Integrating climate, health, resilience, and bill savings into the cost-optimal deployment of solar plus storage on public buildings

by

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Abstract

Climate change, public health, and resilience to power outages are of critical concern to local governments and are increasingly motivating investments in on-site solar and storage. However, designing a solar plus storage system to co-optimize for climate, health, resilience, and energy bill benefits requires complex trade-offs that are not captured in current analyses. To fill this gap, we integrate climate and health benefits into the REopt Lite optimization model using forward-looking, location-specific marginal emissions factors and health costs. Using this novel framework, we quantify the impact of including energy bill, climate, health, and/or resilience benefits on the cost-optimal sizing, battery dispatch, and economic returns of solar plus storage on three public building types across fourteen U.S. cities. We find that monetizing and optimizing for climate and health benefits, as compared to only energy bill savings and resilience, increases the net present value of the modeled solar plus storage systems by $0.2 million to $5 million. Due to changes in the cost-optimal battery dispatch, our expanded optimization results in additional climate and health benefits of $0.50 per dollar invested, as compared to optimizing for only energy bill savings and resilience. Our results illustrate significant differences across geographies and building types, highlighting the need for site-specific analyses of the costs and benefits of solar plus storage.

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I would also like to thank my parents and sister—Colin, Lisa, and Heather—for their unwavering love and support throughout the peaks and valleys of the last two years.

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List of Acronyms and Abbreviations

BAU	business as usual
CAIDI	Customer Average Interruption Duration Index
CapEx	capital expenditures
CRB	Commercial Reference Building
DER	distributed energy resource
DSM	demand side management
EPA	U.S. Environmental Protection Agency
ITC	investment tax credit
k	thousand
kW	kilowatt
kWh	kilowatt hour
LCC	life cycle cost
LMP	locational marginal price
M	million
MACRS	modified accelerated cost recovery system
MW	megawatt
MWh	megawatt hour
NEEDS	National Electric Energy Data System
NEM	net energy metering
NERC	North American Electric Reliability Council
NPV	net present value
NREL	National Renewable Energy Laboratory
O&M	operations and maintenance
PV	photovoltaics
REC	renewable energy credit
ReEDS	Regional Energy Deployment System
REopt Lite	NREL's Renewable Energy Optimization Lite model
ROI	return on investment
SOC	state of charge
solar plus storage	solar photovoltaic and/or battery storage systems
SRMER	short-run marginal emissions rate
t	metric ton
TOU	time of use
VDER	value of distributed energy resources
VoLL	value of lost load
VOS	value of solar

1. Introduction

In the United States, the electricity sector accounts for 25% of greenhouse gas emissions[1] and 11% of air pollution-induced premature mortalities.[2] As extreme weather events increase,[3] the U.S. power system is also seeing more frequent "major disturbances and unusual occurrences"—increasing tenfold from 2000 to 2020[4] and resulting in economic losses and loss of life.[5,6] Moreover, the burdens of climate change, air pollution, and power outages result in stark inequities—having been shown to disproportionately impact people of color and less affluent communities.[7–11]

With the ability to offset emissions from grid-purchased electricity and to provide power during blackouts, on-site solar photovoltaics and battery storage (solar plus storage) are well-poised to simultaneously reduce climate, health, and outage damages along with the system owner's energy bill costs. Grid-connected distributed solar installations in the U.S. have grown over the past two decades, from just under 800 annual installations in 2000 to over 374,000 in 2019 (Figure 1).[12] Meanwhile, the percentage of these systems that integrate storage has also increased to a respective 1.4% and 5% for small and large non-residential systems in 2019 (Figure 1) and is expected to continue to grow.[13,14]

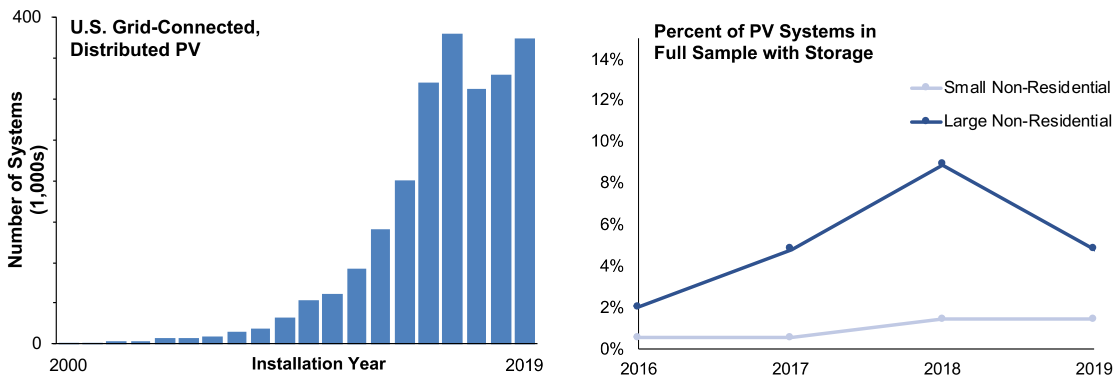

Figure 1. (left) Number of annual installations of grid-connected distributed PV in the U.S. and (right) storage attachment as percentage of installed distributed PV systems (Source: LBNL Tracking the Sun 2020).[12,14]

Given the increasing adoption of solar plus storage, many analyses quantify various costs and benefits of these technologies in diverse siting and operational contexts. A comprehensive understanding of the costs and benefits of solar plus storage can inform policy instruments (e.g., value of distributed energy resources (VDER) tariffs),[15–17] insurance valuations,[18] equity considerations,[19–22] investment decisions,[23–26] and operational strategies.[27–29] However, capturing the collective impact of climate, health, resilience, and energy cost savings within the cost-optimal deployment of solar plus storage remains a challenge that has yet to be addressed.

When paired with microgrid technologies (e.g., appropriate inverters, controls, and electrical infrastructure),[30] solar plus storage can increase resilience, keeping critical loads powered when the primary grid is down. Particularly in the context of critical services and resilience hubs, powering loads through an outage can reduce economic losses and mitigate suffering or loss of life. Considering resilience within solar plus storage system design can result in larger cost-optimal systems and increased resilience.[23,24,31] The value of resilience is typically defined as the economic value of avoided outages, calculated as the quantity of load powered through an outage multiplied by a value of lost load (VoLL).[18,24,32–35] Estimates of VoLL in the literature vary widely due to differences in methodologies (e.g., macroeconomic vs. willingness-to-pay studies), the end user-group studied, and the assumed outage duration.[33] Many previous studies have addressed and optimized for microgrid resilience.[23,24,36–42] Laws et al. (2021) provides the first model to co-optimize microgrids for annual grid-connected and resilience benefits under uncertain outages, while accounting for additional islanding costs and arbitrary utility tariff structures.[43] In this study, we build upon the work of Laws et al. (2021), which is implemented in the National Renewable Energy Laboratory's (NREL's) open source REopt Lite model,[44] by further integrating climate and health impacts.

Analyses of climate and health benefits of distributed energy resources (DERs) typically focus on solar energy (without the time-shifting ability of storage) and assume pre-determined system sizes.[19,45–47] When assessing the emissions impacts of an incremental change in electricity consumption, it is recommended to assume an associated change in production from the marginal generator, rather than considering the average emissions intensity of the grid.[48,49] Many studies assume that the marginal generator is always a natural gas plant,[16,17,50,51] while others assume that the marginal generator differs between off-peak and on-peak hours,[52] varies hourly based on dispatch modeling results,[53] or utilize regressions of historical generation and emissions levels to estimate marginal emissions factors.[19,47] Studies that have addressed the combined emissions impact of solar plus storage have done so in the context of isolated microgrids,[54–57] predefined schedules of demand response actions,[58] while optimizing battery dispatch for alternative objectives (e.g., reducing grid reliance),[27] or while considering general life cycle assessment emissions factors for technology components.[59,60] Avoided CO_2 emissions are typically valued using the social cost of carbon from the U.S. Interagency Working Group.[19,61–63] Avoided criteria air pollutants are typically valued as the compliance cost for emissions reductions from power plants or the estimated cost of medical expenses or mortality risk from emissions, although these damages are less frequently explicitly recognized in value of distributed solar literature and policies.[15,16,64]

We extend the literature by incorporating climate and health impacts, along with resilience, into the cost-optimal sizing of grid-connected solar plus storage. In contrast to previous work, we use location-specific and forward-looking marginal emissions factors and location- and season-specific marginal health costs. Valuation of climate and health impacts is particularly relevant for local governments, who own numerous properties, are responsible for wellbeing of their constituency, and are increasingly making climate commitments.[65] Resilience is also particularly salient for local governments, given that they must maintain power to critical infrastructure during blackouts, often provide the first line of response during disasters, and are well-poised to create resilience hubs to serve vulnerable community members.[66,67]

Using our model, we quantify the impact of including climate, health, and/or resilience costs and benefits on the optimal system sizes, economic returns, and battery dispatch of solar plus storage projects for three public building types across 14 U.S. cities. Our analysis demonstrates how local governments' cost-optimal deployment of solar plus storage would change when considering the costs of emissions damages and power outages in conjunction with investment costs and energy bill impacts.

2. Methods

2.1 REopt Lite Modeling Framework

To quantify climate and health impacts of solar plus storage, we incorporate forward-looking marginal emissions costs of grid-purchased electricity into the National Renewable Energy Laboratory's (NREL's) Renewable Energy Optimization (REopt) Lite model, an open-source Julia package.[44] To quantify the value of resilience, we utilize the method from Laws et al. (2021).[43]

When applied to solar plus storage systems, the REopt Lite model seeks to minimize the life-cycle cost (LCC) of electricity purchases by determining optimal technology sizes and the hourly storage dispatch strategy. For the full formulation of REopt, see Cutler, et. al. (2017).[68] Within the model, the utility costs, building load, and renewable generation in year one are assumed to represent a typical year. REopt Lite thus solves a single-year optimization, ensuring operational constraints are met in each hour, to determine year one cash flows. Cash flows for subsequent years are adjusted based on user-supplied rates of change for future costs (e.g., utility and O&M costs) and are discounted to determine the LCC of an investment.

Prior to our work, REopt Lite's solar plus storage life-cycle cost minimization included capital costs (C_{cap}), operations and maintenance costs ($C_{O\&M}$), the net cost of utility-purchased electricity (C_{elec}), and resilience costs ($C_{maxoutage}$ and C_{mg}). We extend this optimization to include climate ($C_{climate}$) and health (C_{health}) costs such that our objective becomes:

$$minimize\ LCC = C_{cap} + C_{O\&M} + C_{elec} + C_{maxOutage} + C_{mg} + C_{climate} + C_{health} \qquad (1)$$

The value of resilience is captured by $C_{maxoutage}$, which represents the maximum outage cost and C_{mg}, which represents the cost to enable the microgrid system to operate in isolation from the grid.[43] $C_{climate}$ and C_{health} represent climate and health costs, respectively, associated with grid-purchased electricity.

The net electricity cost (C_{elec}) represents energy and demand charges minus compensation for net exports to the grid. The calculation of energy bill savings given an arbitrary utility tariff is described in the REopt Lite documentation.[69] In this work, we incorporate traditional cost considerations, as well as resilience, but focus mainly on the valuation of climate and health benefits.

Figure 2 provides high-level model inputs, data sources, and relevant sections of this paper.

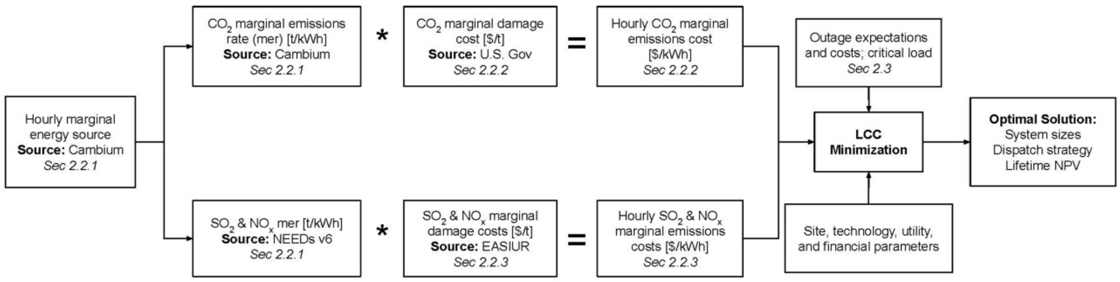

Figure 2. Overview of model inputs and outputs, along with relevant sections of this paper related to the valuation of climate, health, and resilience benefits.

The net present value (NPV) of a proposed investment is calculated as the difference between the "business-as-usual" (BAU) life-cycle costs (LCC_{BAU})—in which a building has neither solar nor storage—and the "investment case" life-cycle costs (LCC_{inv})—in which the model determines the optimal system sizes (Eq. 2).

$$NPV = LCC_{BAU} - LCC_{inv} \quad (2)$$

If the given investment in solar and storage results lower lifetime costs than the BAU case, then the NPV will be positive, and the investment is considered cost optimal. Analogously, we define the net climate, health, and resilience benefits of solar plus storage as the difference between these respective costs in the BAU and investment cases.

