo, J.; Boone, C.; Bolin, B.; Gentile, L.; Schoon, B.; Kane, K. Zoning and Land Use: A Tale of Incompatibility and Environmental Injustice in Early Phoenix. *J. Urban Aff.* **2014**, *36*, 833−853.
(59) Deitz, S.; Meehan, K. Plumbing Poverty: Mapping Hot Spots of Racial and Geographic Inequality in U.S. Household Water Insecurity. *Ann. Assoc. Am. Geogr.* **2019**, *109*, 1092−1109.
(60) Schaider, L. A.; Swetschinski, L.; Campbell, C.; Rudel, R. A. Environmental Justice and Drinking Water Quality: Are There Socioeconomic Disparities in Nitrate Levels in U.S. Drinking Water? *Environ. Heal.* **2019**, *18* (), DOI: 10.1186/s12940-018-0442-6.
(61) Satur, P.; Lindsay, J. Social Inequality and Water Use in Australian Cities: The Social Gradient in Domestic Water Use. *Local Environ.* **2020**, *25*, 351−364.
(62) Farfel, M.; Schwartz, J.; Jacobs, D. E.; Mahaffey, K. R.; Rogers, J.; Clickner, R. P.; Ashley, P.; Lanphear, B. P.; Matte, T. D.; Rabinowitz, M.; Dixon, S.; Succop, P.; Rohde, C.; Dietz, B.; Bornschein, R. L.; Galke, W. The Contribution of Lead-Contaminated

House Dust and Residential Soil to Children's Blood Lead Levels. *Environ. Res.* **2002**, *79*, 51−68.
(63) Sullivan, C.; Meigh, J.; Lawrence, P. Application of the Water Poverty Index at Different Scales: A Cautionary Tale. *Water Int.* **2006**, *31*, 412−426.
(64) Wallenius, J.; Dyer, J. S.; Fishburn, P. C.; Steuer, R. E.; Zionts, S.; Deb, K. Multiple Criteria Decision Making, Multiattribute Utility Theory: Recent Accomplishments and What Lies Ahead. *Manage. Sci.* **2008**, *54*, 1336−1349.
(65) Zietsman, J.; Rilett, L. R.; Kim, S. J. Transportation Corridor Decision-Making with Multi-Attribute Utility Theory. *Int. J. Manag. Decis. Mak.* **2006**, *7*, 254−266.
(66) El Sawalhi, N. I.; El Agha, O. Multi-Attribute Utility Theory for Selecting an Appropriate Procurement Method in the Construction Projects. *J. Constr. Dev. Ctries.* **2017**, *22*, 75−96.
(67) Yoon, S.; Choi, S.; Ko, W. An Integrated Multicriteria Decision-Making Approach for Evaluating Nuclear Fuel Cycle Systems for Long-Term Sustainability on the Basis of an Equilibrium Model: Technique for Order of Preference by Similarity to Ideal Solution, Preference Ranking Organiz. *Nucl. Eng. Technol.* **2017**, *49*, 148−164.
(68) Damkjaer, S.; Taylor, R. The Measurement of Water Scarcity: Defining a Meaningful Indicator. *Ambio* **2017**, *46*, 513−531.
(69) Beecher, J.; Redican, K.; Kolioupoulos, M. (Mis)Classification of Water Systems in the United States. *SSRN Electron. J.* **2020**, 1−38.
(70) United States Environmental Protection Agency *National Primary Drinking Water Regulations: Lead and Copper Rule Revisions*; Federal Register: Washington, D.C., 2021.
(71) United States Environmental Protection Agency. *Safe Drinking Water Information System Federal Reports Search*. https://www.epa.gov/ground-water-and-drinking-water/safe-drinking-water-information-system-sdwis-federal-reporting (accessed September 2020).
(72) Pennsylvania Department of Environmental Protection. *Drinking Water Reporting System*. http://www.drinkingwater.state.pa.us/dwrs/HTM/Welcome.html (accessed September 2020).
(73) Environmental Working Group. *EWG's Tap Water Database: What's in Your Drinking Water?*. http://www.ewg.org/tapwater/ (accessed November 2020).
(74) Lebrón, A. M.; Torres, I. R.; Valencia, E.; Dominguez, M. L.; Garcia-Sanchez, D. G.; Logue, M. D.; Wu, J. The State of Public Health Lead Policies: Implications for Urban Health Inequities and Recommendations for Health Equity. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1−28.
(75) Zahran, S.; Iverson, T.; McElmurry, S. P.; Weiler, S. The Effect of Leaded Aviation Gasoline on Blood Lead in Children. *J. Assoc. Environ. Resour. Econ.* **2017**, *4*, 575−610.
(76) United States Census Bureau. American Community Survey Data. https://data.census.gov/programs-surveys.acs.data.html(accessed September 2020).
(77) The United States Environmental Protection Agency. *TRI Basic Data Files: Calendar Years 1987-2019*. https://www.epa.gov/toxics-release-inventory-tri-program/tri-basic-data-files-calendar-years-1987-2019(accessed September 2020).
(78) United States Environmental Protection Agency. *National Emissions Inventory (NEI)*. https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei (accessed September 2020).
(79) Center for Disease Control. Childhood Lead Poisoning Prevention: Populations at Higher Risk. https://www.cdc.gov/nceh/lead/prevention/populations.htm (accessed September 2021).
