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Weather effects on the lifecycle of U.S. Department of Defense equipment replacement (WELDER)

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ABSTRACT

Extreme weather has a direct and significant impact on buildings and infrastructure, resulting in billions of dollars of damage each year. This problem continues to grow as climate patterns change and buildings are exposed to new and different hazards than what they were designed to withstand. In order to better plan for the long-range sustainment, restoration, modernization, and eventual recapitalization of these buildings, organizations with large building portfolios, such as the U.S. Department of Defense (DoD), must have an awareness of the risks that these extreme weather events present. This research aimed to develop an approach to estimate condition loss and reduction in service life for the components of a building due to extreme weather hazards, to understand the risks that may be present in certain buildings and building systems. To achieve this objective, a damage association matrix was developed that categorizes climate hazards, the damage modes that they produce, and the individual component types impacted. This damage matrix formally links state-of-the-art climate model output, which provides projections of the probability of various climate hazards with a damage effects model that quantifies the consequence on component-level condition and service life. This method is applied to an actual portfolio of buildings in a particular geographic location and with a pre-defined component inventory that comprises the building. This approach can be aggregated to the system-, facility-, and site-level thus helping support billions of dollars in recapitalization decisions related to restoration/modernization of facilities.

1. Introduction

The United States (U.S.) and other countries are experiencing more frequent and intense weather events due to climate change (e.g., Refs. [1–5]). Extreme weather events and climate change can cause catastrophic damage to the facilities, impacting and potentially interrupting critical services (e.g., see Ref. [6]). It has been shown that extreme weather events and climate change affect the lifespan and performance of critical infrastructure, posing the risk of potentially significant additional maintenance and replacement costs over the coming decades (e.g., Ref. [6–8]). Of equal concern is how to best manage infrastructure upkeep in a way that is cost-effective for routine maintenance and protective against infrequent, but potentially damaging, extreme weather events. In the context of these changing natural hazards, facility planners and policymakers need state-of-the-art information that (1) projects long-term extreme events risk, (2) informs them on how these events may alter the depreciation schedules and the performance profile of individual facilities and their constituent systems and components [9], and (3) does so relative to a wide range of extreme event scenarios and the likelihood of potential impacts.

We begin by providing background on recent policies that are closely-related to this topic and describe an existing facility lifecycle management tool in widespread use by U.S. Department of Defense (DoD) planners. The outcome of this research has implications to all infrastructure and not just DoD facilities. Next, we introduce the methods we employ to assess changes in extreme weather risk and evaluate the resulting impact to facilities. We show how extreme weather risk impacts the depreciation of the components that makeup

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facilities through case studies [10]. And we show how our model was validated using damage assessments in the immediate aftermath of Hurricane Laura. Finally, we conclude with a summary of the project and a discussion of the limitations.

2. Background and regulatory context

Facilities owned and operated by the U.S. federal government are exposed to the same extreme events as other facilities; their budget, however, is not necessarily designed to bring these facilities back to full mission readiness following extreme weather events [11]. Reducing the amount of damage caused to these facilities by extreme weather events would in turn reduce the cost of mitigation. On June 30, 2020, the U.S. House Select Committee on the Climate Crisis brought attention to the importance of resilient construction and stronger buildings as part of the "Solving the Climate Crisis: Congressional Action Plan for a Clean Energy Economy and a Heathy, Resilient, and Just America" report. The Congressional Action Plan lays the foundation for resilience to become an integral part of community planning [12].

In addition, a January 27, 2021, Presidential Executive Order (EO) on Tackling the Climate Crisis at Home and Abroad, states that "The United States will move quickly to build resilience, both home and abroad, against the impacts of climate change that are already manifest and will continue to intensify according to current trajectories." [13]. This EO also calls for climate risk analysis that can be incorporated into modeling, simulation, war-gaming, and other analysis, as well as relevant strategy, planning, and programming documents and processes.

Many federal agencies have begun to participate in the effort to define and reduce vulnerabilities within federal facilities. The Federal Emergency Management Agency (FEMA), for example, has defined high wind vulnerabilities to building elements due to hurricanes or tornadoes [14]. These common building elements included roof structure, doors, glazing, roof coverings, and rooftop equipment. The Insurance Institute for Business and Home Safety conducts full-scale demonstrations of building vulnerabilities due to high winds, and wind-driven rain. Individual components of construction materials are evaluated in a small laboratory, which replicate real-world conditions. Both of these agencies have a stake in reducing facility damage. Insurance companies use a risk assessment model, which is a combination of four elementary modules: (1) hazard; (2) exposure; (3) damage; and (4) vulnerability to estimate the potential economic loss. The hazard module physically describes the event and defines the intensity of the windstorms, rainfall and wind speed. The exposure module represents a detailed building inventory and geographic information of the buildings. The damage module calculates the financial loss, and the vulnerability module reflects the correlation with damage and hazard, and quantifies the amount of damage using vulnerability functions [15].

Researchers have studied damage mechanisms due to a variety of natural hazards to determine best design and construction practices [16]. Vulnerabilities can significantly increase based on the location, structure, age, construction quality, engineering and materials used. Older structures may not have been designed to follow new building standards that take into account the most recent best practices, installation guidelines, and stronger codes for improved risk tolerance. Nawari uses data mining algorithms in the prediction and classification of damage due to hurricane and tornadic forces. By determining how various hazards relate to each other and what aspects of the buildings are affected, his research focuses in the prediction, assessment, and classification of building damages by severe windstorms.

Another effect of extreme weather events can be an increased runtime in hours per day of mechanical-electrical-plumbing (MEP) equipment. The number of heating degree or cooling degree-days (HDD and CDD) are based on the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) as the industry standard for weather models. Petri and Caldeira [17] predict changes to the number of HDD and CDD in the United States. Some of their models show large CDD values, which would indicate an increased demand for air conditioning. These demands will exceed the design for the mechanical systems more often; thus reducing the life cycle of the heating, ventilation, and air conditioning (HVAC) units.

A recent FEMA [14] study details the facility components most vulnerable to damage by hurricanes and tornadoes including pressure, wind-borne debris, and wind-driven rain. Their assessments of critical facilities older than 5 years includes performance expectations, reviewing as-built drawings, and conducting field investigations. In the FEMA study, a Level 1 assessment addresses the general condition (i.e., remaining service life) and the Level 2 assessment consists of destructive and/or non-destructive testing.

Our research team found localized examples of approaches to model weather impacts to facilities, but there does not appear to be a generalized framework to estimate the life cycle effects on condition and service life to the individual components of a building across a range of weather hazards. As a result, a goal of this research is to develop a generalized and robust model to quantify the estimated condition loss as well as reduction of service life to the individual components of a facility due to extreme weather events. The model then aggregates these component-level risks into a facility-level to effectively communicate risk of damage across a site or organization.

2.1. Relevant literature

There are numerous methods cited in literature for estimating the service life of building components and building equipment. Many of these approaches however do not account for impacts due to a changing climate. This requires both a way of projecting future climate variables under a changing climate, as well as how those changing climate stressors impart a change on the service life or degradation rate of building components. While the science of climate change is continuously evolving, various climate models exist to project global variables like surface temperature, precipitation patterns, and other variables [18]. Previously these models were applied to simulations run on large spatial scales measured in hundreds of miles [19], but recent climate modeling approaches have employed the increased resolution of regional climate projections [20[21]]. These models rely on more than just the geospatial location, and can leverage machine learning algorithms to account for varying thermal effects from characteristics such as land-use types and heat island effects [22,23]. This increase resolution provides better projections for climate impact analysis on localized infrastructure assets including building and their constituent components.

In addition to climate modeling, past research has focused on the impact of extreme weather events on critical infrastructure assets like power grids, railways, coastal structures, and bridges [24–28]. Effective climate change management however must also address the risks associated with non-extreme events [29], including impact on equipment subjected to operating conditions outside original design assumptions, escalated risk from increased environmental temperature, or increase exposure to corrosive environments [30]. Past research has demonstrated the risk of premature building degradation when the local climate undergoes increased environmental stressors that significantly depart from design assumptions [31[32]]. A continuing challenge with any of these studies is the availability of measurable damage and degradation data, however a common approach to this issue involves the simulation of damage and failure data when actual data is not available [33–36]. Even these simulations require historical data to feed the models, many of which rely on decades-old historical data that may not reflect future climate impacts as current and future weather variables deviate substantially from these historical trends [37].

Despite the contributions from past research, model limitations and gaps in understanding still exist. This research aims to address a number of these gaps by proposing a framework that adjusts key service life and degradation model parameters for building components as the climate variables describing the environment they are projected to operate in are expected to change. Additionally, while past research has focused on global climate change or used older historical data, this research implements regional estimates based on more current data to improve service life forecasts.

3. Methodology

The U.S. Army Corps of Engineer's BUILDER Sustainment Management System—the facility life cycle management tool used by the DoD and several other federal agencies— comprehensively assesses and forecasts facility conditions to support facility maintenance, repair, and recapitalization decisions [38][39]. While BUILDER has been widely used for managing routine infrastructure sustainment, it does not currently have the ability to explicitly consider infrastructure vulnerabilities arising from extreme weather events. The key objective of this study is to incorporate impacts of extreme weather events into the life cycle forecasting used by the system to identify and plan facility sustainment, restoration, and modernization investment needs.

