



Methods for assessing climate change exposure for national park planning



ON THE COVER

View of Exit Glacier from the Harding Icefield Trail in Kenai Fjords National Park, Alaska (top left; credit: NPS), Fort Jefferson in Dry Tortugas National Park (middle left; credit: NPS), Sequoia & Kings Canyon National Parks in California (bottom left; credit: No Barriers Youth, NPS), and a park scientist at Big Bend National Park in Texas studying the impacts of climate change on water availability (right; credit: NPS).

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Abstract

Climate change is already threatening resources, assets, operations, and visitors in national parks. As park managers cope with existing challenges and adapt to a rapidly changing climate, demand is growing for products that characterize how climate is projected to change in the future ('climate exposure'). To meet this demand, the National Park Service Climate Change Response Program has developed park-specific summaries of climate exposure for all parks in the conterminous U.S. to help inform and support a broad range of climate assessments and adaptation efforts and activities. This report describes methods to assess historical climate trends, develop and select relevant, divergent climate futures, and calculate metrics used in the climate future summaries.

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Acronyms and Abbreviations

CCRP: Climate Change Response Program (NPS)

CCVA: Climate change vulnerability assessment

CF: Climate future

CMIP: Coupled Model Intercomparison Project phase (IPCC)

CONUS: Conterminous United States

GCM: Global Climate (or circulation) Model

GHG: Greenhouse gas

IPCC: Intergovernmental Panel on Climate Change

MACA: Multivariate Adaptive Constructed Analogs downscaled climate project data (version 2, using GridMET for downscaling; Abatzoglou 2013)

nClimGrid: Monthly, downscaled historical climate data (NOAA)

NOAA: National Oceanic and Atmospheric Administration

NPS: National Park Service

RCP: Representative Concentration Pathway

USGS: United States Geological Survey

Introduction

The climate crisis requires that climate change threats be routinely addressed in all National Park Service (NPS; list of acronyms and abbreviations) planning and operations (NPS 2021a). Although precisely how the climate will continue to change remains uncertain, the NPS Climate Change Response Program (CCRP) and many others (e.g., Brekke et al. 2009, Lempert et al. 2004, Hoffman et al. 2015, Miller et al. 2022) have developed tools to help resource managers characterize and work with this uncertainty when making management decisions (NPS 2013, 2021a). CCRP recently published *Planning for a Changing Climate* (NPS 2021a), a comprehensive guide to help planners and managers develop forward-looking goals and evaluate strategies and actions in light of a range of plausible future conditions associated with a changing climate. This guide, along with the readily apparent climate change impacts across the National Park System, has fostered escalating demand for products that characterize how climate is projected to change in each park.

To help parks adapt to a rapidly changing climate, CCRP has produced climate futures—descriptions of the physical attributes of plausible future climates that could occur at a specific place and time (Lawrence et al. 2021)—and summaries on climate exposure¹ for all parks in the conterminous United States. Climate futures should be interpreted as representations of future uncertainty, rather than predictive forecasts. This technical report describes the methods used to assess historical climate trends for CONUS parks, develop and select relevant climate futures, and calculate climate metrics used in climate future summaries. It also includes appendices that address frequently asked questions and provide details about data sets and calculations, definitions of key terms, and information on selection of global climate models (GCMs).

Methods and data we used for creating climate futures were restricted to those easily applied to all CONUS park units, so information provided is not suitable or sufficient for all climate change vulnerability assessments (CCVAs). The aim of the climate future summaries is to provide information that can serve as a coarse filter to identifying vulnerabilities or “red flag checks” for areas that may require further evaluation. Information provided by the climate future summaries is widely used by the NPS and partners in many routine planning processes. For example, an assessment of historical and future climate exposure is foundational for CCVAs, scenario-based climate change adaptation, and basic evaluations of proposed infrastructure projects and other climate-sensitive planning. The climate future summaries described here are, in general, most appropriately used as a coarse filter or initial climate assessment that can identify concerns that warrant a more detailed assessment. These summaries use a standardized approach that is not tailored to site-specific issues or climate sensitivities. A more detailed and site-specific climate assessment is required for evaluations of, e.g., requirements of major infrastructure or resource projects that may be highly consequential.

1 Climate exposure is the measure of character, magnitude, and rate of changes that a target may experience, including changes in climate drivers (e.g., temperature, precipitation, solar radiation) and changes in related factors (e.g., sea-level, water temperatures, drought intensity) (Gross et al. 2014, NPS 2021b).

Historical climate trends

To help users understand rates of anthropogenic climate change that parks have already experienced, CCRP's summaries provide parks with analyses of long-term trends from 1885 to the present using the NOAA nClimGrid 5x5 km monthly gridded climate data (Vose et al. 2014).¹ We use gridded climate data (instead of station data) because they provide a complete record for every park (no missing values), and are developed from an extensive networks of climate monitoring stations using sophisticated algorithms (see [Appendix 4](#)). The algorithms employ well-tested quality checks, corrections for complex geographies and removal of artificial inhomogeneities in trends in station data, making their products suitable for consistent application across NPS units in the conterminous U.S., where climate stations are relatively abundant.

