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[This report has been modified for public viewing.]

ACRONYMS

Acronym	Definition
API	Application programming interface
DOE	United States Department of Energy
FEMA	Federal Emergency Management Agency
GCM	Global climate models
GHCN-D	Global Historical Climatology Network - Daily
HURISK	The National Hurricane Center Risk Analysis Program
IBTrACS	NOAA's International Best Track Archive for Climate Stewardship
IPCC	Intergovernmental Panel on Climate Change
LOCA	Localized Constructed Analogs Dataset
NCA	National Climate Assessment
NREL	National Renewable Energy Laboratory
RCP	Representative Concentration Pathway
SLOSH	NOAA Sea, Lake, and Overland Surges from Hurricanes
TCFD	Task Force on Climate-Related Financial Disclosure
USDA	United States Department of Agriculture
USFS	United States Forest Service
WRI	World Resources Institute

EXECUTIVE SUMMARY

Extreme weather events such as high temperatures, flooding, and hurricanes pose a threat to businesses. These events can disrupt operations, damage facilities and harm employees. Climate change is exacerbating exposure to climate hazards, altering weather patterns and influencing extreme events in sometimes unpredictable ways. This poses new challenges for companies as they prepare for and respond to climate change.

Quantifying physical climate risk is an essential step to identifying site-specific risks and opportunities. Measuring climate risk will provide additional information to improve the prioritization of sustainability-related investments, anticipate threats to business continuity, and plan future climate adaptation measures. Furthermore, risk quantification can provide the basis for future voluntary reporting in line with emerging standards on corporate climate risk disclosure.

This project evaluates physical climate risk for a client, a major US-based company, with a focus on five climate-related hazards: extreme heat, flooding, water stress, wildfires and hurricanes. It examines risk associated with these hazards at multiple sites in the United States at present and over the next 20 years, and creates a generalized framework for risk quantification that can be applied to similar manufacturing, lab, office, and warehouse sites outside of the project scope.

The project creates a risk scoring methodology based on scientific data from publicly available sources and best-practices in climate risk disclosure, allowing for the identification of corporate risk hotspots based on site location and hazard. This quantification methodology is presented through an Excel-based risk assessment tool that equips the client's staff to effectively measure and manage physical climate risk throughout the organization.

This analysis provides high-level climate adaptation and resilience options. However, a rigorous cost-benefit analysis for adaptation solutions, as well as detailed site-specific assessments, would strengthen the business case for investment. The analysis is aimed to further guide strategic planning for climate mitigation and sustainability efforts that are both site-specific and company-wide. The increase in awareness of climate impacts, improvements in climate modeling tools, and growing stakeholder engagement on risk methodologies will present new opportunities to understand and manage risks.

This version of the report has been modified from its original form to include only relevant background, methods, and project limitations that might be useful in developing a similar physical corporate climate risk assessment. The report has been modified to protect the client's anonymity while still providing information that the group found to be missing in publicly available methodologies for conducting a climate risk assessment.

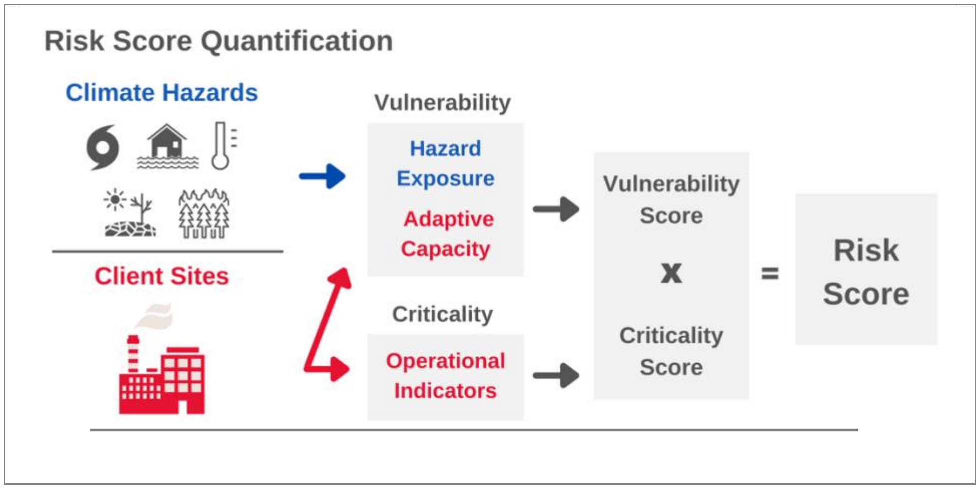

Figure 1. Summary of methods to quantify risk scores. These methods are discussed in detail in section 2 of this report.

SIGNIFICANCE AND OBJECTIVES

This project had three primary objectives:

1. Develop, test, and refine a framework to quantify and score climate-related risks at a set of the client's sites in the United States at present, and in 2025, 2030 and 2040.
2. Develop estimates of potential financial damages and cost increases from climate-related hazards.
3. Implement this framework in a user-friendly Excel-based tool that ranks the identified risks at each site, allowing for parameterized analysis, customization, and analysis of additional facilities.

1. BACKGROUND

This risk assessment builds on climate risk frameworks and methodologies developed by a range of institutions. Here we review key definitions and terminology associated with risk assessments, discuss climate hazards and emissions scenarios, and review how climate risk is calculated and analyzed in the corporate sector. Relevant literature is discussed in the context of project boundaries and goals, informing overall project scope and risk evaluation and scoring methodologies used in the project.

1.1 Climate Change Impacts

In order to inform risk measurement, it is first necessary to understand the scope and scale of potential climate change, how these impacts vary geographically across the United States, and how they may impact the client's operations.

Climate change is increasingly affecting communities and businesses globally. Human influence on the climate system through anthropogenic emissions of greenhouse gases increases the effects of radiative forcing. This results in an increase in global mean temperature, which is expected to increase to 1.5°C above pre-industrial levels between 2030 and 2052 (IPCC, 2014). The last three decades (1990-2020) have been the warmest 30-year period of the last 1400 years in the Northern Hemisphere (IPCC, 2014).

Global temperature increases will result in changes in localized weather patterns and may increase the intensity and frequency of extreme weather and climate events. Although impacts vary regionally, hotter days and longer periods of extreme heat are projected, extreme high sea levels are expected to increase, and heavy precipitation and strong wind events will likely become more frequent and intense (IPCC, 2014). These hazard events have implications for human well-being and society more broadly; chronic events such as heat stress and drought exacerbate existing human health conditions, while extreme events such as wildfires and hurricanes can disrupt utility services and cause physical damage to infrastructure and loss of human life (IPCC, 2012). In this project, we define hazards relying on a description from Brooks (2003) as "physical manifestations of climatic variability or change, such as droughts, floods, storms, episodes of heavy rainfall, long-term changes in the mean values of climatic variables [or] potential future shifts in climatic regimes."

In the United States, climate change will have diverse impacts on climate and weather events, and in turn, on human well-being. Across the US, the number of days with extreme high temperatures is projected to increase. Extreme temperatures put outdoor workers at risk of illness or death and can result in increases in energy consumption for air conditioning, straining energy grids and increasing utility costs (Risky Business Project, 2014). Rising air and water temperatures as well as shifts in precipitation patterns will put stress on freshwater availability and quality. The impacts of droughts are likely to be especially apparent in the Southwest and West United States where groundwater supplies are already stressed (USGCRP, 2018). While inadequate access to water can disrupt operations in severe instances, drought can also introduce new regulatory and reputational risks for companies given competing demands for water. Drier conditions and increasing temperatures also cause increasingly frequent wildfires, which impact infrastructure and regional air quality. Even if a facility is not directly impacted by wildfire, wildfire can result in energy grid disruptions, transportation delays and displacement of evacuated employees. In U.S. coastal regions sea level rise is contributing to increased coastal flooding and erosion, and can exacerbate severe flooding for storm events, in turn damaging local infrastructure. These storm events, including hurricanes in the North Atlantic, will become more severe, while the frequency and severity of intense storms on the West Coast of the United States will increase. In the Midwest and Northeast US, the frequency and intensity of extreme precipitation events already shows signs of increase (USGCRP, 2018). While major floods can result in a significant damage to structures and operational disruptions, even minor floods can be damaging to buildings and their contents.

This summary of impacts is not exhaustive, but is indicative of the potential severity of climate impacts for U.S. businesses in the 21st century. Limiting these effects will require a rapid shift in production practices and energy use, which together with adaptation to forecasted hazards can ultimately limit damages (IPCC, 2014).