Another objective of this project was to develop an application programming interface (API) plug-in for BUILDER—called the Weather Effects on the Lifecycle of U.S. Department of Defense Equipment Replacement or "WELDER"—which allows users to visualize weather event projections and re-prioritize building component repair and/or replacement schedules, and assess costs, according to the likelihood and severity of these events and the expected damage impact on the building portfolio. The WELDER technology consists of five main components: (1) an extreme weather database for multiple future climate scenarios/ time periods; (2) the BUILDER component inventory; (3) an event distress (damage) association matrix; (4) the application programming interface; and (5) a WELDER user interface for exploratory analysis. In addition, we partnered with several demonstration sites at the onset of the project to help guide the development of WELDER.

At the onset of the project we met with key decision-makers at our demonstration sites: Fort Leonard Wood, Fort Cavazos (formerly Fort Hood), and the Florida National Guard. We followed up those initial conversations with a structured set of interviews with local experts. The purpose of the interviews was to collect information about what type of damage to infrastructure might occur (e.g., damage to roof) if extreme weather occurred, and perhaps most importantly, at what extreme weather threshold (e.g., greater than 110 mph wind speed) that damage might first be observed. We then used this information to develop a list of relevant extreme weather metrics and thresholds.

3.1. Extreme weather database

The Community Atmosphere Model version 5 (CAM5) and the Weather Research and Forecasting (WRF) model [40] were the main source of information for the extreme weather metrics. Simulations of CAM5, a global climate model, were selected from a suite of 25 km horizontal resolution integrations [41,42]. WRF, a regional climate model, was integrated at a 27 km horizontal resolution. The CAM and WRF simulations included a 5-member and 10-member ensemble, respectively. The CAM5 simulations include four different climate scenarios to capture the present and future climates: the historical period 1995–2014 (conditions as they actually were ~1 °C above global pre-industrial values), and three twenty-year periods at 1.5-, 2-, and 3-degrees Celsius warmer than pre-industrial conditions, corresponding to the years 2030, 2040, and 2060, respectively, under Representative Concentration Pathway (RCP) 8.5, which is a high greenhouse gas emissions scenario [43]. The WRF simulations include two climate scenarios: the historical period 2001–2010 and a corresponding ten-year period as if it were 2090 under RCP 8.5. The CAM5 model is ideal for this work because of its ability to simulate extreme weather events and because the output data covers the entire United States [41]. The WRF model was chosen in addition to the CAM5 model because of the ability to output data at the fine time scales necessary for some weather metrics (e.g. hourly precipitation rate) [44]. Although the use of only two models is a potential limitation of the extreme weather database, the suite of models in the Coupled Model Intercomparison Project Phase 6 (CMIP6) were deemed too coarse to simulate several of the extreme weather events of interest and statistical downscaling may not include all the processes of interest for the extreme weather database.

To create a temporally continuous dataset, linear interpolation was used with the CAM5 and WRF data. For both models, all historical years and all future years were used to determine a range of percentiles for the extreme weather database. For the continuous time series, the historical time period is therefore represented by the year 2005, the midpoint of the CAM5 and WRF historical datasets. As discussed above, the years 2030, 2040, and 2060 represent the CAM5 future global warming levels of 1.5, 2 and 3 °C above preindustrial temperatures and the year 2090 represents the WRF future warming scenario based on RCP 8.5. Using linear interpolation between the IPCC estimated RCP 8.5 times to global warming levels creates a smooth, continuous dataset in time. Although this assumes that the future change will be approximately linear, interpolation provides a reasonable method to fill in temporal gaps in the available model data. The approach used to develop the extreme weather database focuses on the anthropogenic contribution to any change between the historical and future climates. Natural climate variability would be superimposed on these anthropogenic changes.

Additional 3 km high resolution WRF simulations were performed to better understand the metrics related to severe storm activity [45]. Severe storms are small-scale, but impactful events that are not well-represented in the lower resolution CAM5 and 27 km WRF simulations. Specific severe storms were identified, most notably a tornado event that occurred on December 31, 2010 at the Ft. Leonard Wood military installation in Missouri. This event was designated an EF3 tornado and caused an estimated $90 million in damage [46]. Fig. 1 shows the maximum simulated reflectivity (rainbow contours) and the updraft helicity (grey contours) for (a) historical and (b) late 21st century realizations of a tornadic storm like the event that affected Ft. Leonard Wood. The maximum simulated reflectivity and updraft helicity are indicators of thunderstorms and rotating updrafts, respectively. From Fig. 1, there is a clear increase in the updraft helicity from the historical to the future climate, indicating the potential for stronger tornadoes in future realizations of the Ft. Leonard Wood tornado event. Results such as these highlight the importance of incorporating extreme weather metrics, such as wind speed, into projections of future infrastructure degradation.

The threshold details for each extreme weather metric considered are presented in Table 1, below. As alluded to earlier, demonstration site responses to an extreme weather questionnaire were used to inform the threshold choices for all metrics. The questionnaire was sent to three different military installations: Ft. Leonard Wood, MO; Ft. Cavazos (formerly Ft. Hood), TX; and the Florida National Guard. The questionnaire asked respondents for ranges in weather variables that lead to infrastructure degradation. Input from the US Army Corps of Engineers was also used to establish ranges of threshold values to supplement the information from the questionnaire. The National Oceanic and Atmospheric Administration (NOAA) Livneh near-surface climate dataset was used to bias-correct the temperature metrics [47].

Garfin et al. [6] and others stress the importance of communicating uncertainty in a way that can be readily used by DoD decision-makers. To communicate the likelihood of future extreme weather materializing, a range of percentiles is calculated for each extreme weather metric. Percentiles were calculated for each climate scenario using all available years and ensemble members from CAM5 and WRF. Each metric from Table 1 contains information over the contiguous U.S. (CONUS) for a range of thresholds and for the following percentiles: 5, 10, 15, 20, 25, 50, 75, 80, 85, 90, 95. This range of percentiles allows WELDER users to choose a level of risk and evaluate the corresponding infrastructure degradation. ***By choosing higher percentiles, users will be***

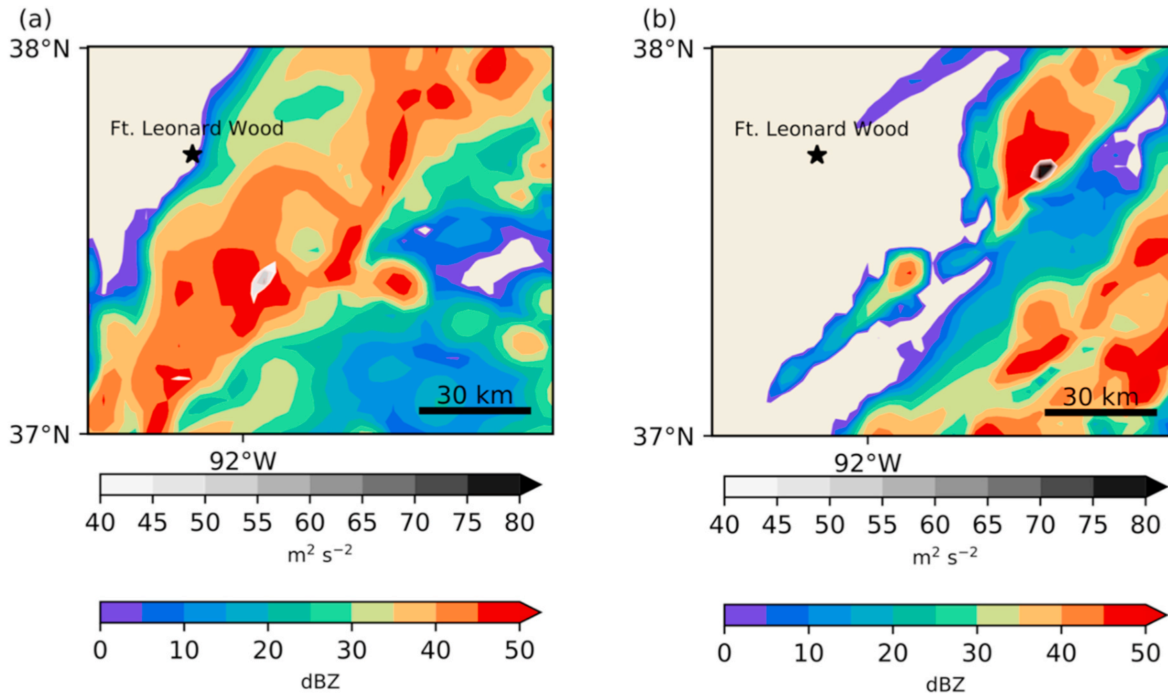

Fig. 1. WRF (a) Historical and (b) Late 21st Century Maximum Simulated Reflectivity (dBZ; rainbow contours) and Updraft Helicity ($m^2\ s^{-2}$; grey contours).

Table 1
Extreme weather metric details.