2.2 Valuing Benefits of Reduced Emissions

We quantify the climate and health benefits of solar plus storage based on reduced emissions from grid-purchased electricity due to these technologies. We do not account for upstream or end-of-life emissions associated with solar or storage. We estimate the hourly costs (or damages) of CO_2, SO_2, and NO_x as the product of each pollutant's marginal emissions rate, marginal damage cost, and net load. The hourly net load reflects net grid purchases, i.e., grid-purchased electricity minus any exports to the grid from the battery and/or PV system.

2.2.1 Marginal emissions rates

We assume a change in grid-purchased electricity in a given hour due to on-site solar and storage results in an associated increase or decrease in generation from the marginal energy source. We obtain forward-looking hourly marginal energy source data at the balancing area scale from NREL's Cambium database.[70] We utilize the marginal energy source (as opposed to marginal generator) to account for time-shifted generation needs resulting from energy-constrained marginal generators (e.g., batteries).[71] Cambium datasets are based on projected generator fleets from the Regional Energy Deployment System (ReEDS) model[72] and hourly fleet operations from the PLEXOS production cost model.[73] Modeled grid data are available for every other year between 2018 and 2050; we assume odd-numbered years have the same generation profile as the previous even-numbered year. We use results from the Mid-Case Scenario, which assumes default or median model inputs regarding the future generation mix and includes existing policies as of June 2020.[74]

From the hourly marginal energy source, we obtain marginal emissions rates for pollutants that impact the climate (carbon dioxide (CO_2)) and public health (sulfur dioxide (SO_2) and nitrogen oxides (NO_x)), for each year of the analysis period (2021-2046).

For climate damages, we consider only emissions of CO_2. While pollutants such as methane (CH_4) and nitrous oxide (N_2O) also contribute to climate damages, the CO_2-equivalent emissions of non-CO_2 pollutants are relatively small for grid-sourced power.[69] We utilize hourly short-run CO_2 marginal emissions rates (SRMERs) from Cambium at the balancing area scale. The hourly SRMER (t CO_2/kWh$_{enduse}$) is the end-use emissions rate of the marginal energy source and is already adjusted for transmission, distribution, and efficiency losses in delivery to the end user.

For health damages, we consider only the impacts of SO_2 and NO_x, which affect human health through their secondary formation of PM2.5. Together, these species account for approximately 82% of mortalities caused by power plant emissions (~75% from SO_2 and 7% from NO_x).[75] Direct emission of PM2.5 also contributes a significant amount (~14%) to PM2.5 exposure and associated mortalities from the electricity sector and should be considered in future work.[75] Future marginal emissions rates for criteria air pollutants are not available from Cambium or other public datasets. Instead, we calculate historic plant-level emissions rates for SO_2 and NO_x using the U.S. Environmental Protection Agency's (EPA's) National Electric Energy Data System (NEEDS) v6 database of U.S. power plant characteristics.[76] We calculate each plant's SO_2 and NO_x emissions rates [t/kWh] as the heat rate [Btu/kWh] multiplied by the SO_2 Permit Rate [lbs/mmBtu] and Mode 4 NO_x Rate [lbs/mmBtu], respectively. We use the Mode 4 NO_x Rate, which assumes state-of-the-art combustion controls are in place, in anticipation of these controls becoming more widely adopted. We subsequently calculate the average SO_2 and NO_x emissions rates by plant type and NEEDS region. NEEDS regions generally represent subdivisions of the 8 North American Electric Reliability Council (NERC) regions. We map region- and plant type-specific SO_2 and NO_x emissions rates to the corresponding hourly marginal energy source in the corresponding Cambium balancing area using the mapping scheme in Table B1.

The resulting average hourly marginal emissions rates (mer^{plant}) for SO_2 and NO_x are subsequently adjusted for transmission and distribution losses using the hourly marginal distribution loss rate ($L_{yr,hr}$) as reported in the Cambium dataset.[71] As a result, we obtain end-use marginal emissions rates (mer^{enduse}) for SO_2 and NO_x for each hour (hr) of the year, for each year (yr) of the analysis period (Eq. 3).

$$\mathrm{mer}_{yr,hr}^{enduse} = \mathrm{mer}_{yr,hr}^{plant} * \left(1 + L_{yr,hr}\right) \tag{3}$$

Since the REopt Lite model determines an optimal hourly battery dispatch strategy for a single year, we cannot utilize hourly marginal emissions rates with profiles that vary year to year. Instead, to account for both hourly variability and annual trends, we select the midpoint year of the analysis to represent the *profile* (or shape) of the marginal emissions rates for CO_2, SO_2, and NO_x. We then scale the mid-point year hourly profiles based on the respective *total marginal emissions* of CO_2, SO_2, and NO_x in each year of the analysis.

For a 25-year analysis beginning in year 2021, we thus have three sets of 25 marginal emissions profiles ($mer_{hr,yr}$) that reflect the CO_2, SO_2, and NO_x hourly marginal emissions shape of 2033 (each hour is scaled from the corresponding hour in 2033), but maintain the total per kWh damage from marginal emissions over each analysis year. Figure 3 shows an example of the resulting hourly profiles over a 24-hour period for 2021-2046. Selecting the profile of the midpoint year accounts for the fact that more emissions-intensive generators are on the margin less often as the years progress from 2021 to 2046 and thus avoids over- or under-sizing the system. For further explanation and justification of this approach, see Appendix A.

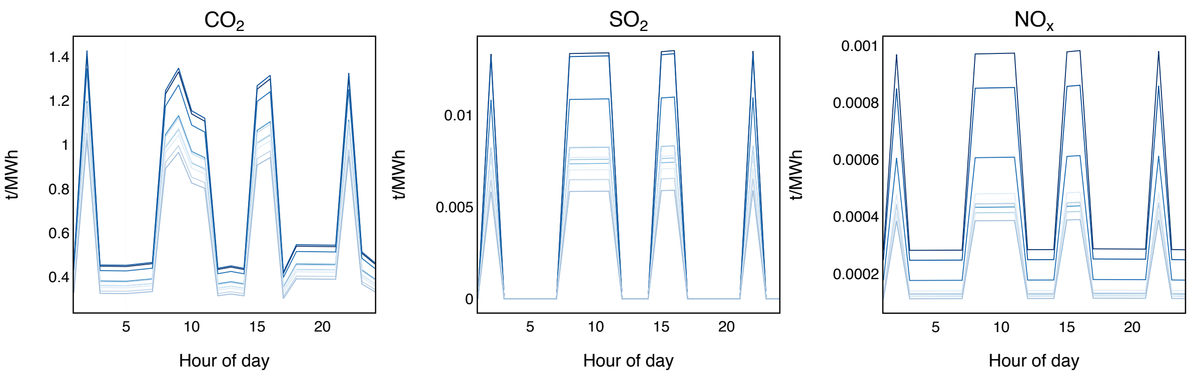

Figure 3. Example CO_2 (left), SO_2 (center), and NO_x (right) hourly marginal emissions rates, scaled to reflect the shapes of the 2033 (mid-point year) hourly profiles. Example shown is for the city of Chicago for one day for the years 2021-2046.

2.2.2 Climate benefits

To monetize the social damages caused by CO_2 emissions, we use the social cost of carbon dioxide (SC-CO_2) from the U.S. government's Interagency Working Group.[63] For our baseline scenario, we utilize $52 per metric ton of CO_2 (in $2020 assuming a three percent discount rate). Consistent with the literature, we assume marginal damage costs in each year of the system's lifetime can be approximated by this 2020 marginal damage cost (prior to discounting).[19,59,61]

We calculate the total climate damage cost ($C_{yr}^{climate}$) in each year (yr) of the analysis period (A) as:

$$C_{yr}^{climate} = SC\text{-}CO_2 * \sum_{\mathrm{hr} \in \mathrm{Hrs}} \left(netload_{hr} * mer_{hr,yr}\right) \forall yr \in A \tag{4}$$

where $SC\text{-}CO_2$ is the social cost of CO_2 [$2020/t] and $mer_{hr,yr}$ is the marginal CO_2 emissions rate [t CO_2/kWh] in each hour (hr) and year (yr) in the analysis period (A), where $A = \{0, 1, 2, \ldots, n\}$. The hourly net load ($netload_{hr}$) equals grid-purchased electricity, which accounts for building load met by solar generation and/or battery discharge, minus exports to the grid from the battery and/or PV system.

The total climate-related cost ($C^{climate}$) is calculated as the NPV of the annual climate costs, using the electricity off-taker's discount rate (d) (Eq. 5). This total cost is incorporated into the model objective in scenarios in which climate costs are considered.

$$C^{climate} = NPV = \sum_{yr \in A} \frac{C_{yr}^{climate}}{(1+d)^{yr}} \tag{5}$$

The climate benefit ($B^{climate}$) of a given system is the difference between the climate costs in the BAU ($C_{BAU}^{climate}$) and investment cases ($C_{inv}^{climate}$) (Eq. 6). The climate benefit can be negative.

$$B^{climate} = C_{BAU}^{climate} - C_{inv}^{climate} \tag{6}$$

2.2.3 Health benefits

The marginal health damage of air pollutants is highly dependent on the local population and atmospheric conditions.[77] These marginal damages are also highly seasonally-dependent, with a U.S. average of 80% of power plant mortality damages attributable to emissions from April to September.[75] To estimate location- and season-specific marginal health damages for emissions of SO_2 and NO_x, we use the Estimating Air pollution Social Impact Using Regression (EASIUR) model.[78] EASIUR utilizes reduced-form air quality modeling to estimate the increase in public health burden caused by a marginal increase (one additional metric ton) of PM2.5 precursor emissions (including SO_2 and NO_x) in a given location. Public health burden is calculated as an increase in mortality (premature deaths) in downwind populations caused by inorganic PM2.5 exposure, using a $8.6 M ($2010) value of statistical life (VSL) and a concentration-response relation from the American Cancer Society.[77] The resulting marginal damage costs are available at a resolution of 36 km x 36 km, for each of the four seasons, for three emissions elevations (ground-level, 105 m, and 300 m). We assume emissions occur at the building location, given that the exact location of the marginal energy source is not available. We assume the income and population year is 2021 and adjust the results to $2020. We use seasonal estimates for 105 m elevation, given that most power plants' stack heights are at or below this height.[79] Similar to our approach to the SC-CO_2, we assume that damage estimates in each year can be approximated by 2021 damage estimates (prior to discounting). Previous studies have shown annual damages obtained from EASIUR to be comparable to, yet slightly lower than, damage estimates obtained using other integrated assessment models, e.g., AP2[19] and AP3 and inMAP.[61]

We calculate the annual health damage cost (C_{yr}^{health}) for each year (yr) of the analysis period ($A = \{0, 1, 2, \ldots, n\}$) as:

$$C_{\mathrm{yr}}^{\mathrm{health}} = \sum_{\mathrm{s} \in \mathrm{S}} \sum_{\mathrm{hr} \in \mathrm{SHr}} \left(\mathrm{mec}_{\mathrm{s}}^{\mathrm{SO_2}} * \mathrm{netload}_{\mathrm{hr}} * mer_{hr,yr}^{SO_2} + mec_{\mathrm{s}}^{\mathrm{NO_x}} * \mathrm{netload}_{\mathrm{hr}} * \mathrm{mer}_{\mathrm{hr,yr}}^{\mathrm{NO_x}} \right) \forall \mathrm{yr} \in \mathrm{A} \tag{7}$$

where s indexes the season in *S={winter, spring, summer, fall}* and the seasonal marginal emissions costs for SO_2 and NO_x (mec^{SO2} and mec^{NOx}) are in units of $2020/t of pollutant. The marginal costs are each multiplied by the hourly net load (*netload* [kWh]) and hourly end-use marginal emissions rates (mec^{SO2} and mec^{NOx} [t/kWh]), for each hour (*hr*) in the set of hours corresponding to each season (*SHr*). The annual health cost is the sum of damages from SO_2 and NO_x over each hour of the year.

The public health cost (C^{health}) over the lifetime of the system is calculated as the NPV of the annual health costs (C_{yr}^{health}), using the electricity off-taker's discount rate (*d*) (Eq. 8). This total cost is incorporated into the model objective in scenarios in which health costs are considered.

$$C^{health} = NPV = \sum_{yr \in A} \frac{C_{yr}^{health}}{(1+d)^{yr}} \tag{8}$$

The health benefit (B^{health}) of a given system is the difference between the health costs in the BAU (C_{BAU}^{health}) and investment cases (C_{inv}^{health}) (Eq. 9). The health benefit can be negative.

$$B^{health} = C_{BAU}^{health} - C_{inv}^{health} \tag{9}$$

2.3 Valuing Benefits of Increased Resiliency

The methods used to value resilience within the REopt Lite Julia Package and the associated model constraints are described in previous work.[43] Below, we summarize key components of the valuation approach with slight modifications considering the unique assumptions of this research.

The outage cost is the maximum expected outage cost ($C^{maxoutage}$) over set *T* of possible outage start times (t_0). We assume the outage occurs annually and adjust the annual cost with a present worth factor (*pwf*):

$$C^{maxoutage} = \max_{t_0} \mathbb{E}\left[C_{t_0}^{outage}\right] * pwf\ , \ \ \forall t_0 \in T \tag{10}$$

In our baseline scenario, we consider an outage of 15 hours, the average duration of major outages in 2020,[4] occurring with 100% probability. Ideally, we would model the outage at each hour of the year for every scenario; however, this approach proved computationally intractable. To reduce the computational intensity of the models while still capturing the uncertain nature of major outages, we determine the set of outage start times (*T*) for each building that results in the 95th percentile of total unserved load in absence of a microgrid. That is, we simulate a 15-hour outage in each hour of the year (assuming no microgrid exists), determine the 438 hours that represent the 5% worst times to experience an outage, and use this set *T* in all optimization scenarios for that building. Appendix B includes histograms showing the outage start hours in set *T* by month and hour of the day.