1.2 Quantifying Climate Risk

Climate science can inform an understanding of the potential frequency and magnitude of climate impacts, and how these impacts may change over time. However, a risk assessment framework is necessary to understand the relative threat that these climate impacts pose to the client. A risk assessment is a measurement of uncertainty which aims to inform its audience with the ultimate goal of better-informed decisions (Kammen & Hassenzahl, 1999). Here we set standard definitions based on leading private and public sector climate risk assessments, which were used throughout this project, and define our project scope using a similar set of vocabulary.

The definition of risk used in this analysis was broadly based on guidance for assessing climate risk from institutions such as the IPCC (IPCC 2012; IPCC 2014). The IPCC (2012) defines climate risk as an accumulation of the probability of potential weather or climate hazards, such as heat stress or wildfire, as compared to exposure and vulnerability of a community. In the IPCC's characterization, exposure and vulnerability are values that vary based on location (exposure) as well as the adverse impacts of potential climate and weather events on a site (vulnerability). Risk, the result of this equation and the objective of this project, can be expressed as either a dollar amount or as a score (IPCC, 2012). In this project, we calculate risk scores and estimate financial damages (financial damage methods not included in the redacted report).

While the IPCC's definition of risk provides a useful analytical frame, it is intended to be broadly applicable to governments, communities and civil society. Thus, operationalizing a climate risk assessment for the corporate sector required a more specific definition and characterization of risk. Yet given that climate risk methodologies are highly variable based on sector, organization type, geographic location and goals of the analysis, identifying replicable definitions and methodologies posed a challenge. Specific methodologies that have been used to characterize climate risk in the private sector are typically proprietary and are not regularly disclosed by companies (Fiedler et al., 2021; Surminski et al., 2018).

We consulted methodologies from utilities, transit agencies, and similar public-sector institutions to identify an appropriate risk framework. Los Angeles Metro's 2019 Climate Action and Adaptation Plan served as an illuminating model for the scoring of asset (i.e., property and equipment managed by an entity) exposure and vulnerability to climate hazards at geographically discrete locations (LA Metro, 2019). In contrast to other climate risk assessments, LA Metro provided a rigorous, detailed and replicable methodology of their scoring framework, exposure calculations, and assumptions.

We adopted the risk measurement framework established by LA Metro, defining risk as a product of a site's vulnerability and criticality. Vulnerability is measured by a site's exposure to a given hazard (for instance, the probability of a hurricane striking the site), as well as a site's adaptive capacity. Adaptive capacity measures a site's ability to adapt to or withstand a climate hazard. (For instance, a site may be hardened against hurricanes, and is able to prepare and respond in order to minimize damage, demonstrating adaptive capacity.) Criticality, on the other hand, is defined as the importance of a site to the client's business. This was measured using a range of operational and financial indicators, including site value and employee headcount. This definition of risk is illustrated in **Figure 2** below, and discussed in detail in Section 2: Methods of this paper.

Figure 2. Basic risk assessment framework used in this analysis, adapted from the definition of risk used in the 2019 LA Metro Climate Action and Adaptation Plan (LA Metro, 2019).

1.3 Considerations for Corporate Climate Risk Assessments

Despite the lack of standardized, detailed methodologies for corporate climate risk assessments, there is growing consensus around the types of climate risk that companies should be measuring. This consensus is driven by the Task Force on Climate-related Financial Disclosure (TCFD), an investor-led, multistakeholder initiative to develop standards for climate risk disclosure. Using TCFD-developed definitions, we further define the scope of the project in this section.

This project quantifies acute and chronic physical climate risk, excluding considerations of transition risk relating to policy, legal, market, or reputational changes (TCFD, 2017). Physical climate risk includes impacts of climate change on a company's sites and asses as well as indirect impacts on supply chain. It is further classified into chronic and acute risk. Chronic physical climate risk, such as changes in precipitation patterns, increased weather variability, and rising sea levels, leads to long-term increased operational and capital costs, increased insurance premiums, and reduced revenues from a reduced production capacity. Acute physical climate risk, such as increased frequency and severity of extreme weather events like hurricanes and floods, leads to short-term damage to sites, reduced revenue from supply chain interruptions, loss of demand, reduced workforce, transportation challenges, and other disruption to production capacity (C2ES, 2017; TCFD, 2017). Given data constraints, we excluded supply chain climate risk analysis in this project, focusing on chronic and acute hazards for a set of the client's sites. Similarly, this project does not examine potential transition risks arising from climate-related policy or legal constraints (TCFD, 2017). While transition risk is important to consider, accurately characterizing it is a largely qualitative exercise requiring in-depth knowledge of a company's business strategy, forecasts and legal constraints.

Similarly, companies can measure direct (or first-order) impacts from climate change, as well as indirect (second-order) impacts. Direct impacts are impacts within the boundaries of the company that directly affect operations and can be estimated as a financial impact for the company (Mazzacurati et al., 2018). Indirect impacts of climate change (e.g., availability of natural resources, disruptions to global trade and supply chains, macroeconomic indicators) will also likely impact corporate operations. This project was limited to an assessment of direct, or first-order, climate impacts related to physical climate risk due to data availability and lack of standardized data for indirect impact modeling (EBRD-GCECA, 2018). More specifically, analysis was limited to direct impacts on the client's site itself, not considering potential impacts from climate hazards in surrounding communities. Climate-related events occurring in a wider geographic reason may also impact sites (through transportation disruption, power grid disruption, etc.); owever, data limitations prevented a wider geographic analysis.

Finally, changes in climate trends and extremes will manifest differently in the short-, medium- and long-term. (Here, short-term refers to a 3- to 5-year timescale, medium-term refers to a 5- to 20-year timescale and long-term refers to a 20+ year scale to align with TCFD guidance (EBRD-GCECA, 2018).) There is an inherent tension in climate risk assessment between short-term corporate planning needs and long-term climate trends. While businesses require information to guide strategic planning and capital allocation on a 3–5-year time scale (often less), climate models may not provide accurate short-term projections given significant uncertainties and variability in natural climate cycles. Projections from climate models are more appropriate for use in long-term planning (Fiedler et al., 2021). Given this tension, we examined medium-term climate risk, analyzing a 20-year time period of 2020 – 2040.

1.4 Climate Hazards and Scenarios

This project focuses on climate hazards identified through thorough review of leading international and national climate assessments, guidance relating to TCFD, and major US-focused climate risk publications (IPCC, 2012; USGCRP, 2018; EBRD-GCECA, 2018; Risky Business Project, 2014; Woetzel, 2020). We focused on five climate hazards: extreme heat, flooding, water stress, wildfires and hurricanes, displayed in **Figure 3** below.

We do not include other potential natural hazards such as tornadoes, landslides, extreme cold or winter storms. These hazards typically cause less damage, and/or have less data availability on their relation to climate change.

Climate risk assessments are also limited in their ability to analyze indirect hazards impacts and compounding risk; physical processes associated with individual climate hazards often interact, increasing overall climate risk; however, these linkages are complex and difficult to model (Zscheischler et al., 2018; Fiedler et al., 2021). Given the limited scope of this and past analyses, climate hazards are analyzed independently of one another.

Figure 3. Climate hazards included in the scope of this analysis.

The magnitude of future climate change is uncertain. Thus, different scenarios, or Representative Concentration Pathways (RCPs) are used in analyses to represent greenhouse gas concentration trajectories. RCP 8.5 represents a high greenhouse gas emission, “worst-case” climate change pathway, corresponding to a 4.3°C increase by 2100, while RCP 4.5 represents a less extreme scenario in which climate policy stabilizes emissions and the climate by the end of the century corresponding to an increase between 2 and 3°C (Riahi et al, 2011; Thomson et al, 2011). A number of prominent climate risk assessments focus analyses solely on RCP 8.5 to draw attention to risks associated with a worst-case scenario; however, RCP 8.5 is now largely considered “implausible” and not appropriate for assessing climate outcomes prior to the middle of the century (Four Twenty Seven, 2019; Woetzel, 2020; Hausfather & Peters, 2020). To examine a range of potential outcomes for this project, climate projections representing both RCP 4.5 and RCP 8.5 scenarios are analyzed for each hazard where possible. This consideration of multiple climate scenarios will better communicate uncertainty for climate-related hazards in the short to medium term.