Temperature (heat)	● Annual number of days where maximum temperature is above 75, 80, 85, 90, 95, 100, 105, and 110 °F ● Annual cooling degree days above 65 °F
Temperature (cold)	●Annual number of days where minimum temperature is below 35, 30, 25, 20, 15, 10, 5, 0 and -5 °F ●Annual heating degree days below 65 °F
Wind	●Annual number of days above 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180, 190, 200 mph
Precipitation	●Annual number of days with rainfall rate exceeding 1.0, 1.5, 2.0, 2.5, and 3.0 in/hr ●Annual number of days with rainfall rate exceeding 2.0, 4.0, 6.0, 8.0, 10.0, 12.0 in/day
Snow	●Annual number of days with the snow water equivalent exceeding 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 6.5, 7.0, 7.5, 8.0, 8.5, 9.0, 9.5, 10.0 in/day
Ice/Graupel	● Annual number of days with ice/graupel rate exceeding 0.01, 0.05, 0.1, 0.5, 1.0 in/day

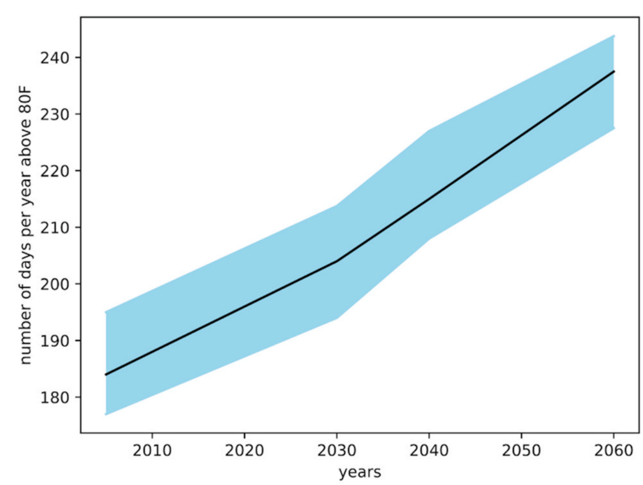

Fig. 2. CAM5 Change in Maximum Surface Temperature (days above 80 °F) at Fort Cavazos. 50th percentile (black line), and 25th and 75th percentiles (blue shading) based on the ensemble spread are shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

evaluating infrastructure degradation using less likely, but more significant changes in extreme weather events.

As an example, consider the CAM5 maximum surface temperature at one demonstration site, Ft. Cavazos. Fig. 2 shows the change over time in the number of days per year where the maximum surface temperature exceeds 80 °F at Ft. Cavazos. The black line is the 50th percentile and the blue areas correspond to the 25th and 75th percentiles. As stated above, percentiles were calculated for each climate scenario using all available years and ensemble members; the global warming levels were associated with specific years based on RCP 8.5 and linear interpolation was used to produce a continuous time series. Metric information, such as that contained in this figure, were then used as input to determine changes to the infrastructure degradation curves.

3.2. Builder component inventory

The BUILDER component inventory is a listing of the key components that comprise each building in the BUILDER inventory. The BUILDER Sustainment Management System currently includes more than 200,000 buildings, >1.9 billion square feet of facility floor area, and >$300 billion in total replacement value. The component-level information within BUILDER represent the major assemblies and installed equipment that make up a facility and represent the management unit where repair and replace decisions reside. Each component is classified with a specific type from the BUILDER component catalog, which organizes building component types by system and subsystem aligning with the Uniformat II standard [48]. In addition to the component classification, which supports associating building components by type, the quantity and year installed is also captured for each building component, in order to support sustainment management activities. By linking these components to the buildings in which they belong, the inspections that are performed against them, and other expected lifecycle attributes, all in the BUILDER relational database, the BUILDER component inventory represents a very rich and complete dataset of the actual components that make up DoD facilities. The building components also include their age, location, existing condition, and replacement value–among other things. This component inventory dataset is already collected, stored, and managed within BUILDER, and the WELDER application uses this component-level information to associate expected extreme weather related-damage modes with the component types identified in the BUILDER component catalog. Infrastructure locations associated with the sites where buildings are located and specifically the BUILDER component inventory contained in those buildings are then merged with latitudes/longitudes associated with the various extreme weather predictions. The resulting database, along with the event distress (damage) association matrix (see below), is then used to determine the extreme weather impacts to component condition and lifespans.

3.3. Event distress (damage) association matrix

The condition degradation curves in BUILDER are based on the generalized Weibull cumulative probability function. The main parameters in this model are (1) a degradation parameter, alpha, that relates to gradual or abrupt degradation and (2) the scale parameter, beta, that relates to the expected service life of the asset. The initialized parameters are tuned and validated based on historic data from inspections (observed changes in condition between inspections) for a particular component type.

Currently, the BUILDER component degradation curves do not differ by location - the degradation profile is unique to a component type, but not to the climate that the component resides in. This project provides the framework to adjust the initial degradation profile based on spatial factors particularly related to extreme weather stressors. We have developed an approach to tune the degradation curve parameters (the Weibull scale and shape parameters) based on historic condition assessment data. We will continue to use this approach to tune and adjust the parameters for individual locations with unique climate variables. This allows us to model how the degradation parameters such as lifespan are impacted by the varying climate variables at different locations, and incorporate the effects of changing extreme weather due to local climate change over time.

For an individual component in BUILDER, the assumption is that the component condition index (CI) equals 100 when the component is newly-constructed and its age is at or near 0 years. The component's condition is then expected to degrade over its age or time in service based on the initial model parameters. As new inspection information for that component is collected, the individual parameters are adjusted to reflect the observations for that specific component instance as it performs in service in its local environment and operating conditions (see Fig. 3).

The result of this parameter adjustment is that each component's degradation profile can take on a unique shape and response based on the observed condition of that component over time due to inspections being performed. However, while future condition projections take past observed inspection information into account, the BUILDER system does not currently adjust for condition and service life effects due to potential extreme weather damage. Therefore, this approach provides the baseline for which we can compare to the weather-adjusted condition degradation and service life estimates from the WELDER analysis discussed above.

A similar approach is taken for the modified condition degradation curves that the WELDER module will employ. The same generalized Weibull cumulative probability function is used. However, the initial degradation and scale parameters are adjusted to account for the impacts from extreme weather.

The methodology uses the building component information from BUILDER along with the hazards and stressors to estimate potential damage modes, types, and effects via the event distress (damage) association matrix. For each component, this gets translated into a service life reduction and an annual risk premium (see Fig. 4). The risk premium is the cost associated with a reduction in a building component's service life due to extreme weather. This risk premium can be aggregated to a system-, building-, or overall site-level.

To estimate these impacts, the damage association matrix is defined, which links characteristic damage modes for a given climate hazard to building component types. The resulting condition loss as measured by a component condition index is associated with each damage mode, along with the likelihood that the damage mode materializes given the hazard occurrence. This is applied to an actual portfolio of buildings in a particular geographic location and with a pre-defined component inventory that comprise the building.

4. Results

Given a weather forecasting model that determines the hazard occurrence likelihood based on building location, as well as the type and age of components in the building, an expected service life reduction is estimated. The approach uses findings at a component level to support building sustainment decisions related to individual component repair/replacement, as well as identify potential mitigation activities to reduce damage extent or likelihood. Two case study examples are provided below which use the methodology presented above to estimate gradual damage caused by extreme weather stressors.

4.1. Case study #1: Extreme heat impact on rooftop air conditioning unit in Panama city, Florida

The first case study evaluates a single component type—a 50-ton rooftop air conditioning unit, exposed to different extreme weather stressors. The unit is currently five years old and has an estimated design life of 25 years, so it is expected to have 20 years of remaining service life. In addition, it is known that the component replacement value is $185,000. This air conditioning unit is installed on a building located in Panama City, FL, where extreme heat is a known hazard, resulting in a climate stressor of excess temperature. We also assume that there is a 20% likelihood that the average number of cooling degree-days (CDD) for that location is expected to increase from 2400 to 3000 over the remaining 20-year lifespan of the component.

The result of this increased temperature environmental stressor is a potential damage mode of "Accelerated HVAC Equipment Deterioration due to Prolonged Run-time". The damage extent associated with this damage mode is identified as moderate, indicating a 25% service life reduction due to the CDD increase resulting in longer periods of runtime per year. The damage likelihood is identified as certain, meaning there is very high likelihood that the CDD increase will result in the damage mode indicated. Taking this into account, the probability of damage is 20% × 100%, or 20%. Since there is a 20% probability of a 25% service life reduction, this results in one year of expected service life reduction over the 20 years remaining service life, as shown in Fig. 5 below. ***The annualized risk premium associated with this service life reduction is estimated at $185,000 x (1/25)/20 or $370 (a one-year effective service life reduction for a 25 year design life; spread over 20 year remaining service life).***

4.2. Case study #2: Hurricane-force wind impact on asphalt roof surface in Panama city, Florida

The second case study example uses the methodology presented above to estimate abrupt damage caused by extreme weather stressors. In this example, a 20,000 square foot low-slope asphalt roof surface is evaluated. The unit is currently five years old and has an estimated design life of 20 years, so it is expected to have 15 years of remaining service life. In addition, it is known that the component replacement

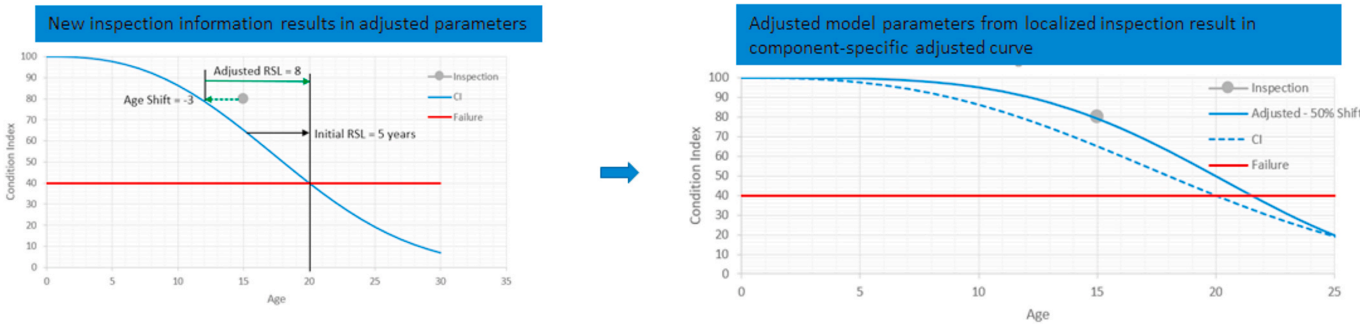

Fig. 3. Adjusting parameters and condition indices based on inspection.