(80) Gleason, J. A.; Nanavaty, J. V.; Fagliano, J. A. Drinking Water Lead and Socioeconomic Factors as Predictors of Blood Lead Levels in New Jersey's Children between Two Time Periods. *Environ. Res.* **2019**, *169*, 409−416.
(81) Beidinger-Burnett, H.; Ahern, L.; Ngai, M.; Filippelli, G.; Sisk, M. Inconsistent Screening for Lead Endangers Vulnerable Children: Policy Lessons from South Bend and Saint Joseph County, Indiana, USA. *J. Public Health Policy* **2019**, *40*, 103−113.
(82) Kaplowitz, S. A.; Perlstadt, H.; Dziura, J. D.; Post, L. A. Behavioral and Environmental Explanations of Elevated Blood Lead Levels in Immigrant Children and Children of Immigrants. *J. Immigr. Minor. Health* **2016**, *18*, 979−986.
(83) The Institute of Medicine Committee on the Consequences of Uninsurance. *Hidden Costs, Value Lost: Uninsurance in America*; National Academies Press: Washington, D.C., 2003.
(84) Slekiene, J.; Mosler, H. J. The Link between Mental Health and Safe Drinking Water Behaviors in a Vulnerable Population in Rural Malawi. *BMC Psychol.* **2019**, *7*, 1−15.
(85) Taylor, S. E.; Stanton, A. L. Coping Resources, Coping Processes, and Mental Health. *Annu. Rev. Clin. Psychol.* **2007**, *3*, 377−401.
(86) Meehan, K.; Jurjevich, J. R.; Chun, N. M. J. W.; Sherrill, J. Geographies of Insecure Water Access and the Housing−Water Nexus in US Cities. *Proc. Natl. Acad. Sci. U. S. A.* **2020**, *117*, 28700−28707.
(87) O'banion, K. Use of Value Functions in Environmental Decisions. *Environ. Manage.* **1980**, *4*, 3−6.
(88) Keeney, R. L. *Value-Focused Thinking: A Path to Create Decisionmaking*; Harvard University Press: Cambridge, 1992.
(89) Michigan Department of the Environment Great Lakes and Energy. *Drinking Water Revolving Fund Fiscal Intended Use Plan Fiscal Year 2019*; Department of Environmental Quality: Lansing, 2018.
(90) Pennsylvania Department of Environmental Protection. *Pennsylvania Infrastructure Authority and Department of Environmental Protection Federal FY 2018 Drinking Water Project Priority List*; Harrisburg, *2018*.
(91) United States Environmental Protection Agency. *Drinking Water Lead and Copper Rule Historical Documents*. https://www.epa.gov/dwreginfo/drinking-water-lead-and-copper-rule-historical-documents(accessed October 2021).
(92) Marcillo, C. E.; Krometis, L.-A. H. Small Towns, Big Challenges: Does Rurality Influence Safe Drinking Water Act Compliance? *AWWA Water Sci.* **2019**, *1* (), DOI: 10.1002/aws2.1120.
(93) United States Environmental Protection Agency. *Environmental Justice Indexes in EJSCREEN*. https://www.epa.gov/ejscreen/environmental-justice-indexes-ejscreen (accessed December 2021).
(94) Del Toral, M. A.; Porter, A.; Schock, M. R. Detection and Evaluation of Elevated Lead Release from Service Lines: A Field Study. *Environ. Sci. Technol.* **2013**, *47*, 9300−9307.
(95) Cory, D. C.; Taylor, L. D. On the Distributional Implications of Safe Drinking Water Standards. *J. Benefit-Cost Anal.* **2017**, *8*, 49−90.
(96) Teodoro, M. P. Measuring Household Affordability for Water and Sewer Utilities. *J. Am. Water Works Assoc.* **2018**, *110*, 13−24.
(97) Pierce, G.; El-Khattabi, A. R.; Gmoser-Daskalakis, K.; Chow, N. Solutions to the Problem of Drinking Water Service Affordability: A Review of the Evidence. *Wiley Interdiscip. Rev. Water* **2021**, *8*, 1−25.
(98) United States Environmental Protection Agency. *Flint Drinking Water Response*. https://www.epa.gov/flint (accessed October 2021).
(99) DC Water. *Lead Free DC by 2030*. https://www.dcwater.com/lead(accessed December 2021).
(100) Potash, E.; Brew, J.; Loewi, A.; Majumdar, S.; Reece, A.; Walsh, J.; Rozier, E.; Jorgenson, E.; Mansour, R.; Ghani, R. Predictive Modeling for Public Health: Preventing Childhood Lead Poisoning. In *KDD '15: Proceedings of the 21st ACM SIGKDD Intenrational Conference on Knowledge Discovery and Data Mining*; *ACM Press*, 2015; pp. 2039−2047, DOI: 10.1145/2783258.2788629.
(101) Lanphear, B. P.; Hornung, R.; Khoury, J.; Yolton, K.; Baghurst, P.; Bellinger, D. C.; Canfield, R. L.; Dietrich, K. N.; Bornschein, R.; Greene, T.; Rothenberg, S. J.; Needleman, H. L.; Schnaas, L.; Wasserman, G.; Graziano, J.; Roberts, R. Low-Level Environmental Lead Exposure and Children's Intellectual Function An International Pooled Analysis. *Environ. Health Perspect.* **2005**, *113*, 894−899.

https://doi.org/10.1021/acsestengg.2c00008
ACS EST Engg. 2022, 2, 1475−1490