2. METHODS

The methods section discusses the analysis completed in this project to score climate risk. Exposure to climate hazards at the client’s sites was identified through analysis of climate and hazard model data. Potential impacts of these climate hazards were assessed through the collection and analysis of site-specific data for facilities. These two components allowed for the characterization of site-level risk. This process was repeated for risk at present day, projected risk in 2025, 2030 and 2040. Key assumptions and limitations for methodologies used in this process are detailed throughout.

2.1 Overall Risk Scoring Approach

Here, we discuss the overall scoring framework that was used to assign risk scores to sites including a discussion of indicators used to calculate vulnerability and criticality for sites, as well as a discussion of qualitative aspects of this approach.

This analysis relied on climate projections, hazard models, and client-provided site-specific information to calculate an overall risk score for each climate hazard at each site. Following this risk definition established in **Figure 2**, climate risk scores were generated by multiplying vulnerability and criticality scores together to find a risk score for each hazard at each site. Hazard models are discussed in subsequent sections.

Risk scores are commonly used to qualitatively measure and communicate complex climate risk (U.S. Federal Government, 2014). To calculate this risk score, separate site-specific indicator scores were first generated for both vulnerability, which includes exposure (being at a certain level of contact to the hazard) and adaptive capacity (ability of the site to prepare and mitigate damage) as subsets, and criticality, which includes a variety of criticality indicators specific to each site, including redundancy (operations able to be completed at other sites), interoperability (number of other sites impacted by operational reductions at a given site), site value, employee headcount, and operational value.

	INDICATOR	VALUE	SCORE (1-5)		
Vulnerability	**Exposure**	Very high flooding exposure	5	5	**Risk Score**
	Adaptive Capacity	No evidence of ability to take adaptive action (or otherwise respond to event) in a way that mitigates potential damage	**5**		
				x	15
Criticality	Redundancy	Low percentage of operations could be completed at other sites	5	**3**	
	Interoperability	Moderate number of sites would be impacted by a site shutdown	4		
	Site Value	Medium-low relative site value	2		
	Operational Value	Medium-low relative operational value	2		
	Energy Consumption	Medium-low relative energy consumption	2		

Figure 4. An example hazard scoring matrix showing the averaging of vulnerability indicators and criticality indicators. These two averaged scores are then multiplied to generate a site-specific hazard risk score.

All indicators are scored on a 1-5 scale, with 1 representing low vulnerability or criticality and 5 representing high vulnerability or criticality. Indicator scores for vulnerability and criticality were then averaged to find an overall category score, and these averaged scores are then multiplied together to find an overall risk score, with a maximum score of 25 (a maximum score of 5 for vulnerability multiplied by a maximum score of 5 for criticality). **Figure 4** illustrates an example of these scoring calculations in action for the flooding hazard. These hazard-specific risk scores will then be aggregated into a heatmap to visually communicate relative climate risks among sites (this heatmap is not included in this edited version of the report). Methods for assessing and scoring vulnerability and criticality are described in further detail in sections 2.3 and 2.6 below.

Vulnerability and criticality are assessed quantitatively where possible; however, limitations posed by the project timeline and gaps in data availability require significant use of qualitative methods to supplement a quantitative approach. This is not uncommon in risk management, which, as a result of weighting and scoring of relevant qualitative and quantitative information, is an in inherently subjective exercise. All assumptions, estimations and extrapolations are detailed in sections 2.2-2.7 below to create a transparent and replicable risk assessment framework.

2.2 Survey Methods

To gather site-specific information necessary to conduct the risk calculations, a 39-question survey was developed and distributed to client staff.

The survey was developed in Microsoft Excel and was adapted for each site to include only applicable hazards and locally appropriate thresholds. The survey was constructed of an introduction sheet, eight question sheets (Flooding, Wildfire, Hurricane, Extreme Heat, Water Use, Water & Electricity, Site Interdependence, and Outdoor Work), and a hidden reference sheet.

Thresholds were established for each of the six hazards as outlined in **Table 1**. Although these thresholds were not consistent with site-specific climate data outputs, they were needed to serve as a baseline and provide a tangible scenario. The survey introduction and questions were worded to encourage best estimates, since many questions may not directly tie to existing site data. Respondents were asked to answer a variety of questions estimating the financial impacts of a scenario in which each threshold was reached, the actions that would be taken in response, and the actions that could be taken to prepare for and reduce the impacts of each scenario. To estimate site exposure to the human health impacts of heat stress, respondents were also asked to estimate how many employees work outdoors for a majority of their workday.

Site criticality was assessed by asking respondents to estimate what percent of onsite work could be done at another site on short notice, as well as how many other the sites would be impacted by their site’s temporary shutdown. Criticality of water and energy availability was measured by asking respondents to list their actions in the face of each scenario, the financial cost of these actions, and how long those actions would sustain the site if an outage continued.

In the survey, impacts of water stress were rephrased as water use, but questions remained the same as for other hazards. The Water & Electricity sheet asked about recent electricity and water utility outages as well as any backup sources, such as generators, available onsite. The Site Interoperability sheet included questions asking respondents to estimate what percent of onsite work could be done at another company site on short notice, as well as how many other sites would be impacted by their site’s temporary shutdown. To estimate site exposure to the human health impacts of heat stress, respondents were also asked to estimate how many employees work outdoors at least 4-hours a day on the Outdoor Work sheet.

Table 1. Thresholds selected as the basis of survey questions. All thresholds were provided by the Bren group except for Sea Level Rise and Extreme Precipitation, which the group asked respondents to establish based on site-specific knowledge and experience.

Survey Hazard Thresholds

CLIMATE HAZARD	THRESHOLD
Heat Stress	Site-specific 95th percentile temperature in °F
Water Stress	Mandated 20% reduction in water use
Sea Level Rise and Extreme Precipitation	Site-defined height of water in 1 or more building(s)
Wildfire	Fire within the site's broader community
Hurricanes	Wind speed > 75 mph

The survey was distributed to site Facilities Managers via email. Besides being used to score Interoperability, Redundancy, Electricity Resilience, and Adaptive Capacity, results were also used to calculate Heat Stress Health Impacts and to corroborate estimated financial damage calculations.

Assumptions and limitations

None of the surveys which were returned were complete, and none of the questions which were used in scoring had 100% response rate. Details for assumptions made about these unanswered questions is available for each appropriate category in sections 2.5.1-2.5.5. While responses were incomplete, they still did contain useful information and highlighted some of the limitations of this project including limited site-specific building information and limited access to required emergency response plans. Although this survey was initially developed to assess impacts of hazards, responses relating to energy consumption, interoperability, redundancy, and hazard-specific adaptive capacity proved the most useful in this assessment.

2.3 Vulnerability Scoring

While sensitivity and adaptive capacity rely largely on data from the client, exposure scores are generated based on third-party climate models and hazard data sets, which we discuss in the Exposure Scoring section. Using third-party data not deliberately prepared for risk scoring presented three major challenges.

First, while a large amount of climate-related data is available, it is often not accessible to non-experts due to the additional processing and large computational power that may be needed. Because of this, the project relied on multiple single-hazard climate models which included data that had already been processed by third parties.

These pre-processed data sets presented a second challenge; the most commonly referenced models for each hazard were not always compatible with one another in terms of timescales or emissions scenarios and were often not geographical or temporally granular enough for use in a corporate risk assessment. Despite these limitations, the group selected data sets which would be accessible to the client's staff for use in future climate risk analysis, and which also fit well with data available on the other hazards. Significant efforts were made to harmonize model parameters for each hazard, including climate models, emissions scenarios, and timeframes; however, there are minor inconsistencies between some models, which are noted below.

Finally, while a fully probabilistic climate risk model would allow for a complete and robust assessment of risk by modeling impacts at any probability for any hazard, this data was not available. Given the data and model limitations described above, development of a fully probabilistic model was not possible.

2.4 Model Selection

The methodologies outlined require the use of multiple existing climate hazard models that allow for the quantification of current and future risk probability for each hazard. Available climate models and data sets were assessed for a number of factors:

- Geographic coverage and resolution: models ideally provide data for the entire United States with a spatial resolution that allows for sub-regional analysis;
- Temporal coverage and resolution: models should provide historical and future projections of climate hazards at a useful scale (i.e., reasonable time steps to allow for short- and medium-term analysis);
- Climate model and scenarios: model should provide information regarding the climate model or ensemble used to generate projections, and should provide output for at least one RCP scenario;
- Credibility: models should ideally be peer-reviewed or otherwise based on best-available climate science.