The cost of each simulated outage is the value of lost load ($VoLL$) [$/kWh] multiplied by the total unserved load (UL) over all hours (hr) of the outage (where the outage starts at time t_0 and lasts until time t_{0+d}):

$$C_{t_0}^{outage} = VoLL * \sum_{hr \in Outage} UL_{hr} \tag{11}$$

Estimates of the VoLL for public buildings are limited. Given the far-reaching impacts of an outage to public facilities—which may provide core health or safety services or be a resilience hub for residents[66,80]—we utilize economy-wide estimates of the VoLL. Several review papers show that economy-wide estimates for mid- to long-duration outages fall within $4-$40/kWh[81–84] (in varying dollar years) while others have estimated the cost of a 16-hour power outage in the U.S. to range from $70-$140/kWh (in $2020) when accounting for indirect impacts.[81]

In this research, we draw upon these wide-ranging estimates and assume that the economy-wide impacts of a mid-duration (15-hour) outage has a minimum cost of $4/kWh and a maximum cost of $140/kWh. We subsequently estimate outage costs for different public facility types based on whether they provide critical or emergency services and whether they will serve as a resilience hub for community members during an outage (Table 1). Critical or emergency facilities are assumed to incur costs at the high end of our defined range. We estimate the cost of an outage to a resilience hub to be the midpoint value and the cost to a non-critical and non-resilience hub facility to be at the low end of the range. VoLL is assumed to be constant throughout the year. This approach to differentiating the VoLL is unique and is constrained by limited data for public facilities; future research in this area will be valuable.

Table 1. Estimated VoLL for different public facility types for a 15-hour outage.

Facility type	VoLL ($2020/kWh)
Critical or Emergency Service	$140
Resilience Hub	$72
Non-critical, Non-resilience Hub	$4

The resilience benefit ($B^{resilience}$) is calculated as avoided outage costs minus the microgrid upgrade cost.

$$B^{resilience} = (C_{BAU}^{maxOutage} - C_{inv}^{maxOutage}) - C_{inv}^{mg} \tag{12}$$

2.4 Model Application across United States

We apply our model to three public building types (hospital, secondary school, and warehouse) in 14 U.S. cities (Albuquerque, Atlanta, Baltimore, Boulder, Chicago, Duluth, Helena, Houston, Los Angeles, Miami, Minneapolis, Phoenix, San Francisco, and Seattle). These building types serve differing roles during a power outage: a hospital provides critical services, a secondary school can serve as a community resilience hub, and a warehouse may serve no special role. For each building, we determine the cost-optimal solar plus storage system size and economic outcomes when considering bill savings, resilience, climate, and/or health impacts (Table 2). Our 14 locations span unique climate zones and balancing areas (Figure 4).[71,85,86] We assume each building has already been deemed suitable for solar given, e.g., roof vintage and loading capacity.

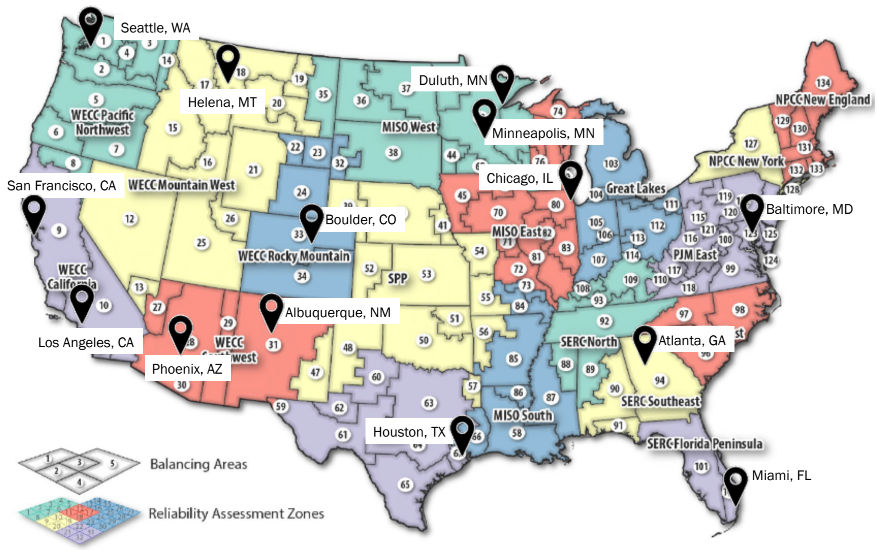

Figure 4. Locations for buildings modeled in this study along with balancing areas and reliability assessment zones used to develop Cambium datasets (Source: Cambium Documentation 2020[71]). *(MISO: Midcontinent Independent System Operator; NPCC: Northeast Power Coordinating Council; SERC: SERC Reliability Corporation; SPP: Southwest Power Pool; WECC: Western Electricity Coordinating Council)*

Table 2. Optimization scenarios, associated acronyms, and LCC calculations used in this study.

Acronym	Monetized value streams	Objective value (minimization)
B	Bill savings	$LCC = C_{cap} + C_{O\&M} + C_{elec}$
BR	Bill savings, resilience	$LCC = C_{cap} + C_{O\&M} + C_{elec} + C_{maxOutage} + C_{mg}$
BRCH	Bill savings, resilience, climate, health	$LCC = C_{cap} + C_{O\&M} + C_{elec} + C_{maxOutage} + C_{mg} + C_{climate} + C_{health}$

We hold several inputs constant across locations, including project finance assumptions (Table 3); technical and cost assumptions for PV and battery storage (Table 4); anticipated outage characteristics (Table 5); available roof space for solar by building type (Table 6); critical load percentage by building type (Table 6); VoLL by building type (Table 6); and the social cost of carbon. Inputs we vary across locations are building loads (Table B2); marginal emissions costs (Figure 5); marginal emissions rates of grid-purchased electricity; utility tariff assumptions (Table B3); and net energy metering (NEM) rates.

Given the 25-year life a PV system, we run our analysis from 2021 to 2046. We assume the projects are directly owned and entirely financed by the local governments, and thus we do not consider tax benefits (e.g., MACRS and ITC). Incorporating alternative financing models, while outside the scope of this research, could make investments more financially attractive for local governments.

In our baseline scenario, we assume an annual outage of 15 hours (the average duration of major U.S. outages in 2020[4]). We estimate the critical load for each facility based on whether it provides critical services or could serve as a resilience hub during a power outage. The building-specific VoLL is accordingly assigned using the values from Table 1.

Climate zone-specific building loads are generated from the U.S. DOE Commercial Reference Building (CRB) models for post-1980 construction for each site.[85] We estimate the total roof area that is suitable for solar as the corresponding CRB total square footage (which is constant across climate zones) divided by number of floors. We assume 50% of the roof is available to host solar panels.

We use a SC-CO_2 of $52/t ($2020) for all analyses. Figure 5 shows the marginal health costs from EASIUR of SO_2 and NO_x by season and location. Marginal health costs are notably higher in Baltimore, Chicago, Los Angeles, San Francisco, and Seattle than the average across all cities, marked by the solid horizontal line. Average marginal CO_2, SO_2, and NO_x emissions rates from 2021-2046 for each location are shown in Figure 6. While these averages illustrate the difference in emissions-intensity of grid electricity in the 14 locations, in our analysis we utilize hourly marginal emissions rates as described in Section 2.2.

We model realistic utility rate structures by selecting an appropriate tariff for each building from the International Utility Rate Database, based on the likely utility company given the location and any applicable energy or demand limits[87] (Table B3). Many of these rates include time-of-use components. The REopt Lite Julia package simplifies multi-tiered rates by using the first tier for energy rates and the last tier for demand rates.[44] For the sake of comparison, Table B3 includes the *average* energy and demand rates in the base case (without solar or storage technologies). We assume net energy metering (NEM) is permitted for all buildings and that net excess generation is compensated at the retail rate. All model instances were solved using the IBM® CPLEX® Optimizer.

Table 3. Financial assumptions for all buildings. All financial values are nominal.

Parameter	Value
Analysis period	2021-2046
Discount rate	8.3%*
O&M cost escalation rate	2.5%*
Electricity cost escalation rate	2.3%*
Tax rate	0%
ITC	Not applied
MACRS	Not applied

*These values are the REopt Lite default values, which draw largely from national averages. See documentation for sources and assumptions.[69]

Table 4. Technical and cost assumptions for PV, battery storage, and microgrid systems for all buildings. All financial values are nominal.

PV Assumptions	**Value**
Technical	
Annual degradation	0.5%*
Rooftop power density	10 watts / sf*
Inverter efficiency	96%*
System losses	14%*
DC/AC ratio	1.2*
PV tilt	10 degrees*
Module type	Standard*
Azimuth	180 degrees*
Hourly PV production	Obtained from PVWatts using location and system characteristics
Economic	
Installed cost	$2.3/W**
O&M cost	$16/kW/year*
Battery Assumptions	**Value**
Technical	
Inverter and storage replacement	Year 10*
Total AC-AC round trip efficiency	89.9%
Internal efficiency	97.5%*
Inverter efficiency	96%*
Rectifier efficiency	96%*
Minimum/initial state of charge	20% / 50%*
Can grid charge battery?	Yes
Economic	
Installed cost	$840/kW, $420/kWh*
Replacement cost (year 10)	$410/kW, $200/kWh*
Microgrid Assumptions	
Economic	
Microgrid premium	30% of solar plus storage capital cost*

*These values are the REopt Lite default values, which draw largely from national averages. See documentation for sources and assumptions.[69]

**U.S.-wide median cost for large non-residential PV systems in 2019.[14]

Table 5. Anticipated outage characteristics

Parameter	**Value**
Outage length	15 hours
Outage start times	Hours in the 95th percentile of most unserved load in absence of microgrid
Outage frequency	Annual

Table 6. Building type-specific inputs for maximum available roof space, critical load, and VoLL.

Building type	**Available roof space [sf]**	**Building purpose during outage**	**Critical load [% of total load]**	**Value of lost load [$/kWh in $2020]**
Hospital	24,100	Critical facility	85%	$140
Secondary School	52,700	Community resilience hub	60%	$72
Warehouse	26,000	Non-critical	10%	$4

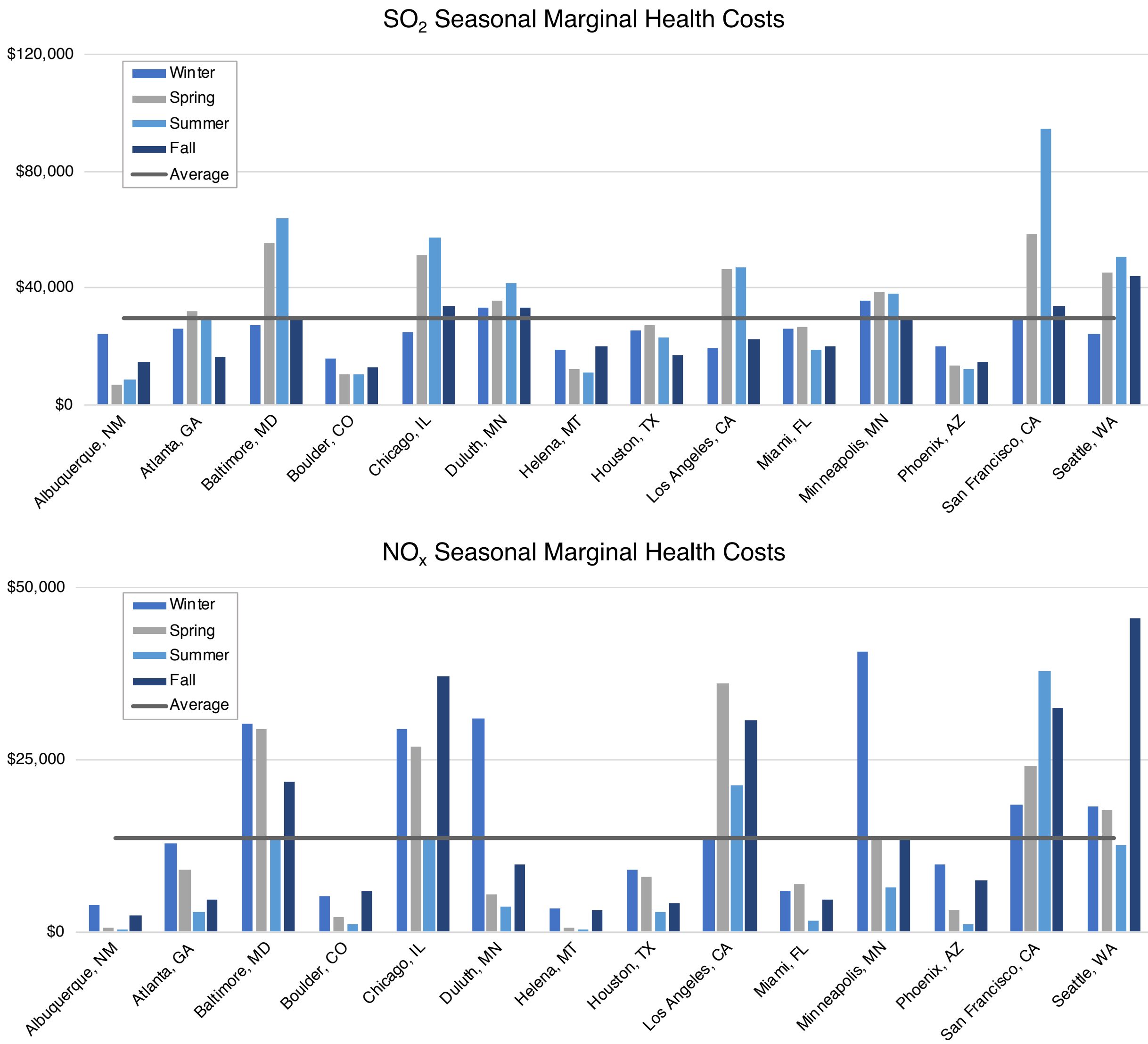

Figure 5. Location- and season-specific marginal health costs for SO_2 and NO_x, assuming a stack height of 150 meters and income and population years of 2021.