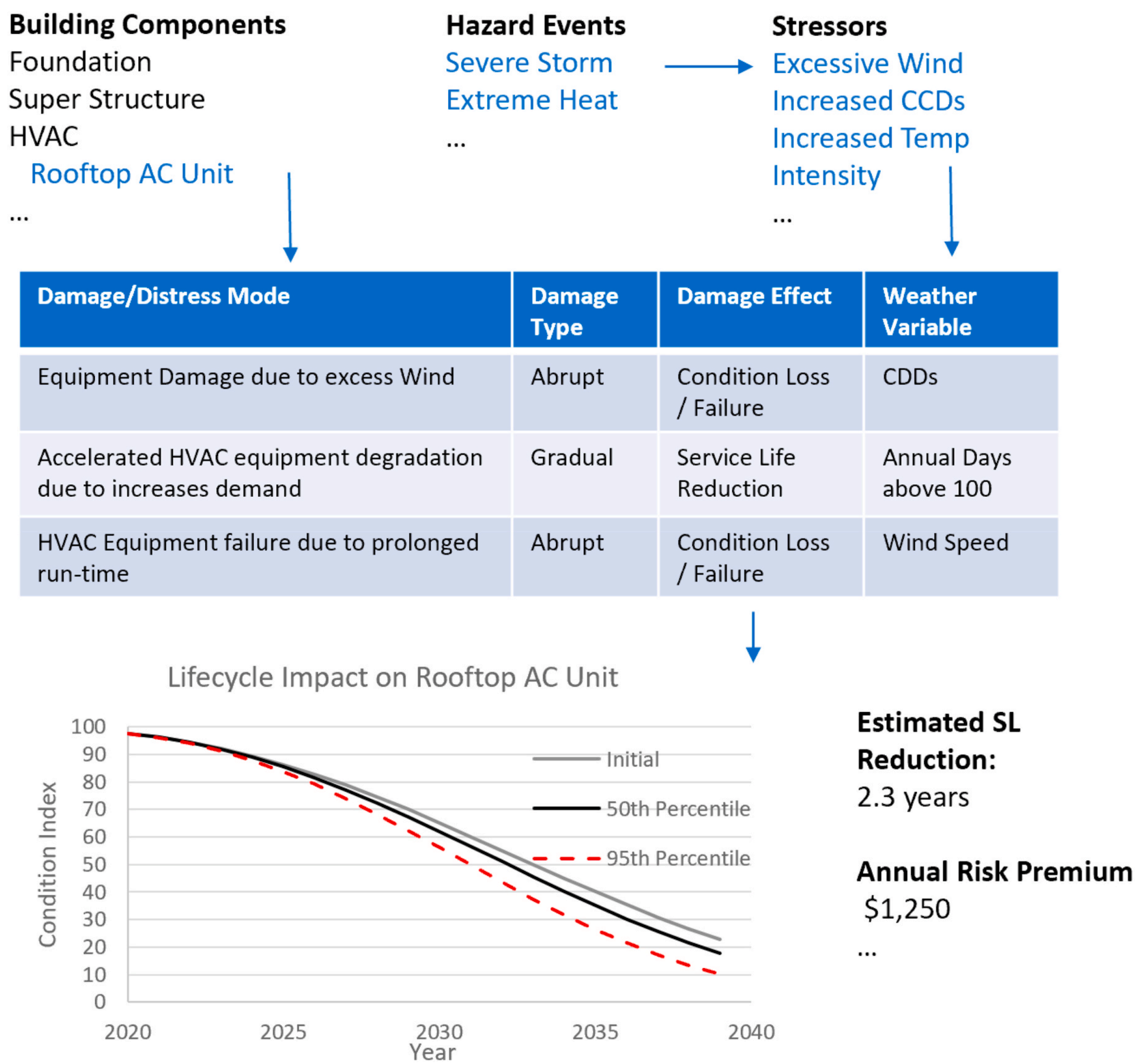

Fig. 4. Schematic of builder event distress (damage).

value is $144,000. This roof surface component is installed on the same building located in Panama City, FL, where hurricanes are a commonly-observed weather hazard, resulting in a climate stressor of extreme wind. Based on the weather information at that location, wind speed in excess of 150 mph, which is the threshold associated with roof surface loss, has an annual reoccurrence probability of 0.2%.

This extreme weather threat results in a potential damage model of "Significant Loss of Roof Covering". The damage extent associated with this damage mode is identified as High, with total condition loss resulting in complete component failure and immediate need for replacement. The damage likelihood is identified as Medium, associated with a 50% likelihood that the extreme weather stressor will result in that damage mode. Taking this into account, the probability of damage is 0.2% × 50%, or 0.1%. Since there is a 0.1% annual probability of total roof failure, this results in 0.11 years of expected service life reduction over the 15-year remaining service life, as shown in Fig. 6 below. ***The***

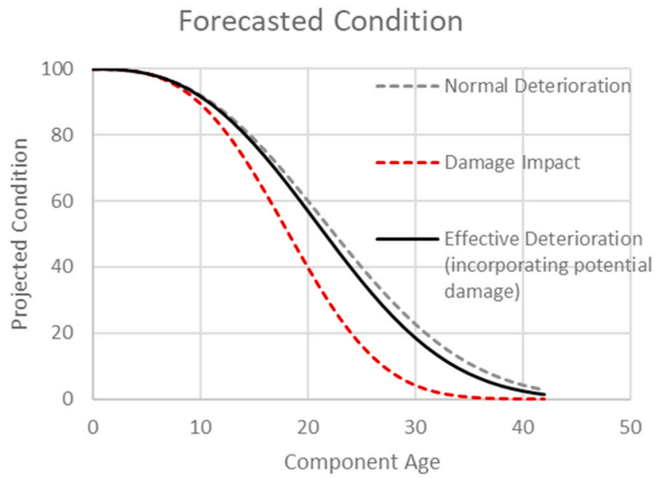

Fig. 5. Life cycle impacts on condition and service life due to excessive heat impacts on rooftop air conditioning unit.

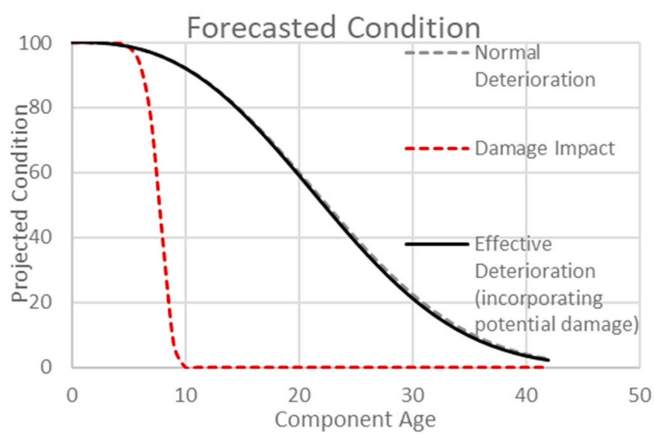

Fig. 6. Life cycle impacts on condition and service life due to abrupt extreme weather impact on low slope asphalt roof surface.

annualized risk premium associated with this service life reduction is estimated at $144k x (0.1%) = $144.

4.3. Case study #3: The WELDER calculation process for multi-modal impacts

This case study shows the calculations in WELDER for a Rooftop Air Conditioning Unit in Austin, TX undergoing simultaneous climate stresses. As discussed above, the BUILDER system tracks certain information about the component (see Table 2).

From this data, a number of initial damage model inputs are calculated, as shown in Table 3.

With these model inputs available, the WELDER system then retrieves the damage modes and additional model parameters from the damage association matrix. Determination of model parameters were based on methodology proposed in Ref. [49]. In this example, there are multiple stressors/damage modes that the component is exposed to, as show in Table 4, below.

Next, for each damage model listed in the table above, the WELDER model finds the closet climate model output for the given location (i.e., near Austin), each specific climate variable and threshold, the confidence level (e.g., 50%), and the year installed. The resulting value determines the baseline value for each damage mode, which is the climate variable at the beginning of the component's service life. These characteristics are also used to determine the projected climate value from the weather dataset at the end of the component's service life, as well as the change between the projected and baseline climate variable. The values for this specific case study are provided in Table 5, below.