Models and data selected for use in the analysis are discussed in detail in sections 2.5.1-2.5.5 below. Additional information regarding model and data analysis can be found in the Technical Appendix.

2.5 Exposure Scoring

A discussion of exposure scoring, including models and data, analysis methods, and key assumptions, is included for each climate hazard in the project scope. Given the diversity of modeling approaches, the resulting differences in model outputs, and the inherent differences in the nature of each hazard, the calculation and scoring of exposure was approached differently for each hazard.

2.5.1 Extreme Heat

2.5.1.1 Data Source and Summary

Exposure to extreme heat was modeled using the Localized Constructed Analogs (LOCA) data set for projected daily temperature (Pierce et al, 2014; Pierce et al, 2015; Scripps Institute, 2016). We chose the LOCA data set because it provides climate projections from a large number of global climate models at a relatively fine geographic scale, allowing for comparative analysis of climate trends within a city or region. Additionally, the LOCA data set is commonly used by authoritative climate impact assessments projects, including the California Climate Assessment and the National Climate Assessment. LOCA data is easily accessible to the general public through web-based tools such as NOAA's Climate Explorer, easily facilitating future analysis for new sites.

Historical observations for daily temperature were obtained from the Global Historical Climatology Network-Daily (GHCN-D), which collects data from a network of weather stations across the United States (NOAA NCEI, 2020).

2.5.1.2 Exposure Analysis Method

Exposure to extreme heat was defined in this analysis as one day with a maximum daily temperature over the historical 95th percentile warm season (May-September) temperature for each site. A percentile-based threshold approach for assessing extreme heat allows for comparison to the "normal" climate for specific geographic areas. This definition of an extreme heat day is consistent with a definition of an extreme heat event used in the 2015 U.S. National Climate Assessment (CDC, 2015).

In order to assess exposure to extreme heat, the mean number of days over the 95th percentile warm season temperature for each analysis period was calculated for RCP 4.5 and RCP 8.5. Projected days over the threshold for 2025, 2030 and 2040 were calculated using projected LOCA data; days over threshold for the historical baseline and present day (2020) were calculated using observed data from GHCN-D.

2.5.1.3 Exposure Scoring

A heat stress exposure scoring method was developed based on a methodology in LA Metro's Climate Action and Adaptation report. An exposure score was assigned based on the increase in number of days over the temperature threshold compared to a historical baseline. Scoring buckets for extreme heat are outlined in **Table 3**.

2.5.1.4 Assumptions and Limitations

There are a number of assumptions and limitations for this method of measuring heat stress. First, the number of days over an extreme heat threshold is only one measure of heat stress. Analyzing consecutive days over a temperature threshold (heat wave), as well as an index of heat and humidity (e.g., wet bulb temperatures) could provide additional information about potential impacts of increasing temperatures.

2.5.2 Flooding

2.5.2.1 Data Source and Summary

The flood exposure data used in this risk assessment was from Flood Factor, an online risk assessment tool built by the First Street Foundation using peer-reviewed methodology for determining flood risk from rivers, extreme precipitation, tides, and storm surge (First Street Foundation, 2020). Flood Factor is unique from other U.S. flood models, such as Federal Emergency Management Agency's (FEMA's) Flood Map, because it couples annual flood probability and expected flood depth at the property level (First Street Foundation, 2020a). For millions of properties, Flood Factor provides projected low, median, and high flood depths, at annual probabilities of .2%, 1%, 5%, 20%, and 50%, and a corresponding map of flood depths for the surrounding area. This expanded map feature allows for visual analysis where property-level data is unavailable. Flood Factor is especially valuable for this project because, as compared to static FEMA flood maps, it projects future flood risk according to an RCP 4.5 scenario.

2.5.2.2 Analysis Method

Where available, expected property-specific median flood depths for sites at given probabilities of .2%, 1%, 5%, 20% and 50% were recorded for 2020, 2035 and 2050 based on Flood Factor outputs. When property-level data was not available, flood depth estimates for each probability and year were assessed visually from the regional flood hazard map. The greatest depth of water in a hazard layer overlapping with a building was recorded as the expected flood depth. As Flood Factor time intervals did not align with the time intervals of this risk assessment, flood depth and probability were interpolated*2.5.2.4 Assumptions and Limitations*

Flood Factor has significant limitations for a rigorous climate risk assessment. First, property-level data is not uniformly available across all properties. If Flood Factor has property data for a location, it produces a table with flood depths at given probabilities. between time periods to find an average annual linear rate of change. This annual rate of change was applied to flood depths and probabilities to estimate exposure at the 5-, 10-, and 20-year intervals of interest.

2.5.2.3 Exposure Scoring

Flood exposure scoring methodology was based on Flood Factor's framework for their proprietary property-level scores. Their scoring method conveys overall exposure using the greatest flood depth and the greatest probability of a flood to calculate a score using a scoring matrix (**Figure 5**). Flood depth categories are consistent with those used in Flood Factor's scoring approach.

		Flood Probability (at any depth)		
		0.2%	1%	5%
Max Depth	Greater than 24in	4	4	5
	Greater than 12in	3	4	5
	Greater than 9in	2	4	4
	Greater than 6in	2	3	3
	Greater than 3in	1	2	3
	Greater than 0in	1	1	2

Figure 5. Exposure scoring for floods, which was based on the Flood Factor scoring methodology (First Street Foundation, 2020). All other exposure scoring is outlined in **Table 2.**

If Flood Factor does not have property data, analysis can still be conducted visually using the provided flood hazard map. However, visually assessing flood depth based on hazard maps where property-level data is not available introduces potential for analyst error in reproductions of this framework. Second, while Flood Factor provides probability and flood depth projections for 2035 and 2050, these projections are made solely based on RCP 4.5 (versus both RCP 4.5 and RCP 8.5). Finally, risk was assumed to scale linearly between time periods. Despite these limitations, we used this as the most readily available and commonly used data source and our inclusion of bounding scenarios helps ensure that the findings of this study are still robust.

2.5.3 Water Stress

2.5.3.1 Data Source and Summary

Exposure to water stress was modeled using the Aqueduct Water Risk Atlas tool to measure baseline and future projections of water risks. The tool is a user-friendly, publicly available global database and mapping tool of highly granular water risk information and can help companies and investors evaluate and disclose geographically relevant water risks (WRI, 2013). The tool is a data platform run by the World Resources Institute, an environmental research organization, and is comprised of tools that help companies, governments, and civil societies understand and respond to water risks – such as water stress, seasonal variability, pollution, and overall access to water (WRI, 2013). The Aqueduct tool maps water risks like floods, droughts, and stress, using open-sourced, peer-reviewed data. The Aqueduct Water Risk Atlas also provides insight on water-related risks and assesses exposure to water risk across multiple locations and is commonly used by corporate entities to assess projected regional vulnerability to water stress. The Aqueduct tool is the most up-to-date methodology in assessing exposure to water-related risk. The indicators selected for this project are based on extensive research and collaboration with WRI's research partners and target audiences utilizing publicly accessible data and literature.

2.5.3.2 Exposure Analysis Method

The client's site locations were imported into the Aqueduct Water Risk Atlas tool to develop risk maps to evaluate exposure to external water risks and contextualize water use information. Climate scenario and projected future risks were parameterized within the online tool to obtain projected fluctuations in risk indicators such as water stress and seasonal variability.

2.5.3.3 Exposure Scoring

The scoring approach for water stress and season variability was obtained from the water risk framework developed by the World Resources Institute. We chose this because the water risk framework follows a composite index approach and allows for multiple water-related risks to be combined (WRI, 2019). Physical risk, water stress and seasonal variability, scores were calculated from utilizing raw values generated by the tool. Baseline and future projected risk scores were used to assess which sites are located in water stressed regions within the United States.

2.5.3.4 Assumptions and Limitations

WRI currently only updates baseline data, not future projections data in the Water Risk Atlas tool. As a result, the datasets are inconsistent as presented in the online tool in that they apply different basin delineation approaches. Two datasets with different geometries are utilized for the future projection data and the baseline data: Global Drainage Basin Database and HydroBASINS respectively. This causes an inconsistency on a robust comparison between baseline and future projected water risk. However, this inconsistency is addressed using the guidance provided in WRI's technical notes and the methodology above; however, any future updates to this analysis should ensure compatibility between baseline and future projections (WRI, n.d.). While only water stress and seasonal variability were considered in this assessment due to limited availability of future projections for other indicators, future water risk assessments could include additional indicators to aid in developing a more robust water management strategy. Given these limitations, the Aqueduct team continues to refine this methodology to ensure that it is constantly updated to maintain its robustness. The team works one-on-one with companies, governments, and research partners to help advance best practices in water resources management and enable sustainable growth in a water-constrained world (WRI, 2013). Since the tool's development, the tool has reached hundreds of thousands of users across the entire world, and informed decision-makers in and beyond the water sector.