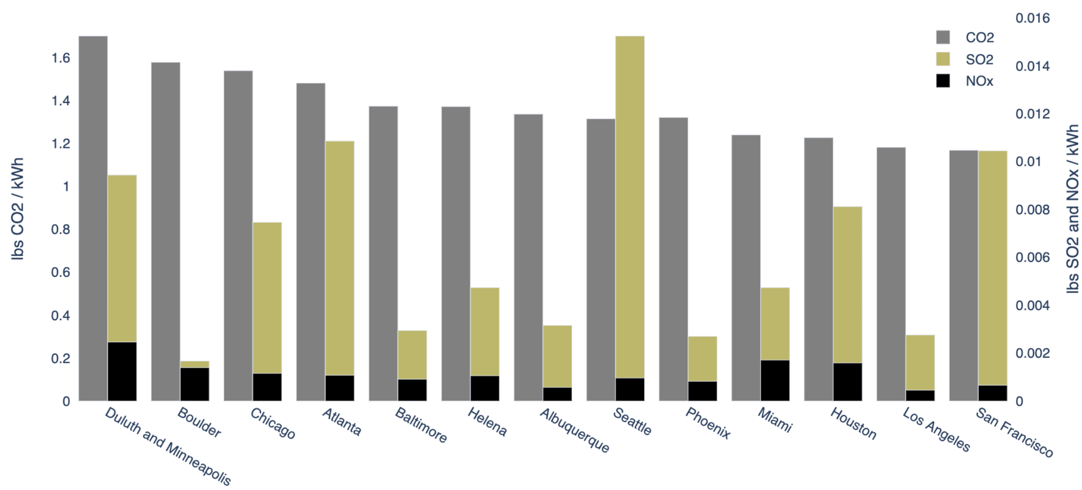

Figure 6. Average marginal emissions rates for CO_2, SO_2, and NO_x over the analysis period (2021-2046).

2.5 Sensitivity Analysis

We explore the sensitivity of our results to several key assumptions, summarized in Table 7.

Table 7. Parameters varied in the sensitivity analysis.

Parameter	**Baseline value**	**Sensitivity values**
Assumed outage length	15 hours	• 3 hours • 48 hours
NEM Assumptions	Full retail rate	• Wholesale rate in all locations

Given differing planning priorities of local governments and the uncertainty of grid outages, we consider a short (3-hour) and multi-day (48-hour) assumed outage length. A 3-hour outage corresponds to the 2019 average Customer Average Interruption Duration Index (CAIDI) for U.S. utilities.[88] This metric typically excludes major outage events but is frequently used to estimate the duration of future outages.[23,24,31] Local governments may also wish to plan for long-duration outages that can have extremely damaging impacts to city operations and residents' safety. To reflect this planning scenario, we assume an expected outage duration of 48 hours.

Given uncertainty regarding the future of NEM policies and to demonstrate the relative impact of NEM on investment decisions, we assume net excess generation is compensated at a location-specific static wholesale rate. This wholesale or locational marginal price (LMP) is calculated as the modeled LMPs in the Cambium Mid-Case Scenario for the corresponding balancing area, averaged over 2021-2046 (Table C1).

3. Results

3.1 Cost-Optimal System Sizing

Figure 7 illustrates the cost-optimal solar and storage system sizes by building type and optimization scenario. When only considering the benefits of bill savings within the optimization (Scenario B), it is not cost-optimal to invest in solar in all modeled locations except Los Angeles, Phoenix, and San Francisco.[a] The median cost-optimal battery sizing across locations in Scenario B is 6 kW/12 kWh for the hospitals and zero for the schools and warehouses. In locations in which storage is cost-optimal, demand cost savings tend to provide the largest proportion of total benefits.

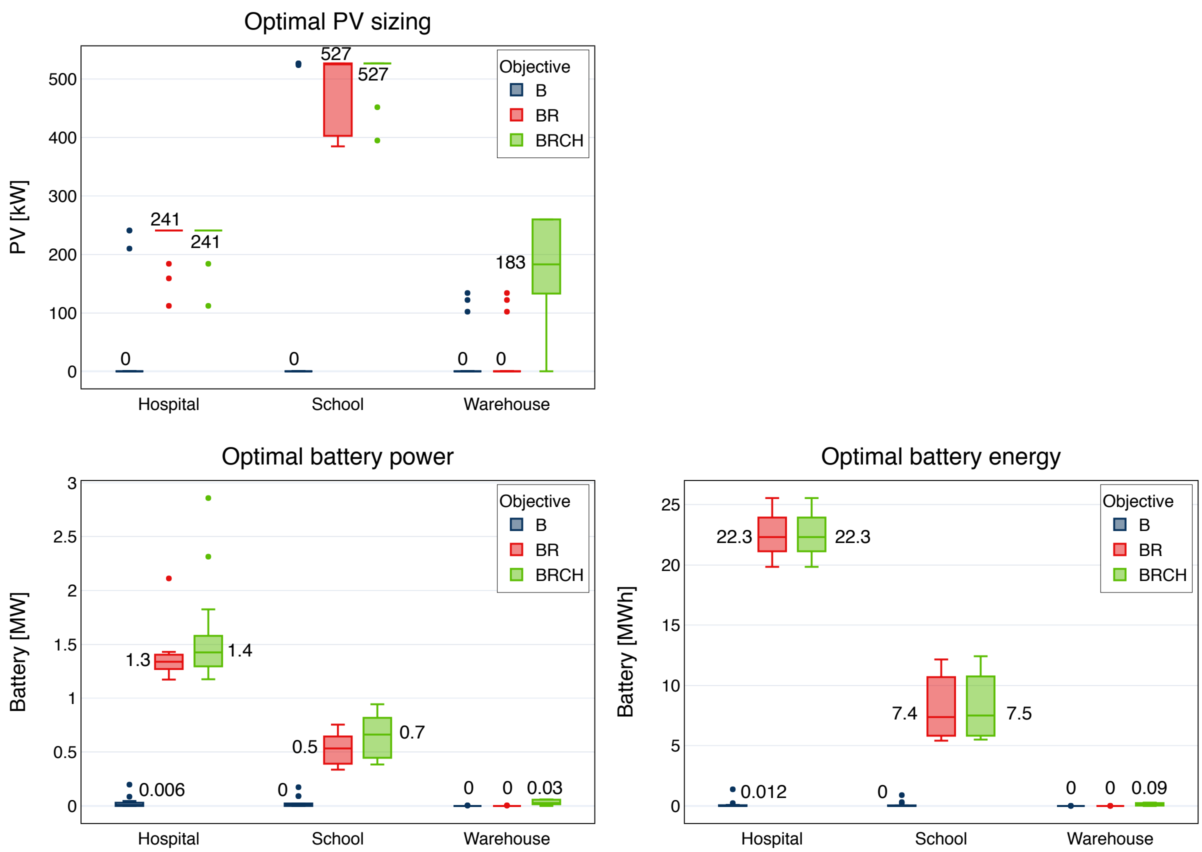

Figure 7. Box plots of cost-optimal solar and storage system sizes by building type and optimization scenario. The ends of each box indicate the lower and upper quartiles, the line inside the box marks the median, and the whiskers extend to the data minimum and maximum, with outliers shown as dots. Median values for each building type and objective scenario are called out.

[a] This is likely due to a combination of strong solar irradiance and utility rate structures. All modeled buildings in Los Angeles, and the hospitals and schools in San Francisco and Phoenix have TOU energy and/or demand rates that align with typical solar generation profiles. The warehouses in San Francisco and Phoenix have relatively high energy rates.

When co-optimizing for resilience benefits (Scenario BR), it becomes cost-optimal to invest in the largest possible PV sizes given available space for the 11 of the 14 hospitals and 9 of the 14 schools. The median cost-optimal battery sizes also increase significantly as compared to Scenario B, to 1.3 MW/22.3 MWh for the hospitals and 530 kW/7.4 MWh for the schools. This increase in optimal solar plus storage sizing is driven by the high cost of incurring an outage in the hospital and school buildings, given their high VoLL ($140/kWh and $72/kWh, respectively) and critical load percentage (85% and 60%, respectively). On the contrary, the warehouse has a low VoLL and critical load ($4/kWh and 10%), so including resilience in the optimization has no impact on system sizing.

When additionally optimizing for climate and health benefits (Scenario BRCH), larger system sizes become cost optimal. The increases are relatively small for the hospital and school building types, for which large system sizes are already cost-optimal under Scenario BR. However, for the warehouses, the increases are relatively large, given that in most cases, solar and storage do not become cost-optimal until climate and health benefits are considered. For warehouses, the median cost-optimal system sizes increase from zero PV and battery in Scenario B to 183 kW PV and 27 kW/90 kWh battery in Scenario BRCH.

3.2 System Economics

In Scenario BRCH, the median NPV of the cost-optimal solar plus storage systems for the hospitals, school, and warehouses are $5M, $3.6M, and $0.2M greater than those of Scenario BR, respectively (Figure 8). The NPV calculation reflects only those benefits for which the system is optimized, thus illustrating the perspective of a local government decision-maker who, by choice or market forces, values bill savings only (Scenario B), or additionally values resilience (BR) and climate and health (BRCH).

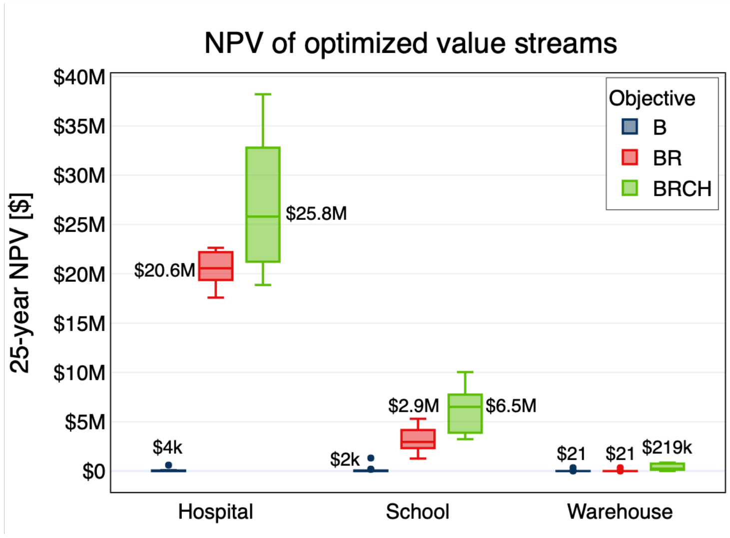

Figure 8. 25-year net present value (NPV) of cost-optimal solar plus storage systems by building type and optimization scenario. In each case, the NPV includes only those value streams included in the optimization objective. The ends of each box indicate the lower and upper quartiles, the line inside the box marks the median, and the whiskers extend to the data minimum and maximum, with outliers shown as dots. Median values for each building type and objective scenario are called out.

Our sensitivity analysis shows that compensating systems at the wholesale as opposed to net metering rate negligibly alters the NPV of the modeled systems because export benefits are a small portion of total benefits. Considering a shorter (3-hr) outage results in a lower NPV for the hospitals and schools due to lower resilience benefits. Unsurprisingly, a longer (48-hr) outage results in a higher NPV for the hospitals and schools due to greater resilience benefits. The NPVs of the warehouses are not influenced by the assumed outage duration due to our assumed low VoLL for this building type. Notably, the *absolute* increase in NPV from Scenarios BR to BRCH is similar to the base case across sensitivity cases. For the hospitals, optimizing for climate and health benefits (Scenario BRCH) resulted in an NPV increase ranging from \$4.3M (in 3-hour outage case) to \$7M (in the 48-hour outage case) as compared to Scenario BR. For the schools, the NPV increase ranged from \$2.35 (in 3-hour outage case) to \$4M (in the 48-hour outage case) (Figure C1).