Climate impact metrics are then calculated by using the climate value data and the component degradation characteristics. Table 6, below, shows these calculations for both the gradual and abrupt failure modes.

The total service life reduction is used to calculate the following adjusted component degradation parameters used in BUILDER to determine sustainment management activities and additional costs (i.e., annual risk premium)—see Table 7.

The risk is considered very high in this example, because the risk premium is more than 2% of the component replacement value. This result may indicate a need for further attention to monitor or mitigate the risk to this particular component.

The result of this process is similar to applying a damage curve that relates the climate threshold to an increased degradation rate, i.e., a service life reduction. The model identifies a damage mode or set of damage modes for a given component type and climate stressor. The team has developed a reference set of damage modes, but a WELDER power-user can also create or edit their own set. Associated to each damage mode is the applicable climate threshold associated low, moderate, high, severe damage likelihood and extent, and each of these combinations has an associated degradation factor. Therefore, for a given component and climate threshold, a discrete damage likelihood/extent state is identified and along with that an adjusted degradation factor.

4.4. Application programming interface

We are developing a module that "plugs into" BUILDER via an Application Programming Interface (API) that integrates these two distinct types of technologies: (1) a system that has the capability of producing high-resolution, long-term projections of extreme weather events for any DoD facility location; and (2) a system to translate the

Table 2
Information about air conditioning unit in Austin, Texas.

Location	Austin, Texas
Component type	D303002 Direct Expansion Systems – Rooftop Air Conditioning Unit – multizone, electric cool, gas heat, 50 ton cooling
Year installed	2019
Component replacement value (CRV)	$686,880
Design life	15 years
Alpha—degradation shape parameter	1.4
Beta—degradation scale parameter	0.89

Table 3
Initial calculated inputs to damage model.

Initial Model Inputs	Equation	Calculated Value
CurrentAge	$CurrentYear - YearInstalled$	5
CurrentCI	$100\left(\frac{100}{40}\right)^{-\left(\left(\frac{\left(\frac{CurrentAge}{DesignLife}\right)}{Beta}\right)^{Alpha}\right)}$	79.319
EffectiveAge	$DL\left(\left(-\log_{\frac{CurrentCI}{100}}\frac{100}{40}\right)^{\frac{1}{2.64}}\right)$	8.91
RemainingDesignLife (RDL)	$DesignLife - CurrentAge$	10
RemainingServiceLife (RSL)	$DesignLife - EffectiveAge$	6.09

Table 4
Multiple stressors and damage modes impacting the rooftop air conditioning unit component.

DamageMode	Flooding	Excess Run Time	Extreme Operating Env
DamageType	Abrupt	Gradual	Abrupt
Stressor	Inches/day	Heat	Excess Temperature
ClimateVariable	Days > rainfall threshold	Cooling degree days	Days > Temp threshold
Threshold	6	65	100
DamageLikelihood (DL)	0.25	0.25	0.75
DamageFactor (DF)	0.8	0.5	0.05

Table 5
Projected climate change impacts for Austin, Texas.

DamageMode	Flooding	Excess Run Time	Extreme Operating Env
Baseline climate value	0.00	923.22	12.16
Projected climate value	0.89	1171.28	30.10
Climate value change	0.89	248.06	17.94

Table 6
Calculations to adjust service life, alpha, and beta parameters.

Failure Type	Model Inputs	Equation	Calculated Value
Gradual (excess run time)	AnnualizedIncrease	$\frac{\frac{ClimateValueChange}{BaselineValue}}{RemainingServiceLife}$	0.04
	DegradationRate	$1 + (AnnualizedIncrease)(DF)(RSL)$	1.21
	AdjustedRSL	$\frac{RSL}{DegradationRate}$	5.01
	AdjustedBeta	$\left\{\frac{\frac{CurrentAge + AdjustedRSL}{DesignLife}, ifRSL > 0}{Beta, if\ RSL \leq 0}\right.$	0.67
	AdjustedAlpha	$\log\left(-\log_{\frac{CurrentCI}{100}}\frac{100}{40}\right)\frac{\frac{CurrentAge}{DesignLife}}{AdjustedBeta}$	1.98
	ServiceLifeReduction	$\frac{RSL - AdjustedRSL, ifRSL > 0}{0, if\ RSL \leq 0}$	1.08
Abrupt (flooding and extreme operating environment)	ServiceLifeReduction	$\frac{(RSL)(DL)(DF)\left((1-)\frac{(365 - ClimateValueChange)^{365}}{365}\right), ifRSL > 0}{0, if\ RSL \leq 0}$	0.71 (flooding) 0.23 (extreme operating environment
Combined	**TotalServiceLifeReduction**	**ServiceLifeReduction (Gradual) + ServiceLifeReduction (Abrupt)**	**2.02**

uncertainty of extreme weather impacts to facility condition indices and lifespans, Work Action reports, and associated repair/replacement costs within the BUILDER Sustainment Management System.

4.5. WELDER user interface

We developed an online user interface[1] that allows users of BUILDER to dive deeper into the extreme weather projections and anticipated response for building components. Users are able to click a link within BUILDER, which will automatically log them into the WELDER exploratory analysis tool.

Figures A1 through A7 in Appendix A are screenshots of the following pages from the WELDER online exploratory analysis tool.

- Home Page
- View Scenarios Page
- Organization-level View
- Site-level View
- Facility-level View
- Component-level View
- Climate Reconnaissance ("Climate Recon") View

4.6. Model validation and calibration

Because there is still limited data available detailing specific component damage following extreme events, Monte Carlo simulations were performed to randomly degrade a large population of components to mimic BUILDER's degradation profile. Next, we introduced an additional factor that models the likelihood of a component failing due to an extreme weather event. This factor is derived based on a machine learning model that characterizes the impact of various weather variables on component lifespan [49]. This allowed us to simulate a large population of condition observations that include the effects of weather in order to tune and validate the modified degradation curves in WELDER. Fig. 7, below, details the results of some of the Monte Carlo simulations showing the age (x-axis) at when components fail with and without extreme weather impacts.

4.7. Summary, limitations, and conclusion

4.7.1. Summary

The WELDER extreme event simulations and engineering relationships are state-of-the-art and reflect our best understanding of the effect of climate change on extreme weather and the resulting impact on infrastructure. The WELDER model is designed to take component-level inventory from BUILDER, apply a range of climate stressors based on location, and estimate the change in degradation and resulting service life caused by these climate stressors. This represents a capability that has not been fielded before, particularly for a large facility dataset like the BUILDER Sustainment Management System. The WELDER software is flexible so that users can change the uncertainty—and associated lifecycle impact to building components—based on their understanding of local conditions, the current state of the infrastructure, and the desire to proactively respond to the extreme event threats. WELDER is able to be calibrated for all regions of interest within the contiguous United States and is scalable to handle additional demonstration sites and broader deployment across the U.S. military.

4.7.2. Limitations

At the same time, this tool represents an initial operating capability, and there are limitations to this model due to the early development of

[1] The WELDER exploratory analysis website is accessible at: https://welder.lbl.gov/login.

Table 7
Extreme weather-informed parameters to determine sustainment management activities and additional costs in BUILDER.

Model Results	Equation	Calculated Value
TotalAdjustedRSL	$RSL - TotalServiceLifeReduction$	4.07
TotalAdjustedBeta	$\dfrac{\frac{CurrentAge + TotalAdjustedRSL}{DesignLife}, if RSL > 0}{Beta, if\ RSL \leq 0}$	0.60
TotalAdjustedAlpha	$\log_{\left(-\log_{\frac{CurrentCI}{100}}\frac{100}{40}\right)} \dfrac{\frac{CurrentAge}{DesignLife}}{TotalAdjustedBeta}$	2.31
AnnualRiskPremium	$(CRV)\left(\dfrac{\frac{TotalServiceLifeReduction}{DesignLife}}{RSL}\right)$	\$15,183
RiskLevel	$\begin{cases} Very\ Low, if \left(\frac{AnnualRiskPremium}{CRV}\right)[< 0.1\%] \\ Low, if \left(\frac{AnnualRiskPremium}{CRV}\right)[0.1\%\ to\ < 0.5\%] \\ Medium, if \left(\frac{AnnualRiskPremium}{CRV}\right)[0.5\%\ to\ < 1\%] \\ High, if \left(\frac{AnnualRiskPremium}{CRV}\right)[1\%\ to\ < 2\%] \\ Very\ High, if \left(\frac{AnnualRiskPremium}{CRV}\right)[\geq 2\%] \end{cases}$	Very High

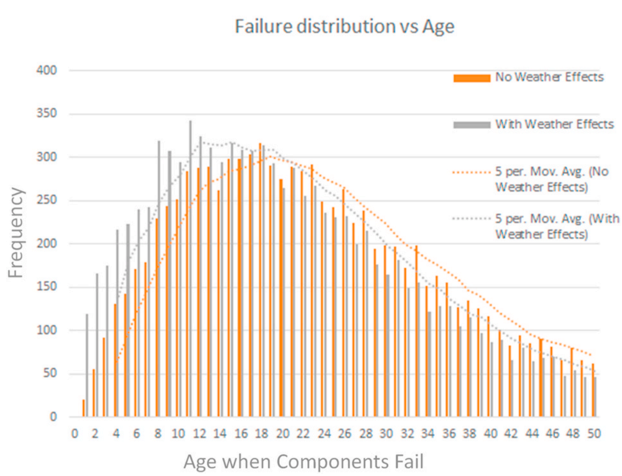

Fig. 7. Builder degradation profile with extreme weather effects.

this concept. Sufficient information for projecting extreme weather into the future may not be present for all locations or future climate conditions. In these situations, we used observational and high resolution model data where available and coarser resolution global model data when necessary. Due to resource constraints, the research team was only able to generate extreme weather projections for one representative concentration pathway (RCP) scenario—the high greenhouse gas (GHG) emission scenario RCP8.5. To address this and other shortcomings, a number of enhancements to the climate modeling component of WELDER have been identified. These proposed improvements include, but are not limited to: utilizing information from an ensemble of models, considering multiple climate change RCP scenarios, and making bias corrections to the model-generated wind speeds values across the United States.