2.5.4 Wildfire

2.5.4.1 Data Source and Summary

Data for wildfire exposure came from the *Wildfire Risk to Communities: Spatial Datasets of Landscape-Wide Wildfire Risk Components for the United States* model provided by the U.S. Department of Agriculture (USDA) (USDA, 2020). This model provides annual data on burn probability, direct wildfire risk to buildings and wildfire intensity on a community and county scale. *Wildfire Risk to Communities* bases this information on fuel availability, soil moisture, and regional building vulnerability.

Community-scale data is most accurate in showing localized fuel availability surrounding the client's sites and was used for exposure and vulnerability scoring in this assessment. One major drawback of this model is that it does not include future projected change in risk based on climate scenarios. To account for the projected global increase in wildfire frequency, regional values from the U.S Global Change Research Program and U.S. Forest Service (USFS) were used for sites in the Southeast and California (NCA, 2018; USFS, 2012). For sites where regional data was not available, IPCC's RCP 4.5 global increase of 37.8% by 2040 was used (IPCC, 2012). The burn probability, direct and indirect risk, and intensity outputs were scaled linearly by these literature values based on 2020-2040 to provide projected site wildfire exposure. The Wildfire section of the surveys was not distributed to sites with a burn probability below $10x10^{-5}$. Since it was later decided that wildfire scores would be calculated for all sites, these sites were assigned inflated adaptive capacity scores. It was assumed that sites in low fire-exposure regions do not the knowledge or infrastructure in place to adapt to wildfire.

2.5.4.2 Exposure Analysis Method

The USDA community-scale data was filtered to include only communities where the client's sites are located. Wildfire exposure was calculated using burn probability, fraction of buildings directly exposed to fire, and conditional risk to structures. A site was considered directly exposed to wildfire if the area surrounding the site was covered by flammable vegetation that would lead to the ignition of the building. In this analysis, these two types of exposure were summed together as both scenarios could result in the spread of a fire and substantial impacts to the client's sites. Exposure was quantified as the present-day probability of a wildfire occurring and the intensity potential of fire in the region. Intensity potential was measured using expected flame length as a proxy. This analysis method is based on methodology used in a report by the USFS and an analysis by the state of Colorado where flame length is directly proportional to the extent to which a building is damaged (USFS, 2013, State of Colorado, 2020).

2.5.4.3 Exposure Scoring

The 1-5 exposure scoring scale for wildfire exposure was based on two indicators: potential fire intensity in the community and the probability of a fire occurring in the community. Probability of a fire in the community was divided into 20% intervals and compared to present-day national probability. Fire intensity potential was scored similarly to exposure, but instead used the "mean conditional risk to potential structures percentile within nation", as a proxy for fire intensity. This category describes the impacts of a wildfire on buildings in a community relative to the rest of the nation. Scoring for wildfire intensity was based on an existing fire intensity index. The index is distributed as a relative percentage across the US. 2020 intensity values are used as a baseline for 2020-2040 projections (Dillon et al.). Scoring buckets for wildfire are outlined in **Table 2**.

2.5.5 Hurricane

2.5.5.1 Summary

Tropical cyclone intensity is measured using the Saffir-Simpson Hurricane Wind Scale, which uses average wind speed sustained over 1 minute to estimate potential property damage on a scale from Category 1 to Category 5 (National Weather Service, n.d.). Hurricanes are cyclones which have an average sustained wind speed of over 75 mph. As there is no standard model of projected future hurricanes, future hurricane hazard projection relied on historical data and scientific consensus on projected increase in storm intensity. Although hurricane strength is measured in wind speed, flooding from extreme precipitation is often the most damaging element of a tropical cyclone; however, historical observed precipitation has not been well documented and so cannot be modeled (Emanuel et al., 2006).

To account for the projected increase in hurricane severity associated with climate change, the history observed wind speeds were scaled linearly to associate a 3% increase in wind speed with the year in which global mean temperature increased by 2°C under each RCP (Knutson et al., 2020).

Hurricane exposure was modeled at six sites. Although other sites have been exposed to tropical storms in the past, none of this exposure was at hurricane-strength wind speeds (≥ 75 mph). The projected 3% increase in storm severity did not project exposure to hurricane-strength winds at any of the other sites during the time period examined in this assessment.

2.5.5.2 Data Sources

Hurricanes bring damage from both: high speed winds and from flooding through storm surges. NOAA's International Best Track Archive for Climate Stewardship (IBTrACS) Version 4 was used as the base dataset for all projections (National Centers for Environmental Information, 2020). The IBTrACS dataset provides storm tracks at a 0.1-degree resolution based on observations recorded every 3 hours. Where 3-hour observations were not available, they were interpolated based on observations recorded every 6 hours (National Centers for Environmental Information, n.d.). Each site's exposure to hurricanes was modeled using the return period, the frequency at which a hurricane of a given intensity can be expected, of a hurricane as well as the percent of storms falling into each Saffir-Simpson category. Both values were calculated using methodology outlined by The National Hurricane Center Risk Analysis Program (HURISK) (National Hurricane Center, 1991). This analysis was conducted in R and is summarized in the Appendix.

NOAA Sea, Lake and Overland Surges from Hurricanes (SLOSH) model is the standard measurement of storm surges and is often used in evacuation planning in the event of an active storm; however, this analysis used the Flood Factor data described above (National Hurricane Center and Central Pacific Hurricane Center, n.d.).

2.5.5.3 Assumptions and Limitations

This method of modeling hurricane exposure and severity has several limitations and major assumptions. While modeling based on past exposure can introduce errors, doing so is consistent with NOAA's National Hurricane Center's exposure projections and was necessary given the lack of access to a complex climate forecast model (National Hurricane Center and Central Pacific Hurricane Center, n.d.). Second, the HURISK methodology filtered past storms to only include those which passed within 75 nautical miles (nmi) (86.3 miles) of each site. This selection assumes that any storms which passed within the 75 nmi radius resulted in an impact on the site, which was not possible to verify, due to a lack of site-level data. Third, this model assumes that past observed wind speeds account for all aspects of complex storm behavior, including increased storm decay upon landfall and any local-specific friction caused by the land's natural and manmade surface features.

The methodology outlined above and in the Appendix is not an easily replicable process for other sites. In conducting further risk analyses, the group recommends using past hurricane frequency data from the Environmental Protection Agency's (EPA) Creating Resilient Water Utilities project (EPA, 2020). Although the EPA's data lists a count of observed storms falling in each category rather than observed windspeeds, it is more easily accessible than IBTrACS, which requires some knowledge of GIS to access and manipulate.

2.5.5.4 Scoring

This analysis resulted in two hurricane vulnerability scores based on a 5-point scale: Hurricane Frequency (return period) and Hurricane Severity (% "severe" storms, Category 3 or higher). Scoring buckets for both are outlined in **Table 2**. Frequency was bucketed along a 1-5 scale following non-climate corporate risk assessment standards (Deloitte & Touche LLP, 2012).

2.6 Criticality Scoring

Criticality scores, including scores for interoperability, redundancy, operational criticality, and site criticality, determine the relative severity of the impact of a climate hazard.

2.6.1 Interoperability

The Site Interoperability indicator, a measure of how many additional sites would be impacted by a closure or reduction in operations at a given site, was generated directly from data collected in the survey. Based on the multiple-choice options on the survey, five scoring buckets were developed, which are outlined in **Table 3**.

2.6.2 Redundancy

Table 2. Vulnerability scoring parameters for all hazards and adaptive capacity, excluding flooding. Wildfire and hurricane each had exposure, severity, and adaptive capacity as vulnerability indicators, and water stress had exposure, seasonality, and adaptive capacity vulnerability indicators. Extreme heat and water each only had an exposure and adaptive capacity vulnerability indicators. Rationale for bucketing is outlined in each individual hazard's methods.