Even when not considered within the optimization, solar plus storage systems have climate and health impacts during their operation. Figure 9 illustrates the climate and health "return on investment (ROI)" by optimization scenario, calculated as:

$$Climate\ ROI = \frac{B_{climate}}{C_{cap}+C_{O\&M}+C_{mg}} \quad \text{and} \quad Health\ ROI = \frac{B_{health}}{C_{cap}+C_{O\&M}+C_{mg}} \tag{13}$$

Normalizing by investment costs gives an indication of the additional climate and health benefits that accrue due to operational strategies, rather than system size. Comparing the BR and BRCH cases is particularly illustrative, given that in both cases the value of bill savings and resilience are incorporated. The combined climate and health ROI is much larger for Scenario BRCH (\$0.06 to 2.06 with a median value of \$0.57) than for BR (\$-0.07 to \$1.71 with a median value of \$0.06) or B (\$-0.07 to \$1.71 with a median value of \$0.13) (Figure 9). The median combined climate and health ROI is higher in Scenario B than in Scenario BR because in several cases solar, but not large storage or microgrid systems, are cost-optimal, leading to climate and health benefits at a much lower upfront investment cost. However, in Scenario B, resilience benefits (not depicted in Figure 9) are never incurred.

In Scenario BRCH, health benefits typically exceed climate benefits in the cost-optimal systems (for all but five of the 42 buildings). In fact, in the case of the Seattle hospital, the cost-optimal system in Scenario BRCH incurs additional climate damages (amounting to \$340k) compared to BAU operations while accruing \$3.8M in health benefits.

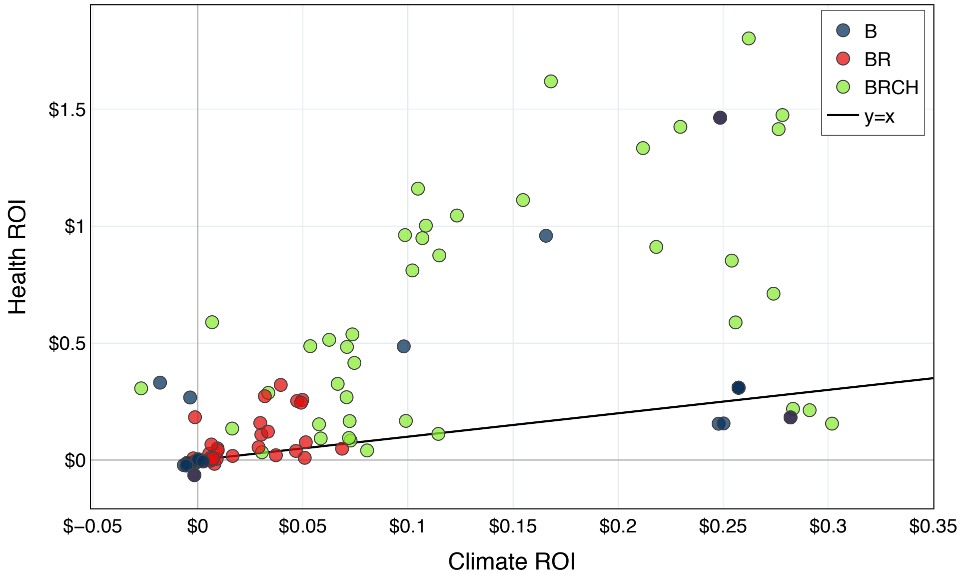

Figure 9. Climate and health return on investment (ROI) for each modeled building by optimization scenario. Note that systems accrue additional non-emissions benefits (i.e., bill savings and/or resilience), not included in this ROI calculation. A combined climate and health ROI of $1.00 or greater indicates that with these benefits alone, the system pays itself back.

Previous work accounts for the value of resilience in cost-optimal solar plus system sizing.[43] We thus evaluate the *additional* costs and benefits incurred when co-optimizing for climate and health (i.e., we compare Scenarios BR and BRCH) in Figure 10. Additional health and climate benefits vary by location and building type; co-optimizing for these benefits in some cases results in additional costs. The additional benefits incurred when moving from scenario BR to BRCH are largely driven by avoided health costs, which range from $463k-$16.3M in added benefits for the hospitals, $139k-$5.1M for the schools, and $0-$1.2M for the warehouses. Our sensitivity analysis shows that these additional climate and health benefits are not sensitive to the assumed outage length or net export compensation rate (Figure C2).

Averaging across the three building types, the combined additional climate and health benefits (in Scenario BRCH as compared to BR) are relatively high (exceeding $6M) in Chicago, Atlanta, Duluth, and Minneapolis and relatively low (below $1M) in Albuquerque, Boulder, Los Angeles, and Phoenix. The locations on the high end of the spectrum have marginal SO_2 health costs that are higher than the sample mean in at least one season (Figure 5) and higher than average SO_2 and CO_2 average marginal emissions rates (Figure 6). The locations that see lower additional climate and health benefits (in Scenario BRCH compared to Scenario BR) have CO_2 (with the exception of Boulder) and SO_2 average marginal emissions rates that are lower than the sample mean, and lower than average SO_2 and NO_x costs (with the exception of Los Angeles).

For 60% of the modeled buildings, the cost optimal systems in Scenario BRCH have lower energy bill savings than those of Scenario BR. Across all buildings, an average of $0.27M in lifetime energy bill savings are forgone when co-optimizing for climate and health benefits (Scenario BRCH) as compared to Scenario BR. For many of the modeled warehouses, it is not cost-optimal to invest in solar and storage until climate and health are considered in the objective, and thus additional capital and O&M costs, along with climate, health, and bill savings benefits are accrued in Scenario BRCH case as compared to Scenario BR.

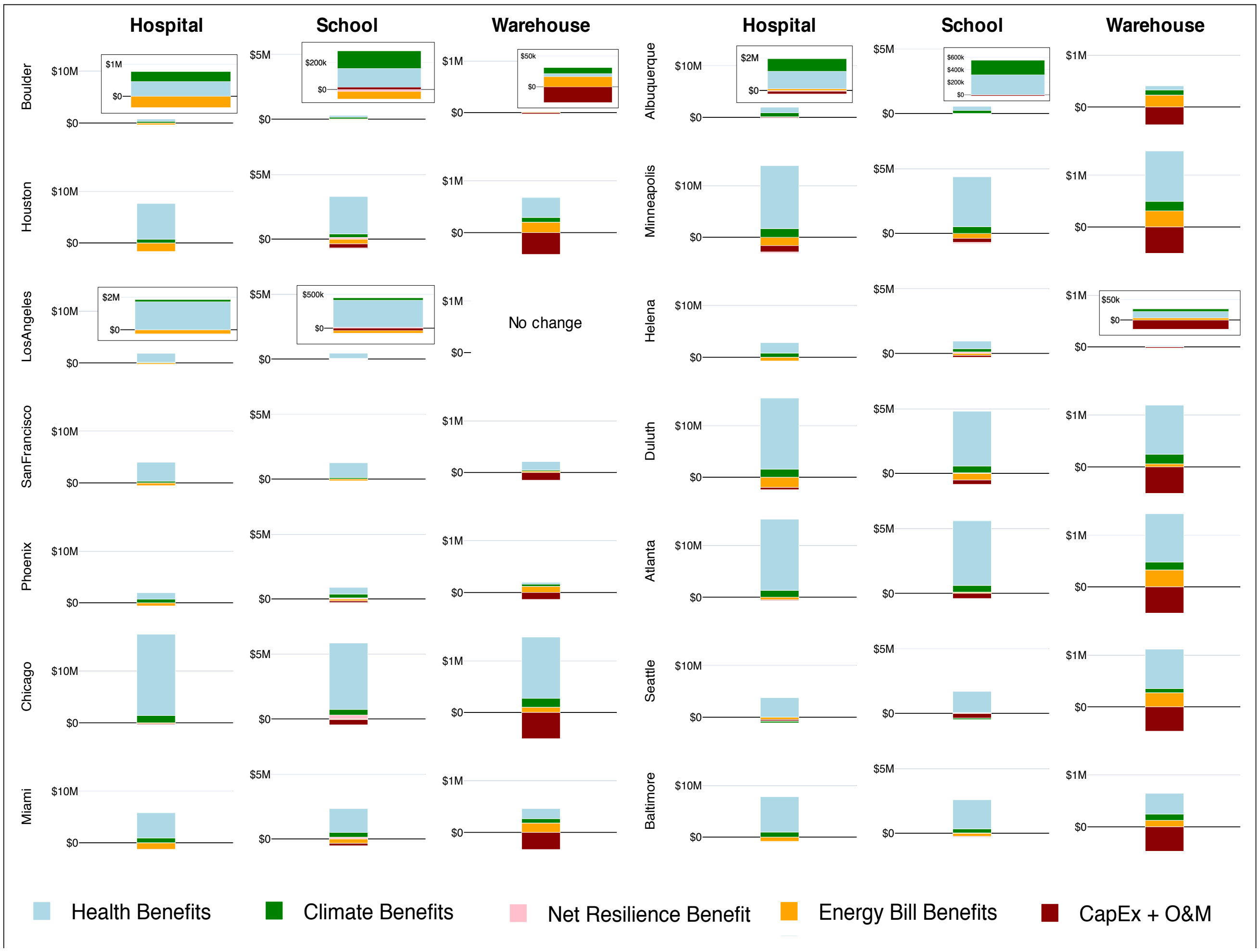

Figure 10. Additional costs and benefits accrued in Scenario BRCH as compared to Scenario BR by building type and location. Net resilience is calculated as avoided outage costs minus the microgrid upgrade cost.

3.3 Optimal Battery Dispatch

The battery dispatch strategy strongly influences the climate and health benefits of a solar plus storage system. The dispatch strategies vary between the three optimization scenarios (Figure 11). In all scenarios, the minimum state of charge (SOC) is 20% and the battery can be charged by the grid or solar but cannot discharge to the grid.

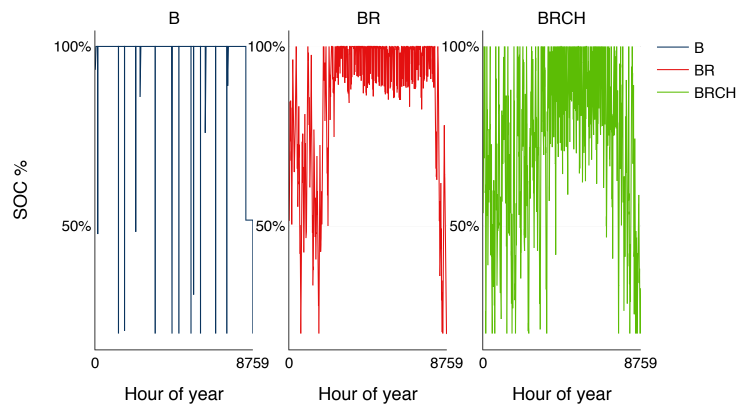

Figure 11. Example optimal battery state of charge profiles for the modeled Miami hospital under Scenario B, BR, and BRCH.

In Scenario B, the battery charges and discharges to avoid peak demand charges and/or high TOU energy rates. Similar to Scenario B, in Scenario BR the battery discharges to avoid peak and TOU charges, but also is rewarded for maintaining a high SOC to avoid outage costs in cases where the VoLL and critical load are high. In Scenario BRCH, battery operations are influenced by bill savings, outage costs, and the emissions intensity of the grid, and thus the battery dispatches much more frequently and to greater depths.

To illustrate the intensity of use of the battery systems under each optimization scenario, we compare the annual battery SOC "mileage" by building type and optimization scenario (Figure 12). We calculate the SOC mileage as the sum of the absolute change in battery SOC between each hour, where T is the set of hours in a year:

$$SOC\ mileage = \sum_{hr \in T} |SOC_{hr} - SOC_{hr-1}| \tag{14}$$

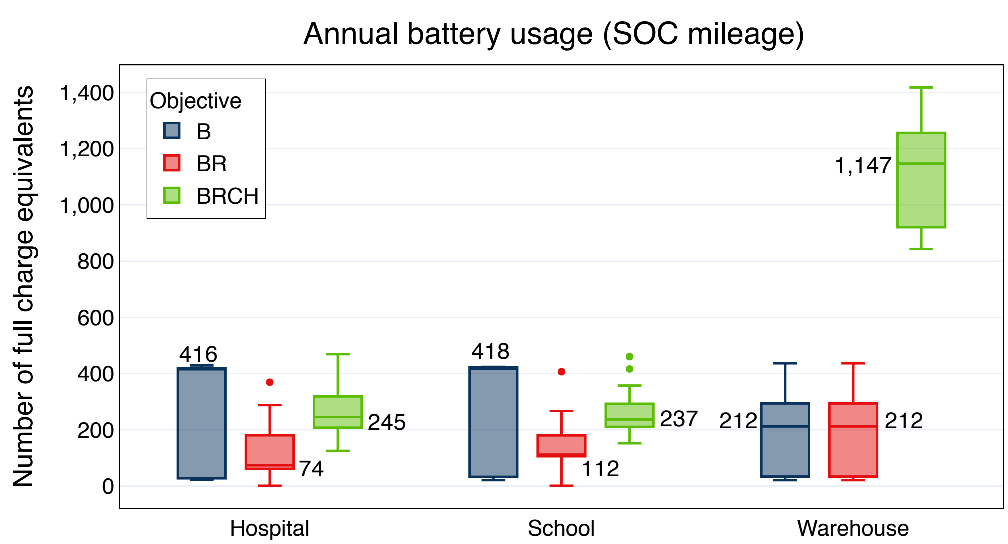

Figure 12. Box plot of annual battery state-of-charge (SOC) mileage by modeled building type and optimization scenario. Results are shown only for buildings for which batteries are cost optimal. The

SOC mileage shows total use (charge and discharge) of the battery and can be conceptualized as units of equivalent full (100%) battery charges (or discharges). The ends of each box indicate the lower and upper quartiles, the line inside the box marks the median, and the whiskers extend to the data minimum and maximum with outliers shown as dots. Median values for each building type and objective scenario are called out.