Another limitation is that the climate stressors evaluated for this project are more often related to extreme weather events. Of course, there are other climate stressors, while not necessarily extreme in nature, that impact facility conditions. These effects may include increased corrosion, moisture problems in buildings, and mold growth potential. Another limitation is that the model considers the impact to individual weather events independently. Due to the less frequent occurrence of the most extreme events, this assumption seems reasonable, since the likelihood of multiple event occurrences in the same timeframe is less likely. However, as extreme events become more frequent, or non-extreme event stressors are included, additional research may be warranted.

Furthermore, we may not have sufficient detail on the existing and/or extreme event-degraded condition, functionality, and mission dependency indices of facilities. We intend to address this shortcoming by working with a group of trained inspectors—and staff at the demonstration sites—to determine the condition index (CI), facility condition index (FCI), and mission dependency index (MDI) for a representative group of facilities and locations. Accordingly, we have proposed developing a BUILDER post-disaster damage assessment module so that localized information can be used to continuously calibrate and validate the WELDER predictive model impacts to building lifecycle.

In addition, the WELDER modeling is performed at the individual component-level. While cost metrics can be aggregated to the service-, site-, system- or facility-level, it does not perform a holistic analysis of facility- or site-level adaptation alternatives. For example, DoD planners may be faced with a decision to (1) continue to maintain an existing facility that is at-risk to extreme weather or (2) relocate or rebuild the entire facility. In short, a key unanswered question is at what point do the expected, cumulative maintenance costs of multiple components drive a decision to replace (relocate) the entire facility? Future research could allow users to make more informed decisions when making these types of trade-offs.

Finally, there is evidence that "tools alone do not constitute an approach to climate adaptation [at military facilities]" [6]. We are addressing this shortcoming by giving public presentations and hosting meetings to highlight the importance of coupling the WELDER deployment with a "clear mandate to develop adaptation options and affect change"—as suggested by the aforementioned researchers.

WELDER helps users make informed decisions about facility sustainment, restoration, and modernization activities under different extreme weather scenarios. The weather events under consideration include conditions of extreme heat and cold, high winds (e.g. hurricanes), heavy precipitation, snow, and ice. WELDER provides policymakers with the ability to aggregate the costs of these component repair and replacement activities—under different threat and response scenarios—to the system-, facility-, site-level. The widespread adoption of WELDER will help decision makers achieve the goal of a more resilient, cost-efficient, and productive portfolio of facilities.

CRediT authorship contribution statement

Peter Larsen: Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis, Conceptualization. **Michael Grussing:** Writing – review & editing, Writing – original draft, Validation, Supervision, Formal analysis, Conceptualization. **Emily Bercos-Hickey:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation. **Christine Bidner:** Writing – review & editing, Writing – original draft, Formal analysis. **Kristina LaCommare:** Writing – review & editing, Writing – original draft, Supervision, Project administration. **Kirsten Landers:** Writing – review & editing, Writing – original draft, Software, Data curation. **Brenda Mehnert:** Writing – review & editing, Writing – original draft, Formal analysis. **Christina Patricola:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation. **Austin Powell:** Writing – review & editing, Writing – original draft, Software. **Michael Spears:** Writing – review & editing, Writing – original draft, Software, Data curation, Conceptualization. **Michael Wehner:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Peter Larsen reports financial support was provided by U.S. Department of Defense ESTCP. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary information

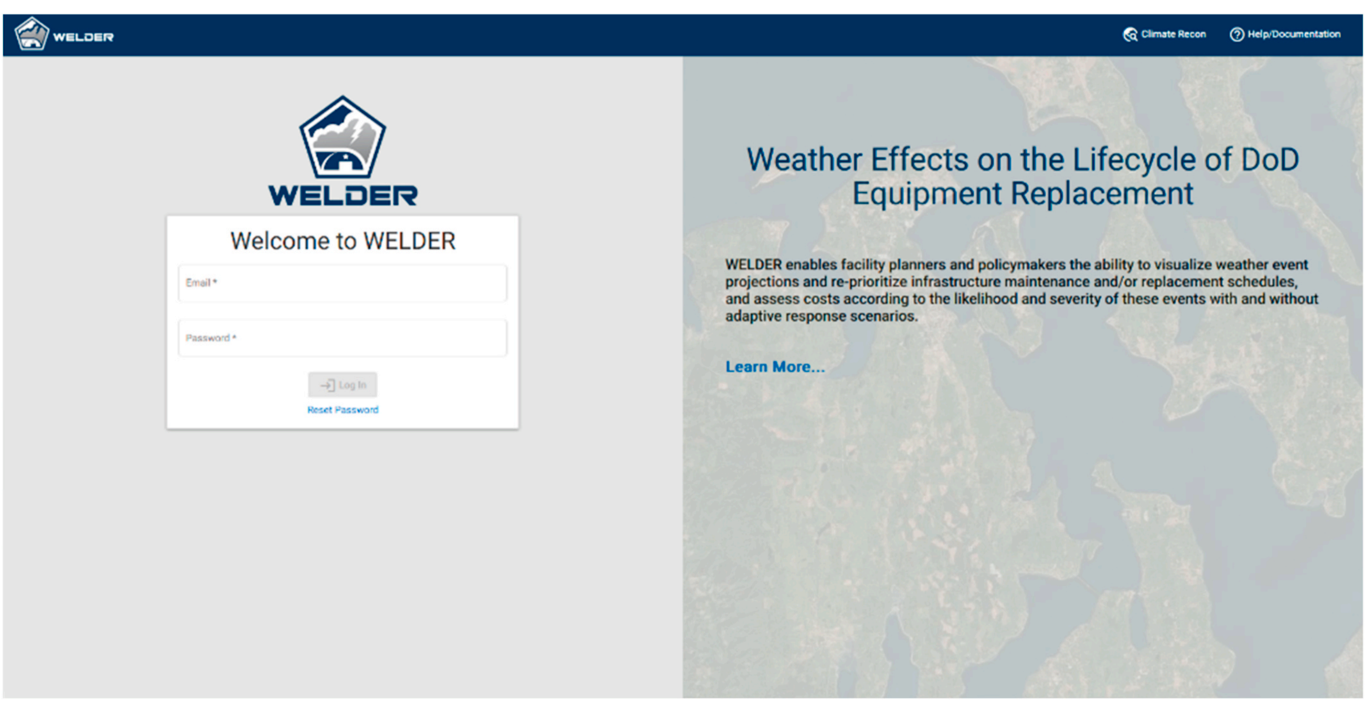

Fig. A1. Home Page for WELDER Exploratory Analysis Tool.