Vulnerability Indicator Scoring

SCORE	EXTREME HEAT EXPOSURE	WATER STRESS EXPOSURE	SEASONAL VARIABILITY	WILDFIRE EXPOSURE	WILDFIRE SEVERITY	HURRICANE EXPOSURE	HURRICANE SEVERITY	ADAPTIVE CAPACITY
5	>28 day increase in annual days over summer 95th percentile threshold temperature compared to historical baseline	4.5-5.0 water stress score from World Resources Institute Aqueduct Water Risk Atlas	4.5-5.0 seasonal variability score from World Resources Institute Aqueduct Water Risk Atlas	>0.0002 annual probability of wildfire	80-100% intensity relative to mean wildfire intensity in the United States	Once every 0-2 years	40-100% of storms Category 3 or higher	No evidence of ability to take adaptive action (or otherwise respond) to a hazard in a way that mitigates potential damage
4	21-28 day increase in annual days over summer 95th percentil threshold temperature compared to historical baseline	3.5-4.5 water stress score from World Resources Institute Aqueduct Water Risk Atlas	3.5-4.5 seasonal variability score from World Resources Institute Aqueduct Water Risk Atlas	0.00008-0.0002 annual probability of wildfire	60-80% intensity relative to mean wildfire intensity in the United States	Once every 2-25 years	30-40% of storms Category 3 or higher	-
3	14-21 day increase in annual days over summer 95th percentile threshold temperature compared to historical baseline	2.5-3.5 water stress score from World Resources Institute Aqueduct Water Risk Atlas	3.5-4.5 seasonal variability score from World Resources Institute Aqueduct Water Risk Atlas	0.00005-0.00008 annual probability of wildfire	40-60% intensity relative to mean wildfire intensity in the United States	Once every 25-50 yeaı	20-30% of storms Category 3 or higher	Some evidence of ability to take adaptive action (or otherwise respond) to a hazard in a way that mitigates potential damage
2	7-14 day increase in annual days over summer 95th percentile threshold temperature compared to historical baseline	1.5-2.5 water stress score from World Resources Institute Aqueduct Water Risk Atlas	1.5-2.5 seasonal variability score from World Resources Institute Aqueduct Water Risk Atlas	0.00001-0.00005 annual probability of wildfire	20-40% intensity relative to mean wildfire intensity in the United States	Once every 50-100 yeı	10-20% of storms Category 3 or higher	-
1	< 7 day increase in annual days over summer 95th percentile threshold temperature compared to historical baseline	0-1.5 water stress score from World Resources Institute Aqueduct Water Risk Atlas	0-1.5 seasonal variability score from World Resources Institute Aqueduct Water Risk Atlas	<0.00001 annual probability of wildfire	<20% intensity relative to mean wildfire intensity in the United States	Once every 100 years or less	0-10% of storms Category 3 or higher	Evidence of ability to take adaptive action (or otherwise respond) to a hazard in a way that mitigates potential damage

The Site Redundancy indicator, a measure of the percent of site work which could be conducted remotely or at another site, was again generated directly from data collected in the survey (Metro Climate Action and Adaptation Plan 2019, 2019). Five scoring buckets were developed based on this information. Details on all five buckets is outlined in **Table 3**.

2.6.3 Operational criticality

2.6.3.1 Summary

The criticality of site operations to the client's overall business was scored based on estimated per site worker operational output measured in dollars. This financial value was divided into five percentile-based scoring buckets with 1 being the lowest value and 5 being the highest.

2.6.4 Physical criticality

Physical criticality represents the total insured value of a site. In the event of damage from a climate-related hazard, the physical criticality represents the extent to which the company as a whole is impacted by direct physical damage to the site and equipment. Data used to score operational criticality was obtained directly from the client. The financial value was divided into five percentile-based scoring bucks with 1 being the lowest value and 5 being the highest.

2.6.5 Energy Use Criticality

Energy use criticality represents the total annual amount of energy consumption for operational purposes within each of the client's sites. Total energy use accounts for energy consumed for electricity generation, natural gas, chilled water and heated water. Data used to score energy use criticality was obtained directly from the client. The total energy use was divided into 5 percentile-based scoring buckets with 1 being the lowest values and 5 being the highest values of energy use.

2.6.6 Water Use Criticality

Water use represents the total annual amount of water consumption, in thousands of gallons, across all sites. Water criticality was assessed using data that was obtained directly from the client. Total water consumption was divided into 5 percentile-based scoring buckets with 1 being the lowest and 5 being the highest amount of water consumed relative to the other 20 sites.

2.7 Financial Damages Calculations

In addition to generating risk scores for each hazard that provide generalized information and incorporate qualitative information about sites, this assessment also calculated

Table 3. All criticality scoring buckets. These indicators were not used across all hazards. Extreme heat included redundancy, interoperability, operational criticality, energy use, and heat health indicators. Flooding included redundancy, interoperability, operational criticality, and physical criticality indicators Water stress included redundancy, interoperability, operational criticality, and water use indicators. Wildfire included redundancy, interoperability, operational criticality, physical criticality, energy use, and wildfire health indicators. Hurricane included redundancy, interoperability, operational criticality, physical criticality, and energy use indicators. Additional information on data sources and bucketing rationale is provided in the criticality scoring methods section. Thresholds including sensitive values are excluded from the table below.

Criticality Indicator Scoring

SCORE	INTEROPERABILTY	REDUNDANCY	OPERATIONAL CRITICALITY	PHSYICAL CRITICALITY	ENERGY USE	WATER USE	HEAT HEALTH	WILDFIRE HEALTH
5	5th quantile high number of sites impacted by a site shutdown	5th quantile site redundancy	5th quantile annual operational value ($)	5th quantile total insured value ($)	5th quantile annual electricity and natural gas use (Btu)	5th quantile annual use (gallons)	5th quantile annual outdoor worker hours	5th quantile employee headcount
4	4th quantile moderate number of sites impacted by a site shudown	4th quantile site redundancy	4th quantile annual operational value ($)	4th quantile total insured value ($)	4th quantile annual electricity and natural gas use (Btu)	4th quantile annual use (gallons)	4th quantile annual outdoor worker hours	4th quantile employee headcount
3	3rd quantile low number of sites impacted by a site shutdown	3rd quantile site redundancy	3rd quantile annual operational value ($)	3rd quantile total insured value ($)	3rd quantile annual electricity and natural gas use (Btu)	3rd quantile annual use (gallons)	3rd quantile annual outdoor worker hours	3rd quantile employee headcount
2	2nd quantile unknown number of sites impacted by a site shutdown	2nd quantile site redundancy	2nd quantile annual operational value ($)	2nd quantile total insured value ($)	2nd quantile annual electricity and natural gas use (Btu)	2nd quantile annual use (gallons)	2nd quantile annual outdoor worker hours	2nd quantile employee headcount
1	1st quantile no sites impacted by a site shutdown	1st quantile site redundancy	1st quantile annual operational value ($)	1st quantile total insured value ($)	1st quantile annual electricity and natural gas use (Btu)	1st quantile annual use (gallons)	1st quantile annual outdoor worker hours	1st quantile employee headcount

estimates of expected financial damages. We calculated damages for each hazard except water stress. No direct connection was found between increasing water stress and financial costs to companies, and data is not readily available.

Financial damages estimates were provided as an expected annual damage, which is an estimate of the annual cost of a hazard if all probabilities and severities were spread out equally over time (Colorado Water Conservation Board, 2020). As probabilities of many of the specific hazards exampled in this assessment are often low but damages from these events are high, financial impacts are communicated as an average annual expected cost to level expected costs throughout the 20-year period. Separate calculations are conducted for each hazard and accompanying criticality indicators. Financial damage calculation methods were removed from this version of the report.

3. Discussion

3.1 Risk Assessment Tool

A major deliverable of this climate risk assessment is the Excel-based risk assessment tool which the client can use to analyze and communicate risk to internal stakeholders.

3.2 Project Limitations and Considerations

The quantification of business climate risk is a rapidly emerging and evolving space. Despite improvements in climate data and models, significant challenges were still faced in this analysis, and exist for the assessment of corporate climate risk more generally. In this section, we discuss limitations to this climate risk assessment and considerations for its use.

First, despite advances from the Task Force on Climate-related Financial Disclosures and other institutions in providing guidance on climate risk quantification, this guidance is inconsistent and insufficient. A recently report by the World Resources Institute examined the current state of corporate climate risk disclosure, finding that “the body of leading disclosure guidance does not fully equip companies and financial organizations with a common approach to systematically identify and assess the complex set of physical climate risks.” They find that institutions like the IPCC and TCFD use inconsistent terminology, there is no comprehensive set of climate risk metrics, and institutions do not provide a “clear, science-based framework for assessing physical climate risk” (Pinchot et al., 2021). This lack of clear, science-based guidance proved to be a limiting factor in this project; however, this guidance will likely improve over time, providing an opportunity to improve on the methodology established.