The intensity of use decreases from Scenario B to BR for the hospitals and schools, likely due to larger solar and battery system sizes in Scenario BR and the reward for keeping a high SOC to avoid outage damages. The SOC mileage is identical for the warehouses in Scenario B and BR due to identical system sizes and the low VoLL (making it cost-optimal to incur outage costs). Conversely, the intensity of use increases from Scenario BR to BRCH, as the median SOC mileage is 3.3 times higher for the hospitals, 2.1 times higher for the schools, and 5.4 times higher for the warehouses. The frequency and/or depth of battery discharge is greater in Scenario BRCH as compared to Scenario BR due to the incentive to avoid grid purchases during hours with relatively higher marginal health and climate costs.

4. Discussion

To illustrate how the monetization of additional value streams would change local governments' decision-making, we developed a novel approach to optimize solar plus storage systems for climate, health, resilience, and energy bill benefits. Our methods integrate hourly, forward-looking marginal emissions rates and location- and season-specific marginal health costs into the REopt Lite model to provide detailed estimates of avoided climate and health damages from grid-purchased electricity.

Our analysis of three building types across 14 U.S. locations shows that larger solar and storage systems become cost-optimal when co-optimizing for climate, health, resilience, and bill savings and that the NPV of these systems (from the decision-maker's point of view) increases dramatically compared to optimizing for bill savings only or for bill savings and resilience. When co-optimizing for climate, health, and resilience benefits, health benefits largely outweigh climate benefits, and health and climate benefits are greater in areas with higher marginal emissions rates and higher marginal emissions costs. As compared to optimizing for bill savings and resilience, additionally co-optimizing for climate and health results in 2.1-5.4 times greater utilization of battery storage, due to the incentive to avoid grid-purchases in high emissions times.

These findings could have significant implications for local, state, and federal policymaking, as these entities increasingly seek to meet climate pledges, increase resilience to natural disasters, and improve public health. Cities such as Ann Arbor, MI are already developing climate action plans that include proposals for internal carbon pricing and resilience hubs.[89] Similarly, a recent U.S. Government Executive Order declares it essential that agencies "capture the full costs of greenhouse gas emissions as accurately as possible," while the proposed $2 trillion American Jobs plan specifically addresses economic losses from power outages.[90] This work shows how a granular carbon price and monetization of avoided outage damages would alter investments in solar and storage, and provides motivation for local and federal stakeholders to additionally consider health damages of grid-purchased electricity. Our methods can also support the design of more tailored value of distributed energy resource

(VDER) rates, which tend to focus solely on solar generation without consideration of the load shifting capabilities of storage, and infrequently account for health impacts along with climate.[15,16,64]

Fully accounting for climate and location-specific health damages of emissions, which disproportionately burden communities of color, can support a transition to a more just energy system by decreasing distributional injustices.[91] While negative externalities of emissions are not currently incorporated into hourly energy tariffs, new technologies (e.g., WattTime[92]) will enable storage to shift energy consumption to lower-emissions times. Local governments can be first movers in this space; providing internal incentives to decrease inequitable societal damages that result from power consumption of public facilities. Local governments can further advance recognition and distributional justice by differentiating the value of lost load used in solar plus storage assessments to reflect the degree of vulnerability of the surrounding community to power outage damages. Our work provides a framework to quantify the costs and benefits of addressing both emissions and resilience inequities through investments in solar plus storage.

In this work, we consider the use-phase climate and health impact of solar plus storage based on avoided grid emissions, but do not consider the impact of battery inefficiencies, which have been shown to be significant.[27] Further, the manufacture and disposal of these technologies can result in climate and health damages, which should be incorporated in future work and should be considered in the interpretation of these results. Our optimization model assumes the battery has perfect information, e.g., regarding future marginal emissions rates, in order to determine an optimal dispatch strategy. Future work could explore models in which the battery system lacks perfect information, as in Fares and Webber (2017).[27] Finally, while this work focuses on solar plus storage, a similar approach to valuing hourly health and climate damages could be applied to other demand side management (DSM) interventions[58,93,94] and could be used to draw comparisons to fossil fuel-based microgrid technologies. Notwithstanding these limitations, our analysis reveals stark differences between the "optimal" deployment of solar plus storage on public facilities when climate, health, and resilience value streams are or are not monetized within the cost-optimization of these systems.

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Appendix A: Discussion of marginal emissions rates scaling approach

Due to the fact that REopt Lite models a single year timeseries of battery operation, in this work we scale the CO_2, SO_2, and NO_x annual marginal emissions profiles (shapes) of the midpoint analysis year (2033) to the total marginal emissions of the respective pollutants in each year of the analysis (2021-2046).

An alternative approach would be to assume that the emissions profile of a single year repeats for the entire analysis period. Below, we demonstrate a sample of optimal outcomes using this alternative approach by assuming the emissions profiles in every year (2021-2046) are the same as those in 2021, 2033, and 2046, respectively (Table A1). Because Cambium's marginal emissions rates decrease from 2021-2046,[70] using the first and last year of the analysis period provides a lower and upper bound to the assumed emissions intensity of the grid and, accordingly, the cost-optimal system sizing to avoid climate and health damages from grid-purchased electricity.

Assuming marginal emissions in each year of the analysis are the same as marginal emissions in 2021 results in an over-sizing of the battery system and an over-estimate of the climate and health benefits of the solar plus storage system. Assuming year 2046 emissions in each of the analysis (2021-2046) results in under-sizing of the storage system and an under-estimate of the climate and health benefits. Our results are similar to those obtained assuming 2033 emissions in each year, indicating that marginal emissions rates decline somewhat linearly between 2021-2046.

Table A1. Sample of optimal results under Scenario BRCH under differing annual emissions assumptions.

Optimal result	2021 emissions for all years	2033 emissions for all years	2046 emissions for all years	2033 emissions scaled to each year*
Atlanta Warehouse				
PV	260 kW	260 kW	260 kW	260 kW
Battery	72.8 kW / 345 kWh	60 kW / 224 kWh	57 kW / 216 kWh	61 kW / 238 kWh
Health Benefit	$1.24M	$873,914	$743,596	$936,421
Climate Benefit	$158,875	$148,587	$128,067	$150,964
Seattle Warehouse				
PV	227 kW	226 kW	240 kW	226 kW
Battery	42 kW / 60 kWh	17 kW / 26 kWh	0 kW / 0 kWh	18 kW / 28 kWh
Health Benefit	$876,376	$751,776	$721,759	$763,374
Climate Benefit	$58,763	$84,482	$82,835	$79,241

*Approach used in this study.

Appendix B: Supplementary tables and figures

Table B1. Marginal energy source types reported in NREL's Cambium database and associated plant types reported in EPA's NEEDS v6.

Marginal energy source in Cambium	Plant type in NEEDS
battery	Energy Storage
biomass	Biomass
canada*	n/a
coal	Coal Steam
coal-ccs*	n/a
csp	Solar Thermal
distpv	Solar PV
dropped_load	n/a
gas-cc	Combined Cycle
gas-cc-ccs*	n/a
gas-ct	Combustion Turbine
geothermal	Geothermal
hydro	Hydro
nuclear	Nuclear
o-g-s	O/G Steam
phs	Pumped Storage
upv	Solar PV
wind-ofs	Offshore Wind
wind-ons	Onshore Wind

* SO_2 and NO_x emissions data from NEEDS are not available for these energy sources reported in Cambium; however, these plant types are rarely (or never, in the case of CCS) on the margin across the locations considered in this analysis, and thus we do not seek alternative estimates for these emissions rates.

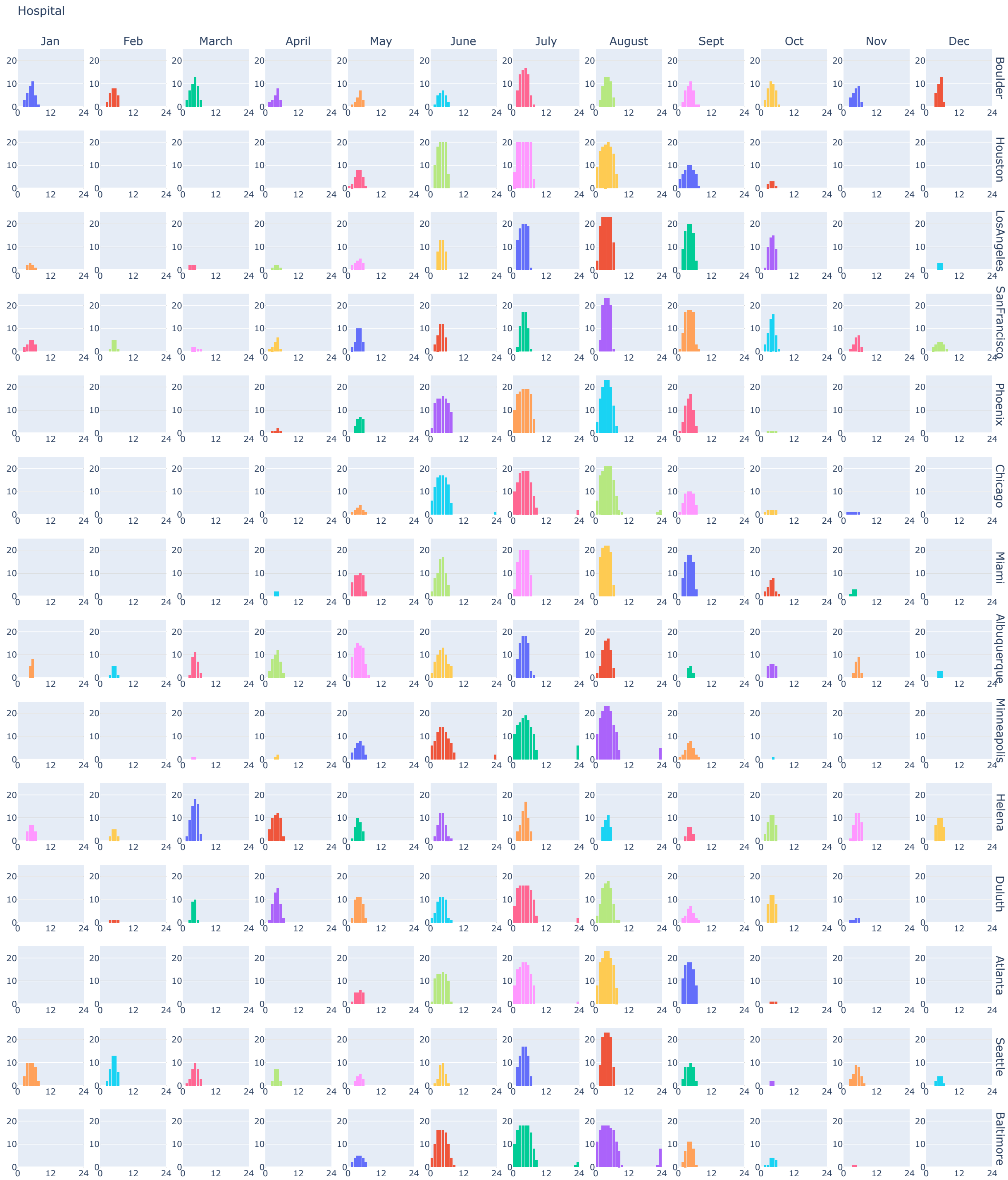


Figure B1. Histogram of hours, by hour of day and month of year, that make the 95th% cutoff for total unserved load during a 15-hour outage in the modeled hospital building type in each of the fourteen cities considered in this study. These hours represented in this histogram constitute the set T in Eq. 10.