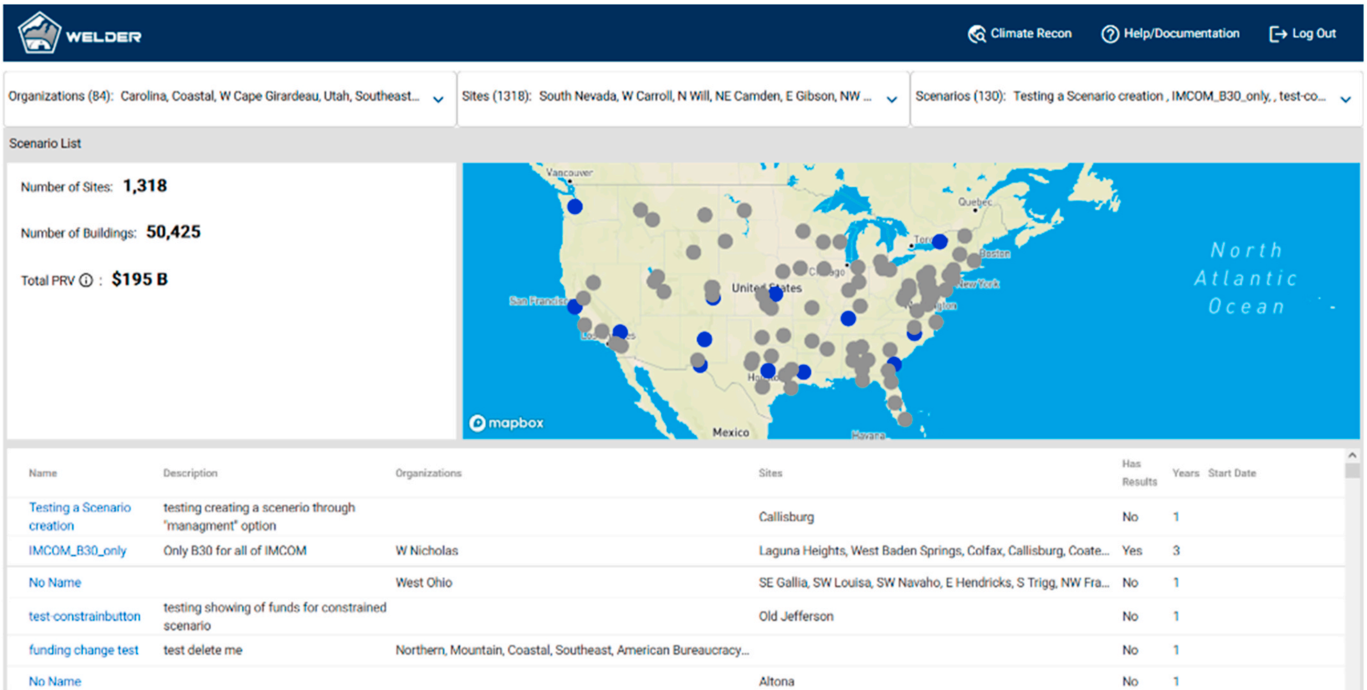

Fig. A2. Example List of Extreme Weather Scenarios Created for Deeper Analysis.

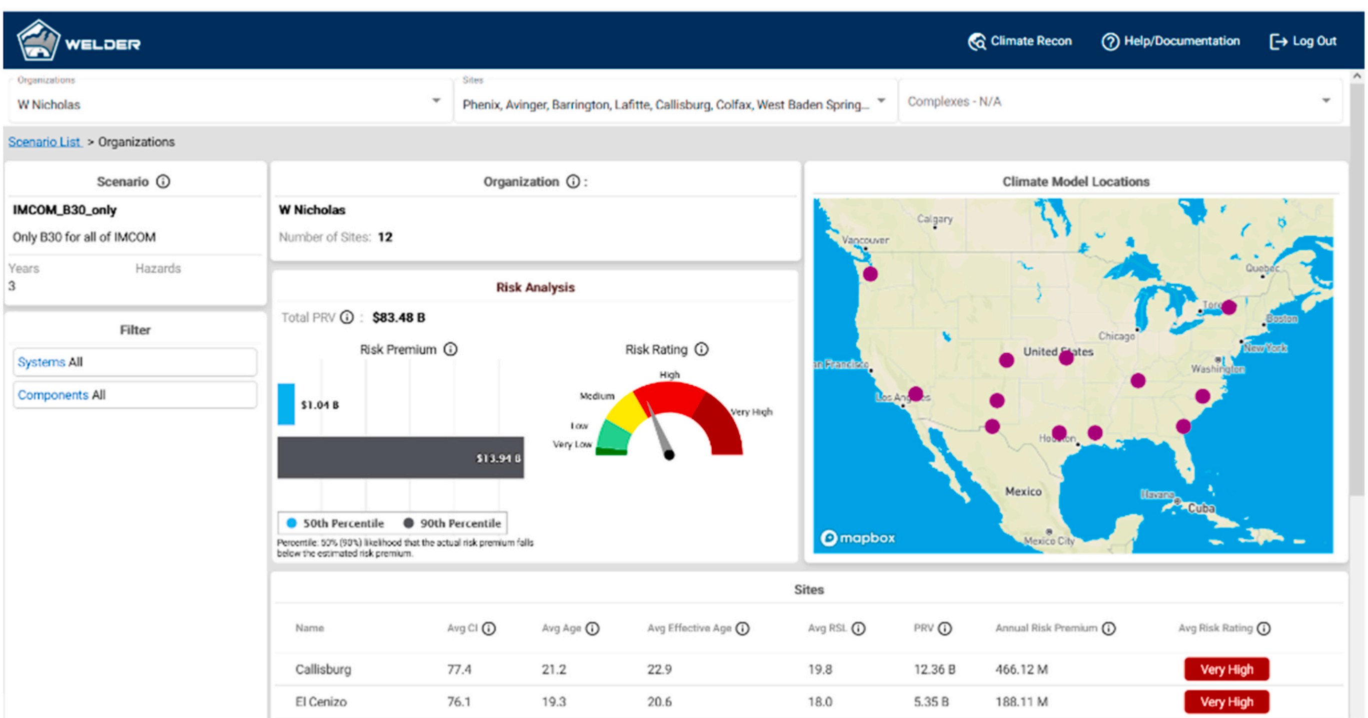

Fig. A3. Individual Scenario (organization-level view) and Extreme Weather Risk Premium.

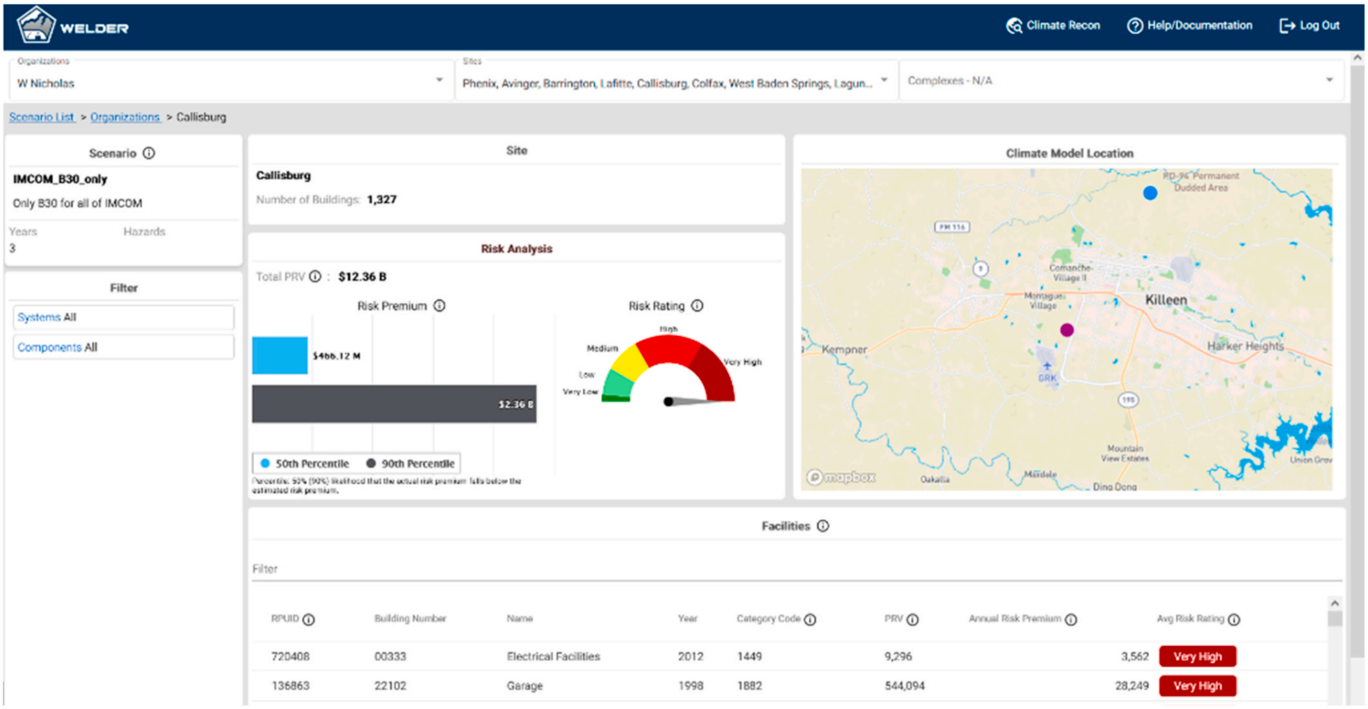

Fig. A4. Individual Scenario (site-level view) and Extreme Weather Risk Premium.