Furthermore, there are fundamental limitations in the use of open-source climate models to assess short-term, firm-level climate risk. Despite growing demand from regulators and investors for climate risk information, there is significant concern from the scientific community about the appropriate use of climate data and models to provide this information. According to a recent study, "calls for the integration of climate science into risk disclosure…[have] leap-frogged the current capabilities of climate science and climate models by at least a decade" (Fiedler et al., 2021). Uncertainty in climate modeling is very high for short-and medium-term analysis, as well as for local, asset-level geographic analysis. Natural climate variability can mask signals of climate change in the short-term, while downscaling techniques at present cannot fully capture local variations in weather that amplify or mitigate overall changes in climate (Fiedler et al., 2021).

Finally, the scope of this analysis was limited to risk and damage at the client's sites; however, climate-related events in surrounding communities can also directly or indirectly impact corporate operations. For example, widespread flooding could prevent employees from commuting to sites, or wildfire smoke may prevent employees from working effectively from home. Despite limitations in the use of this analysis in tool in evaluating community risk, site hazard exposure quantification could serve as a proxy for community risk. This is especially the case for hurricane, fire and flooding, where an impact at a site could be assumed to mean that surrounding communities are also facing similar impacts. The client could further examine climate hazard models used in this analysis to understand how risk may change based on local geography. For example, the USFS Wildfire Risk to Communities interactive dataset could be used to assess how fire risk changes in surrounding communities compared to site location. Similarly, Flood Factor hazard maps could be used to assess the likelihood of widespread community flooding. While potentially imprecise, this approach could improve understanding of community hazard exposure and risk.

3.3 Emerging Areas of Research and Next Steps

The client could expand upon this analysis to develop a more complete view of the climate-related risks that it faces. In this section, we discuss potential areas for future research and analysis.

The risk assessment methodology developed in this project highlights risk hotspots and estimates potential financial damages; however, where risk has been identified, it may be necessary to conduct further work with experts to "ground truth" findings. Assessments conducted by environmental services or engineering firms would be able to further verify hazard exposure based on site- or building-specific characteristics. For example, a detailed analysis of building characteristics for sites with identified hurricane exposure would be able to identify the extent to which structures have already been hardened against high winds. Similarly, a site-specific assessment of flood risk may identify local features and building characteristics that reduce or heighten the flood exposure identified in national models.

High-level climate adaptation and resilience options were identified in this analysis, but a rigorous cost-benefit analysis for adaptation solutions would strengthen the business case for investment. A cost-benefit analysis could rely on damage estimates developed in this analysis to understand the potential benefits associated with avoided damages from climate impacts. Benefits in the form of avoided physical damage could be supplemented by quantifying the value of energy resiliency using a recent methodology developed by the National Renewable Energy Laboratory (NREL, 2018). These benefits should especially be quantified if the client is assessing new energy infrastructure, such as solar-plus-storage systems.

Finally, physical climate risk to owned and operated sites is only one component of a company's overall climate risk. The client should conduct additional analysis of physical climate risk in its value chains. It should also conduct further assessments of transition risk from economic, legal and political changes in a low-carbon transition.

This analysis relied on web-based, publicly accessible and free climate data and models to measure exposure. Future work could incorporate updated or enhanced climate hazard data, and further automate calculations through the use of climate data application programming interfaces (APIs). Climate analytics tools are increasingly available for corporate users, and the client could consider using updated data or models as they become available (Fiedler et al., 2021). Furthermore, the risk assessment tool developed for this project relies on manual data entry from existing models. Many data sets and models can be accessed through an API allowing for automatic updates of data for new and existing sites. For example, downscaled climate data can be automatically accessed through an API developed by Azavea, while the Flood Factor tool provides an API to access its national flood model data (Azavea, 2017). The incorporation of climate data API would require additional programming expertise, would vastly increase the usability and accessibility of a risk assessment tool for the client.

Climate change poses risks to the supply chain, increasing costs, disrupting the delivery of goods, and increasing uncertainty around the scale of potential disruptions (BSR, 2019). The scope and scale of modern supply chains, as well as limited information available about supplier exposure and resilience, make supply chain analysis challenging. The risk assessment tool created in this analysis could be used to quantify supplier exposure to climate hazards in the United States if the location of key supplier sites were known, but a lack of site-specific information for suppliers would preclude the use of the tool for measuring criticality and adaptive capacity. Assessments from professional climate risk firms, such as Four Twenty Seven or The Climate Service, may be necessary to understand the full scope of value chain risk.

TCFD recommends measuring and disclosing not just physical climate risks, but so-called "transition risk" posed to companies from future climate-related economic, legal and political changes. For example, the client may face future climate-related regulations that impact corporate performance, such as a national price of carbon. The use of scenario analysis is recommended to understand these potential transition risks. In a scenario analysis, the potential business implications of a range of possible future climate states (i.e., 2°C of warming), and resulting political and economic environments, are systematically considered. This analysis can reveal additional long-term strategic and financial risks to operations (TCFD, 2017). Additional consulting expertise may be required to conduct a scenario analysis exercise.

4. Conclusion

This project contributes to a rapidly growing body of work around the use of climate data in quantifying corporate climate risk. It can serve as a potential framework and methodology for future corporate use, highlighting the use of web-based, open-source climate modeling tools. It also highlights significant challenges for the business community, namely the lack of standardized risk quantification methodologies. Despite these challenges, increasing corporate awareness of climate impacts, improvements in open-source climate modeling tools, and growing stakeholder engagement on risk methodologies will present new opportunities to understand and manage risks.

Appendix: Technical Appendix

Heat Stress

Additional Technical Information for Exposure Scoring

The Localized Constructed Analogs (LOCA) data set for temperature projections was chosen for use because it provides provide increased spatial resolution to global climate model (GCM) outputs. While a number of other downscaled climate data sets are available (using a variety of downscaling techniques to increase spatial resolution of GCM outputs), LOCA was chosen for two primary reasons. First, it has been used extensively in authoritative national climate impact and climate risk assessments. Second, processed LOCA data and summary statistics for all locations in the continental United States are available for download using the Climate Explorer (NOAA, 2020) interface. Additionally, the LOCA data set represents extreme events more effectively than other downscaling methods (Pierce et al, 2014).

Raw projected daily maximum temperature data from the Localized Constructed Analogs (LOCA) data set were downloaded from the Lawrence Livermore National Laboratory Green Data Oasis. The LOCA data set provides downscaled projections for 32 global climate models associated with CMIP 5. Data from all 32 models was requested and downloaded for both RCP 4.5 and RCP 8.5 for a time period of January 1980 to December 2050 in tabular CSV format. Data was requested for the data grid square (3.7 miles x 3.7 miles) that included the site of interest.

Historical climate data (via the Global Historical Climatology Network-Daily) was used to create a baseline for comparison. Weather stations were selected to geographically match the location of sites to the greatest extent possible. However, given the close proximity of some sites to large cities, the same weather station data was used to calculate a baseline. Historical climate data was downloaded in tabular CSV format through Climate Explorer (NOAA, 2019).

Projected climate data was analyzed by averaging projections over time periods to estimate the expected value at a given year. While climate data is best averaged over a long timescale (20-30 years), averaging over shorter time periods is necessary in this analysis to accommodate short time steps. The time periods analyzed were:

- Historical baseline: 1975-2005 (subset from historical data)
- 2020: 2005-2020 (subset from historical data)
- 2025: 2020-2030 (subset from LOCA projections for RCP 4.5 and RCP 8.5)
- 2030: 2020-2040 (subset from LOCA projections for RCP 4.5 and RCP 8.5)
- 2040: 2030-2050 (subset from LOCA projections for RCP 4.5 and RCP 8.5)

The historical 95th percentile maximum daily temperature for warm season months (May-September) used to assess exposure was calculated using the quantile function in R against observations from the historical baseline data subset. To represent current (2020) heat stress exposure, the 2005-2020 data was filtered to find the total number of days during that time period which exceeded the 95th threshold. This count was divided by 15 years (the total years in observed time period) to find an average annual value. For each future interval, the count of days over the 95th percentile threshold was found for each of the 32 climate models in the LOCA data set. This day count was divided by the number of years in the relevant modeled time period to find the annual average for each of the 32 models. These model-specific averages were again averaged to generate an expected annual count of days over the temperature threshold.