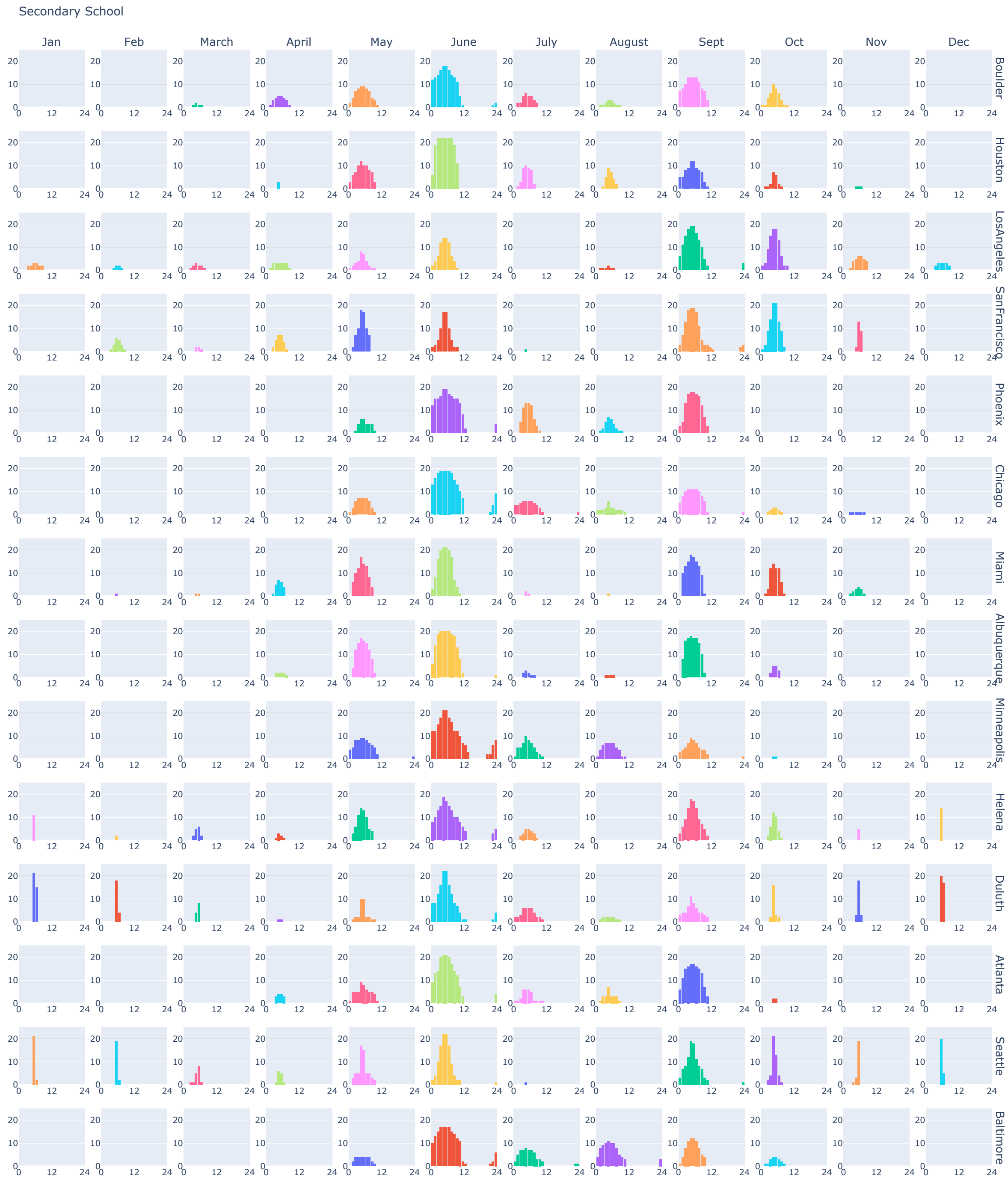


Figure B2. Histogram of hours, by hour of day and month of year, that make the 95th% cutoff for total unserved load during a 15-hour outage in the modeled school building type in each of the fourteen cities considered in this study. These hours represented in this histogram constitute the set T in Eq. 10.

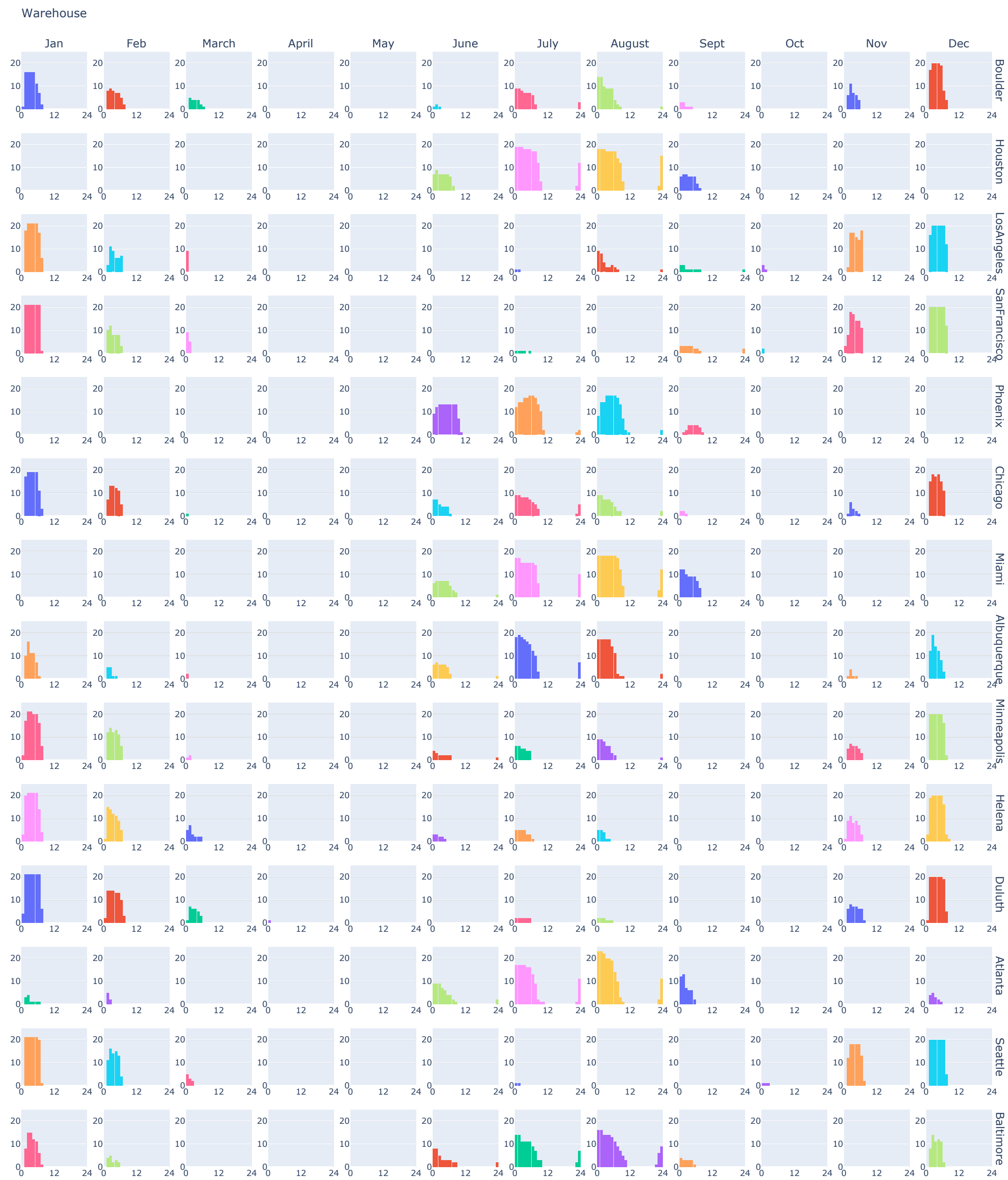


Figure B3. Histogram of hours, by hour of day and month of year, that make the 95th% cutoff for total unserved load during a 15-hour outage in the modeled warehouse building type in each of the fourteen cities considered in this study. These hours represented in this histogram constitute the set T in Eq. 10.

Table B2. Climate zones, annual building loads, balancing area (per Cambium), and region (per NEEDS v6) for each site.

City	CRB Climate Zone[86]	Hospital Annual Load [kWh]	Secondary School Annual Load [kWh]	Warehouse Annual Load [kWh]	Cambium Balancing Area[70]	NEEDS Region[76]
Albuquerque, NM	4B	8,468,546	2,588,879	228,939	31	WECC_NM
Atlanta, GA	3A	9,054,747	2,849,901	223,009	94	S_SOU
Baltimore, MD	4A	8,895,223	2,698,987	229,712	123	PJM_SMAC
Boulder, CO	5B	8,281,865	2,441,588	243,615	33	WECC_CO
Chicago, IL	5A	8,567,087	2,568,086	245,750	80	PJM_COMD
Duluth, MN	7	8,134,328	2,333,466	256,575	43	MIS_MNWI
Helena, MT	6B	8,068,698	2,357,548	252,245	18	WECC_MT
Houston, TX	2A	9,634,661	3,421,024	221,593	67	ERC_REST
Los Angeles, CA	3B-Coast	8,498,389	2,584,380	182,085	10	WEC_LADW
Miami, FL	1A	10,062,043	4,074,081	202,082	102	FRCC
Minneapolis, MN	6A	8,425,063	2,498,647	249,332	43	MIS_MNWI
Phoenix, AZ	2B	9,265,786	3,503,727	241,585	28	WECC_AZ
San Francisco, CA	3C	7,752,817	2,327,074	185,889	9	WEC_CALN
Seattle, WA	4C	7,912,504	2,282,972	210,300	1	WECC_PNW

Table B3. Selected utility rates and average energy and demand costs for each building.

City and building type	Utility and rate name	Average energy cost [$/kWh]*	Average monthly demand cost [$/kW]**
Albuquerque			
Hospital	Public Service Co of NM: 3B General Power TOU (PNM-Owned Transformer)	$0.029	$20.732
School	Public Service Co of NM: 3B General Power TOU (PNM-Owned Transformer)	$0.031	$20.950
Warehouse	Public Service Co of NM: 3B General Power TOU (PNM-Owned Transformer)	$0.030	$21.099
Atlanta			
Hospital	Georgia Power Co: SCHEDULE TOU-HLF-5 TIME OF USE - HIGH LOAD FACTOR	$0.038	$0.000
School	Georgia Power Co: SCHEDULE TOU-HLF-5 TIME OF USE - HIGH LOAD FACTOR	$0.043	$0.000
Warehouse	Georgia Power Co: SCHEDULE TOU-MB-4 TIME OF USE - MULTIPLE BUSINESS	$0.075	$0.000
Baltimore			
Hospital	Baltimore Gas & Electric Co: Schedule GL General Service Large - Secondary	$0.077	$6.510
School	Baltimore Gas & Electric Co: Schedule GL General Service Large - Secondary	$0.083	$6.510
Warehouse	Baltimore Gas & Electric Co: Schedule G - Secondary	$0.042	$0.000
Boulder			
Hospital	Public Service Co of Colorado: SG - Secondary General Service	$0.032	$16.152
School	Public Service Co of Colorado: SG - Secondary General Service	$0.032	$14.926
Warehouse	Public Service Co of Colorado: SG - Secondary General Service	$0.032	$15.641
Chicago			
Hospital	Commonwealth Edison Co: RDS - Watt-Hour Delivery Class	$0.032	$0.000
School	Commonwealth Edison Co: RDS - Watt-Hour Delivery Class	$0.032	$0.000
Warehouse	Commonwealth Edison Co: RDS - Watt-Hour Delivery Class	$0.032	$0.000
Duluth			
Hospital	Minnesota Power Inc: RIDER FOR STANDBY SERVICE (General Service-Primary Distribution)	$0.016	$8.233
School	Minnesota Power Inc: RIDER FOR STANDBY SERVICE (General Service-Primary Distribution)	$0.016	$8.462
Warehouse	Minnesota Power Inc: RIDER FOR STANDBY SERVICE (General Service-Primary Distribution)	$0.016	$8.328
Helena			
Hospital	NorthWestern Corporation: GSEDS-1 Secondary Demand	$0.010	$7.200
School	NorthWestern Corporation: GSEDS-1 Secondary Demand	$0.010	$7.200
Warehouse	NorthWestern Corporation: GSEDS-1 Secondary Demand	$0.010	$7.200
Houston			
Hospital	Entergy Texas Inc.: Large General Service (Secondary)	$0.038	$14.299
School	Entergy Texas Inc.: General Service (Secondary)	$0.057	$7.511
Warehouse	Entergy Texas Inc.: General Service (Secondary)	$0.057	$7.511
Los Angeles			

Hospital	Southern California Edison Co: GS-1 TOU A General Service Non-Demand Three Phase (At 220 kV)	$0.114	$0.000
School	Southern California Edison Co: GS-1 TOU A General Service Non-Demand Three Phase (At 220 kV)	$0.118	$0.000
Warehouse	Southern California Edison Co: GS-1 TOU A General Service Non-Demand Three Phase (At 220 kV)	$0.116	$0.000
Miami			
Hospital	Florida Power & Light Co.: GSLD-1 (General Service Large Demand)	$0.044	$13.630
School	Florida Power & Light Co.: GSLD-1 (General Service Large Demand)	$0.044	$13.630
Warehouse	Florida Power & Light Co.: GSD-1 (General Service Demand)	$0.049	$11.240
Minneapolis			
Hospital	Northern States Power Co - Minnesota: General Service Time-of-Day Metered (A15) Secondary Voltage	$0.072	$14.050
School	Northern States Power Co - Minnesota: General Service Time-of-Day Metered (A15) Secondary Voltage	$0.074	$14.283
Warehouse	Northern States Power Co - Minnesota: General Service (A14) Secondary Voltage	$0.086	$13.787
Phoenix			
Hospital	Arizona Public Service Co: Large General Service TOU (E-32 L) Secondary	$0.055	$19.879
School	Arizona Public Service Co: Large General Service TOU (E-32 L) Secondary	$0.057	$19.808
Warehouse	Arizona Public Service Co: Medium General Service (E-32 M) Secondary	$0.090	$10.645
San Francisco			
Hospital	Pacific Gas & Electric Co: E-20 Maximum demand of (1000 KW or more) (Secondary)	$0.110	$34.978
School	Pacific Gas & Electric Co: E-19 Medium General Demand TOU (Secondary)	$0.123	$36.640
Warehouse	Pacific Gas & Electric Co: A-1-Small General Service-Non-Time of Use Rate (Poly-Phase)	$0.244	$0.000
Seattle			
Hospital	City of Seattle, Washington (Utility Company): Schedule LGD - Large Network General Service (Transformer Investment Discount)	$0.075	$7.460
School	City of Seattle, Washington (Utility Company): Schedule MDC - Medium Standard General Service: City	$0.077	$3.857
Warehouse	City of Seattle, Washington (Utility Company): Schedule SMC - Small General Service: City	$0.100	$0.000

*The average energy cost is calculated as total annual energy charges divided by annual energy grid electricity use in the BAU case (i.e., no solar or storage)

**The average demand cost is calculated as total annual demand charges divided by the sum of monthly peak demands.

Appendix C: Sensitivity analysis

Sensitivity analysis scenarios are outlined in Table 7 of the main text.