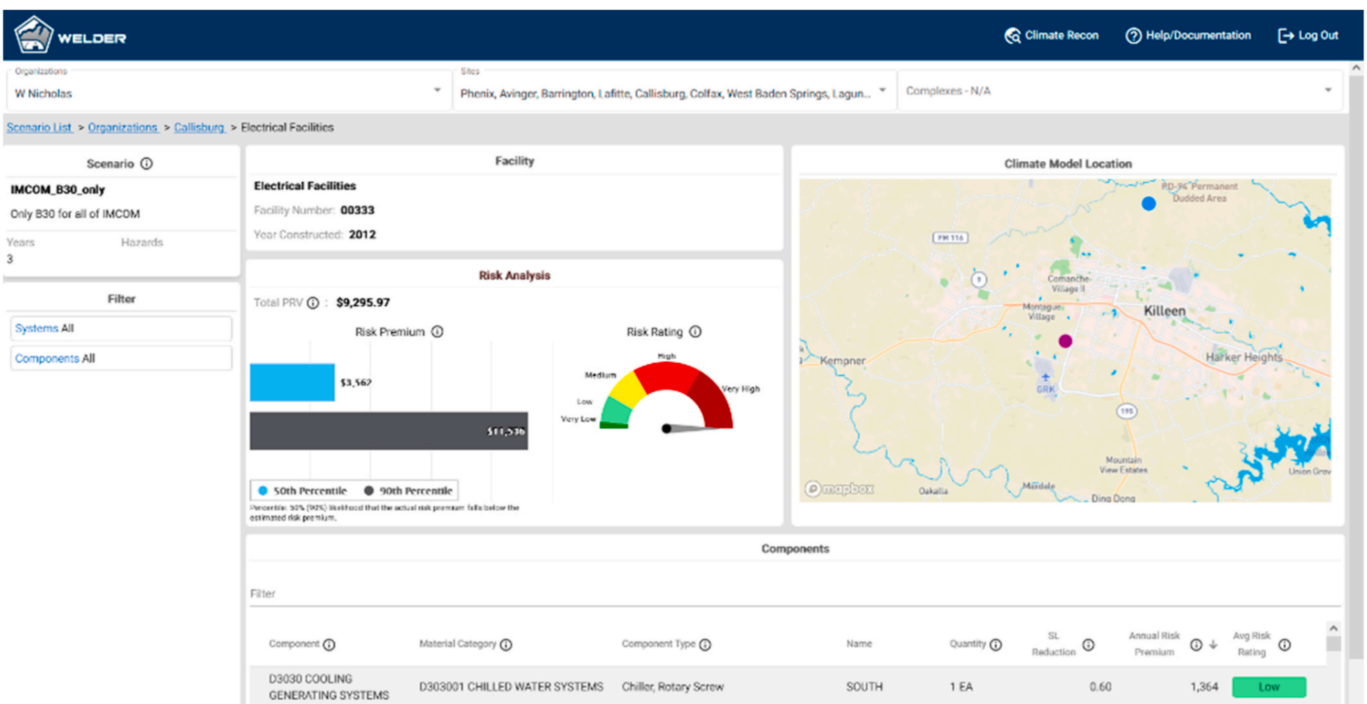

Fig. A5. Individual Scenario (facility-level view) and Extreme Weather Risk Premium.

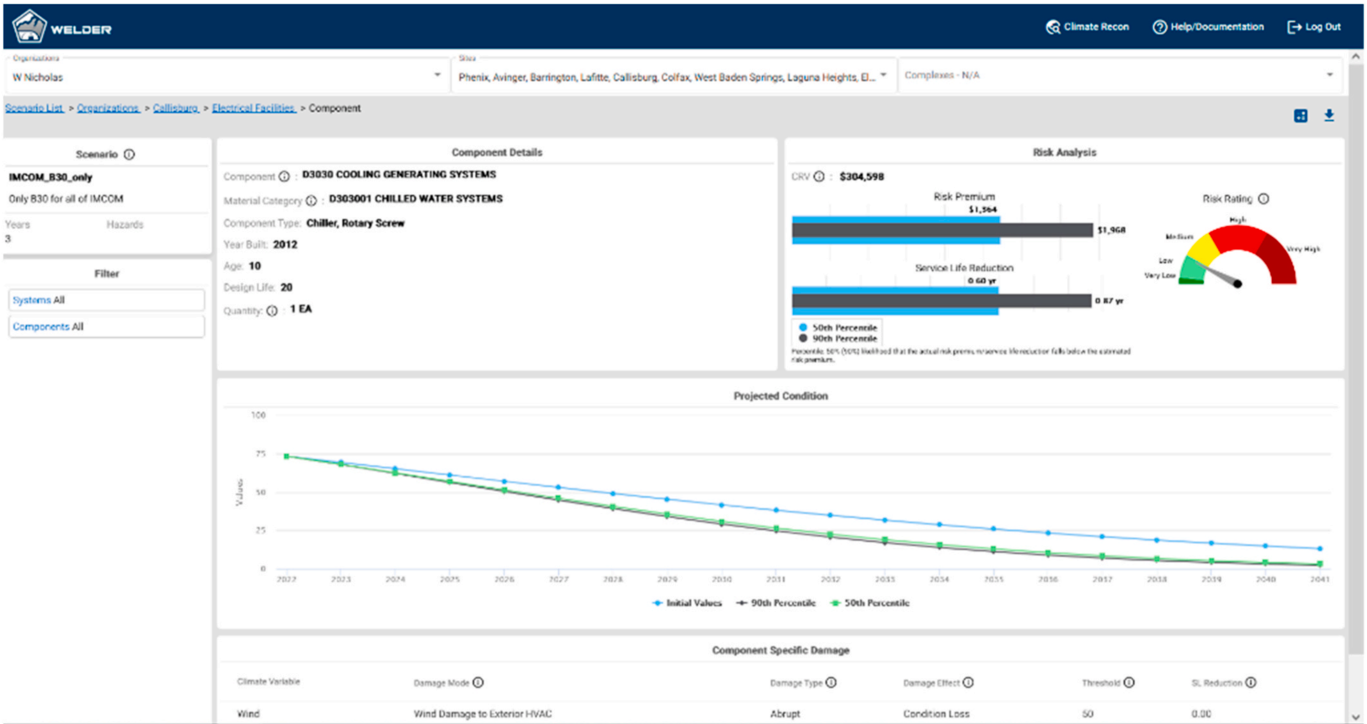

Fig. A6. Individual Scenario (component-level view) and Extreme Weather Risk Premium.

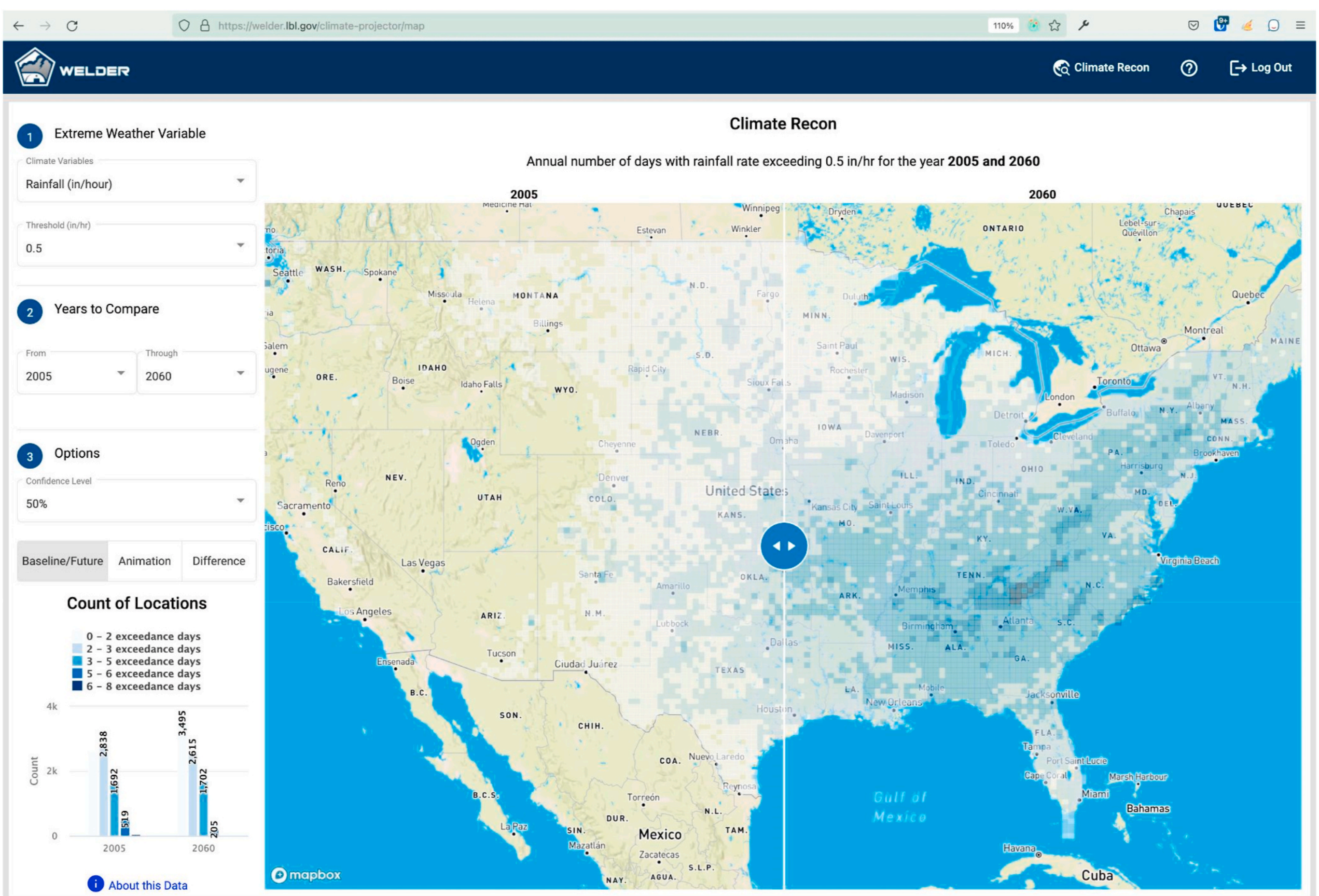

Fig. A7. Climate Recon Feature within WELDER.

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