Comparing gridded climate projections in the LOCA data sets to historical observations from discrete weather stations introduces some inconsistency in the analysis. Ideally gridded projections should be compared to gridded historical climate data. Finally, downloading and analyzing LOCA data is relatively technical and may not be conducive to a replicable process for the client. Thus, in future risk analyses, the group recommends using climate projections from Climate Explorer (NOAA, 2019).

Flooding

Additional Technical Information for Exposure Calculations

Flood Factor was chosen due to its ability to dynamically model flood impacts from multiple hazard and changes in those hazards over time. The Flood Factor tool is especially useful for analysis when compared to FEMA Flood Maps. FEMA maps that display 100- and 500-year floodplains were the main flood risk tool used in the majority of climate risk assessments reviewed in the literature. While commonly used for planning and risk management, FEMA maps may significantly underestimate flood risk. FEMA maps are static, out-of-date, and do not reflect environmental changes associated with climate change (Scata, 2017; DHS OIG, 2017, ASFPM, 2020). Flood Factor explicitly models climate change impacts in flood projections, including changes in precipitation patterns and impacts from sea level rise.

Despite these benefits, Flood Factor has major limitations. In order to simply communicate flood risk for a property, the tool only presents limited outputs. Most importantly, full probability distributions for flood thresholds are not available. This precludes the accurate assessment of the probability of flood exposure at any depth. For example, the tool may show that a building has a 5% annual chance of 3 feet of flooding, and a 20% chance of 0 feet of flooding. This suggests that there may be between a 5-20% chance of flooding somewhere between 0 and 3 feet; however, it is not possible to determine this relationship based on data available. In practice, this limits the ability to determine the probability of small, relatively common floods, as well as an accurate cumulative probability for flood events at a given depth.

This analysis was conducted using the free version of Flood Factor, so some of these drawbacks may be addressed by access to the full gridded model outputs. Gridded hazard data is available for purchase via an API from the First Street Foundation. However, integrating API data requires additional programming skills and may not be realistic for the client's staff.

Water Stress

Additional Technical Information

Water stress exposure relies on the Aqueduct Water Risk Atlas tool from the World Resources Institute (WRI). This WRI Aqueduct tool utilizes a combination of publicly available datasets and spatial and statistical models to translate global hydrological data into indicators and scores that can inform planning for a broad range of users. This model identifies 12 water risk indicators which are divided into three categories: quantity, quality, and reputational. For the purposes of this project, we focused on two indicators within the water quantity category: water stress and seasonal variability, both of which are calculated only for future projections (WRI, 2020).

The Water Risk Atlas defines water stress as the ratio of total water withdrawals to the available renewable surface and groundwater supplies. The exported water stress data included raw values with higher values indicate more competition among users. Seasonal variability is a measure of the average annual variability of available water supply where higher raw values indicate wider variations of available supply within a given year.

Additional Technical Information for Exposure Analysis

The Water Risk Atlas provides water risk data for sites for 2020, 2030, and 2040 for two climate scenarios, RCP 4.5 and RCP 8.5, and two shared socioeconomic pathways, SSP2 and SSP3. (SSPs act as reference pathways defining the primary socioeconomic drivers of water use. SSP2, representing a “business-as-usual" scenario, was chosen for analysis as it captures a centralized distribution of plausible outcomes for the challenges to mitigation and adaptation (O’Neill et al, 2014)). Since data was not provided for 2025, extrapolation between given time periods was conducted to create a linear annual rate of change in water stress and seasonal variability for each site.

To obtain baseline and projected data for each site, site locations were imported into the Water Risk Atlas, and parameters for baseline and future projections were selected and exported to a tabular spreadsheet. Columns from the exported spreadsheet were filtered to only contain variables providing raw values of water stress and seasonal variability. Raw values for water stress and seasonal variability were used to calculate exposure scores.

Baseline water stress and seasonal variability scores were provided by the Water Risk Atlas. To calculate future exposure, raw values for both water indicators, “change from baseline” raw values from the future projection's dataset, and baseline indicator raw values were multiplied together. These raw values were then utilized in equations provided by WRI to generate scores on the 1-5 scale consistent with the other hazards (Hofste et al, 2019). Equations below were used to score water stress and seasonal variability.

$$score = \max\left(0, min\left(5, \frac{ln(r) - ln(0.1)}{ln(2)} + 1\right)\right)$$

$$score = \max(0, min(5, 3r))$$

Assumptions and Limitations

WRI currently only updates baseline data, not future projections data in the Water Risk Atlas tool. As a result, the datasets are inconsistent as presented in the online tool in that they apply different basin delineation approaches. This inconsistency was addressed using the guidance provided in WRI's technical notes and the methodology above; however, any future updates to this analysis should ensure compatibility between baseline and future projections (WRI, n.d.). While water stress and seasonal variability are analyzed due to availability of future projections for these indicators, future water risk assessments could also include additional indicators to aid in developing a more robust water management strategy.

Wildfire

Additional Technical Information for Wildfire Exposure

The USFS dataset was obtained from the online tool in wildfirerisk.org. It was used for wildfire exposure and provides data variables at a city (community) wide scale. It was downloaded from the "data publication support files" link provided in the catalog. For communities that were not directly available in the dataset, namely site Q and site R, the geographically closest community data was used.

The dataset uses a combination of datasets on vegetation and wildland fuel, and models burn probability and intensity into developed areas and a 30m resolution to evaluate risk to structures. The three variables used from the dataset included Mean Burn Probability of a building in the community, its wildfire hazard potential, and flame length exceedance probability and 4 and 8 feet.

To account for the projected global increase in wildfire frequency, regional values from the U.S. Global Change Research Program and USFS were used for sites in the Southeast and California (both at a 30% increase) (NCA 2018, USFS 2012). For sites where regional data was not available, IPCC's RCP 4.5 global increase of 37.8% by 2040 was used (IPCC 2012).

Hurricane

Additional Technical Information for Hurricane Exposure

The IBTrACS dataset, downloaded as a shapefile, was subset in ArcGIS to include only observed tropical storms with sustained wind speeds over 39 mph which had passed within 75 nmi of each site (National Centers for Environmental Information, 2020). The Near Tool was then used to measure the distance between each observation and the site. This 75 nmi radius was recommended in the HURISK methodology (National Hurricane Center, 1991). Only sites which had previously experienced hurricane-strength winds in the past were evaluated for hurricane risk.

The attribute table from each site was exported to CSV and read into R for further analysis. Observed storm tracks were filtered to only include data for each storm's closest point of approach. The projected annual probability of a single tropical storm was calculated using the following formula recommended by HURISK:

$$P(1) = \frac{e^{-m}m^1}{1!}$$

with *m* being the average number of storms occurring per year based on historical observations. Next, a distribution was developed to model the percentage of storms that fall into each Saffir-Simpson hurricane category again following HURISK methodology and the closest point of approach wind speeds filtered down in R. These were plotted as a histogram to observe trends and visually confirm that the HURISK-recommended Weibull distribution to modeling wind speed distribution was a good fit for observed historic wind speeds. It was determined to be useful for all six sites, and fitdist() was used to generate the location (μ), shape (γ), and scale (α) for each site, which were then used in the following equation:

$$f(x) = \left(\frac{\gamma}{\alpha}\right)\left(\frac{x-\mu}{\alpha}\right)^{(\gamma-1)} \exp\left(-\left(\frac{x-\mu}{\alpha}\right)^{\gamma}\right)$$

This distribution was integrated, using the integrate() function in R, to determine the percent of storms that would fall into Category 1-5 strength wind speeds.

Climate change is projected to increase tropical cyclone Intensity and the associated precipitation. There is not as strong of agreement within the scientific community on impacts of overall storm frequency, but it will likely stay the same or decrease. A 2°C global mean temperature increase is projected to lead to a 3% median increase in tropical cyclone intensity in the North Atlantic (Knutson et al., 2020). To account for this increase, the IBTrACS observed wind speeds were increased assuming a linear increase under both RCP 4.5 (2°C threshold reached in 2100) and RCP 8.5 (2°C threshold reached in 2055), and a Weibull distribution was created for 2025, 2030, and 2040 under both RCP 4.5 and RCP 8.5 for each site.

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