Table C1. Average locational marginal price (LMP) over the analysis period (2021-2046) for each city considered in this study. Hourly LMP data (*energy_cost_enduse*) were obtained from the Cambium Mid-Case Scenario for the balancing authority corresponding to each city.[71] These LMP values are used in the "wholesale rate" sensitivity analysis.

City	Average LMP [$/kWh]
Seattle	$0.0322
Houston	$0.0313
San Francisco	$0.0344
Los Angeles	$0.0343
Chicago	$0.0333
Helena	$0.0306
Phoenix	$0.0327
Atlanta	$0.0352
Albuquerque	$0.0312
Boulder	$0.0317
Miami	$0.0346
Duluth and Minneapolis	$0.0304
Baltimore	$0.0343

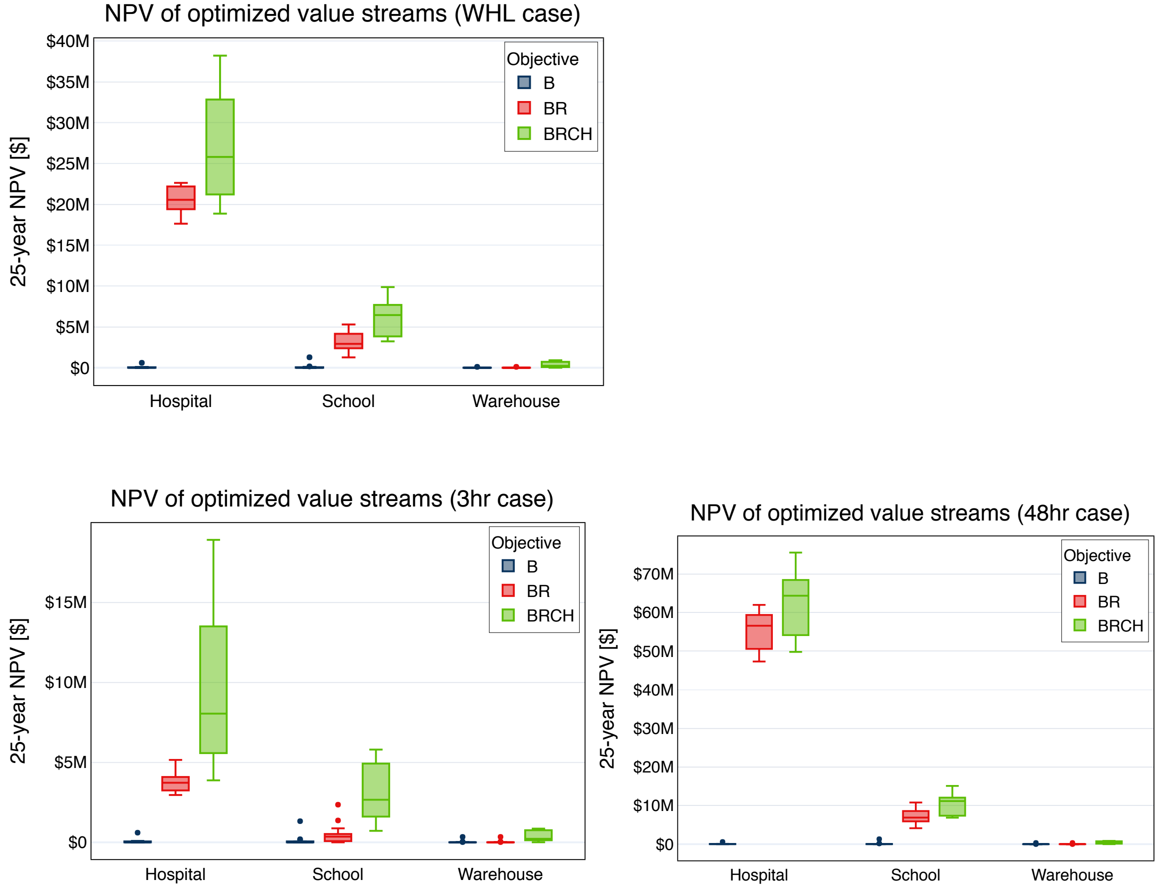
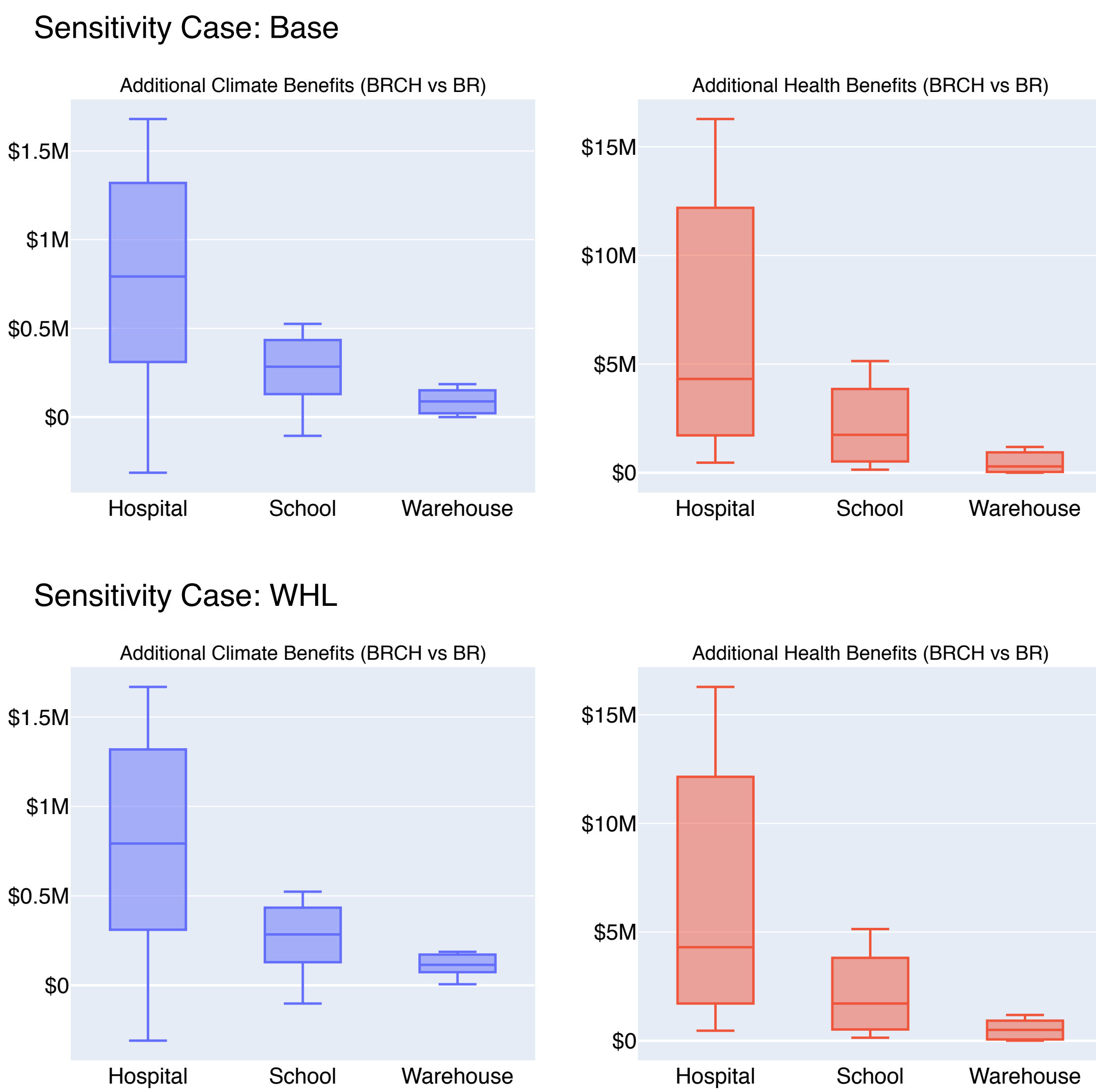


Figure C1. 25-year net present value (NPV) of cost-optimal solar plus storage systems under Scenario B, BR, and BRCH for each sensitivity analysis (wholesale rate (WHL) compensation, 3-hour outage, 48-hour outage). In each case, the NPV includes only those value streams included in the optimization objective. The ends of each box indicate the lower and upper quartiles, the line inside the box marks the median, and the whiskers extend to the data minimum and maximum, with outliers shown as dots. Compare to Figure 8 in the main text.

Previous work has accounted for the value of resilience in cost-optimal solar plus system sizing.[43] We thus evaluate the *additional* costs and benefits incurred when co-optimizing for climate and health in addition to resilience and bill savings. Figure C2 shows that the additional climate and health benefits in Scenario BRCH versus BR are not very sensitive to the assumed outage duration or compensation rate for net excess generation.



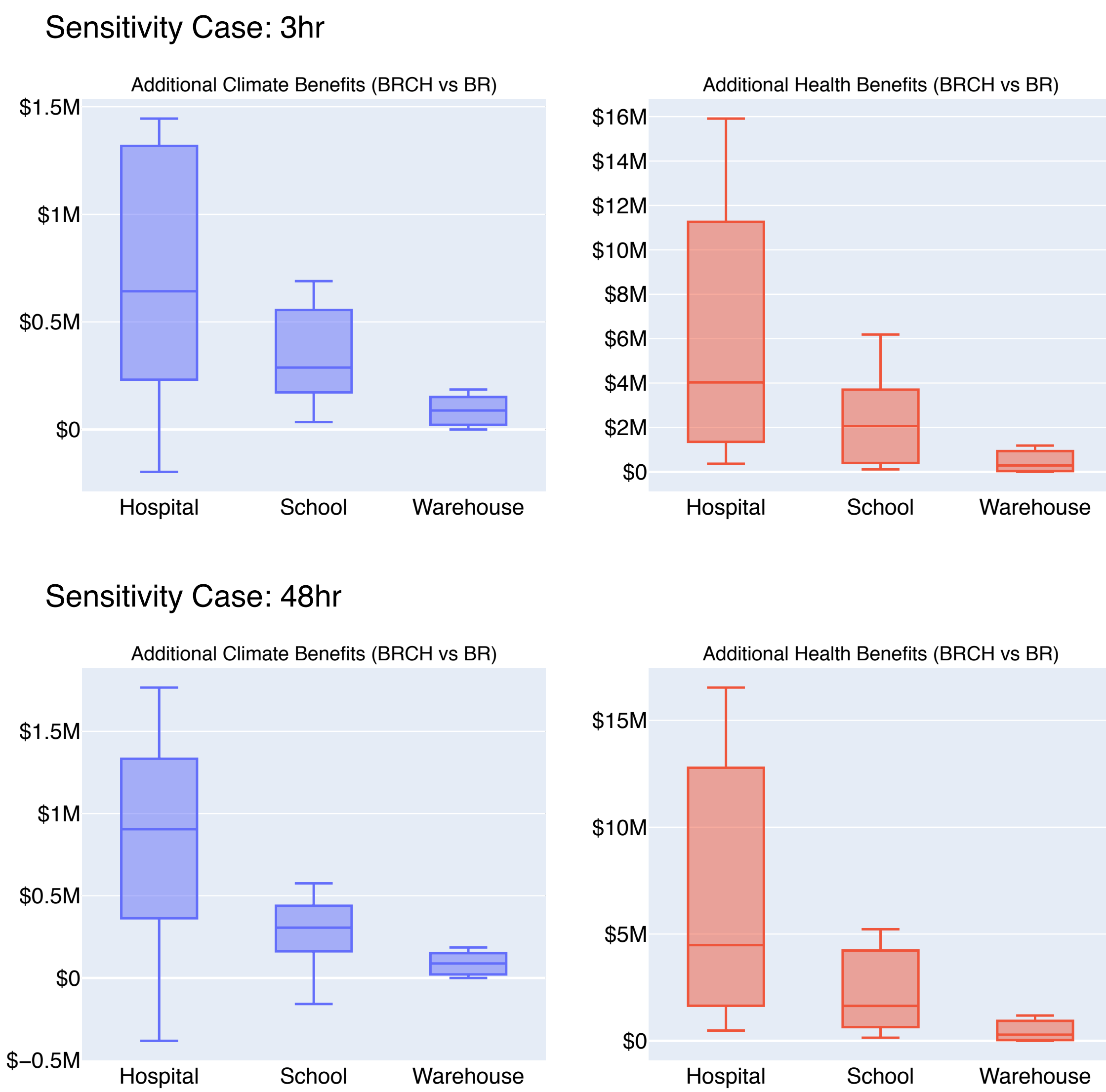


Figure C2. Box plots of additional climate (left) and health (right) benefits when co-optimizing for bill savings, resilience, climate, and health (Scenario BRCH) versus solely bill savings and resilience (Scenario BR) across all modeled locations. The ends of each box indicate the lower and upper quartiles, the line inside the box marks the median, and the whiskers extend to the data minimum and maximum.