We downloaded historical monthly climate data and extracted the timeseries from the grid cell overlaying the centroid of the park unit. We calculated trend estimates of annual average, maximum, and minimum temperature, and precipitation using a linear robust regression² for two time periods (1895-present; 1971-present) where the slope is expressed as the rate of change per 100 years. We selected 1971 as the start for the recent period because airborne pollutants caused a “global cooling” (due to industrial pollution) from about 1940-1975, masking the warming effects of anthropogenic climate change (Wild et al. 2007). The introduction of pollution-control measures reduced aerosol emissions and the cumulative effects of increasing GHGs started to dominate in the 1970s, resulting in a continuous and accelerated warming trend, at which point warming trends that reflect the anthropogenic rate of change resumed. The results can be used to understand long-term trends, recognizing the centroid-based approach may result in bias for parks of different sizes and elevation gradients and that spatially explicit characterizations or climate futures for multiple sites in a park may be needed to better evaluate results for these circumstances.

¹ Downloaded from: <https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc:C00332>

² The R function `lmrob()` was used for the linear robust regression. This identifies and downweights outlier observations.

Climate future creation

To help park planners and managers address a wide range of plausible future climate conditions, CCRP produced climate futures that capture the breadth of projections of future temperature and precipitation. Climate futures are expressed in terms of physical metrics and indices such as temperature, rainfall, snow, humidity, soil moisture, and radiation (Lawrence et al. 2021). These are the basis for more comprehensive scenarios that describe the resource consequences of each climate future (e.g., Runyon et al. 2021). GCMs produced by institutions around the world provide differing simulations of future climate. Key factors that affect climate projections include variations among individual GCMs in the representation of atmospheric processes and variations among greenhouse gas emission scenarios (or Representative Concentration Pathways, RCPs¹). Climate scientists use complex models (GCMs) to project future climate, but our understanding of all the factors that determine Earth's climate is incomplete, and each model differs in its representation of the various physical and biological forces that influence climate patterns. Consequently, each GCM produces a slightly different (yet plausible, given current science) estimate of future climate, and the range of estimates constitutes a key source of uncertainty in the climate system (known as “model uncertainty”). This is particularly evident over timescales that are frequently important to NPS decisions (i.e., the next 30-50 years; [Figure 1](#); Hawkins and Sutton 2009, Wuebbles et al. 2017, Terando et al. 2020). We combined climate models (GCMs) with different GHG emissions (RCPs) to produce a range of projected climate futures that captured two key sources of uncertainty: model and socioeconomic uncertainty ([Figure 1](#)). Natural variability accounts for most of the climate projection uncertainty in the near-term, particularly in precipitation, yet it is irreducible in both the short and long term (Rangwala et al. 2021). A set of divergent climate futures drawn from climate projections can therefore describe a broad range of conditions and support information needs of decision makers, including understanding a spectrum of potential resource responses to climate change, developing strategies robust to that range, and preparing for highly consequential surprises (Lawrence et al. 2021).

Climate data

CCRP developed plausible and divergent climate futures from climate projections produced for the World Climate Research Programme's Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012), which was used for the IPCC Fifth Assessment Report (IPCC 2013). For park-level planning, broad spatial scale results from GCMs need to be downscaled, or converted from a large grid (say, 50 x 50 km [~ 30 x 30 miles]) to a finer resolution that better represents conditions found at a specific location. CCRP used data downscaled by the MACAv2-METDATA (Multivariate Adaptive Constructed Analogs) method (Abatzoglou and Brown 2012), a statistical downscaling² method with a unique multivariate weighting scheme that ensures climate metrics are physically compatible (Kim et al. 2022). This results in a more physically realistic product at regional scales. This method has been shown to be preferable to direct daily interpolated bias correction in regions of complex terrain due to its use of a historical library of observations and its multivariate approach (Abatzoglou and Brown 2012). The product is available at a daily timestep and downscaled to 1/24 degree (~4 km).

We downloaded surface maximum/minimum temperature, surface maximum/minimum relative humidity, and precipitation data for a grid cell that encompassed the park's centroid ([Figure 2](#)) for moderate (RCP 4.5) and high (RCP 8.5) greenhouse gas emissions pathways. Experiences from previous engagements with parks (e.g., Schuurman et al. 2019, Runyon et al. 2021, Benjamin et al. 2021) have shown that a single site can be sufficient to evaluate changing trends across a whole park, but additional analysis may be warranted for large parks or those with complex topography. Only when we need to identify and/or model specific resource responses, each with unique climate sensitivities, is unusually fine-scale climate information warranted (see Lawrence et al. 2021 for

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- 1 RCPs were used rather than SSPs because CMIP5 was used for the analysis. When high-resolution, downscaled CMIP6 becomes available, the analysis will be updated with newer climate projections.
 - 2 Downscaling is a method that derives local- to regional-scale (<1 to ~50 km) information from larger-scale models or data analysis. Statistical downscaling relies on a fixed statistical relationship between observed (historical) climate metrics and projections from a GCM (NPS 2021b [Glossary]).

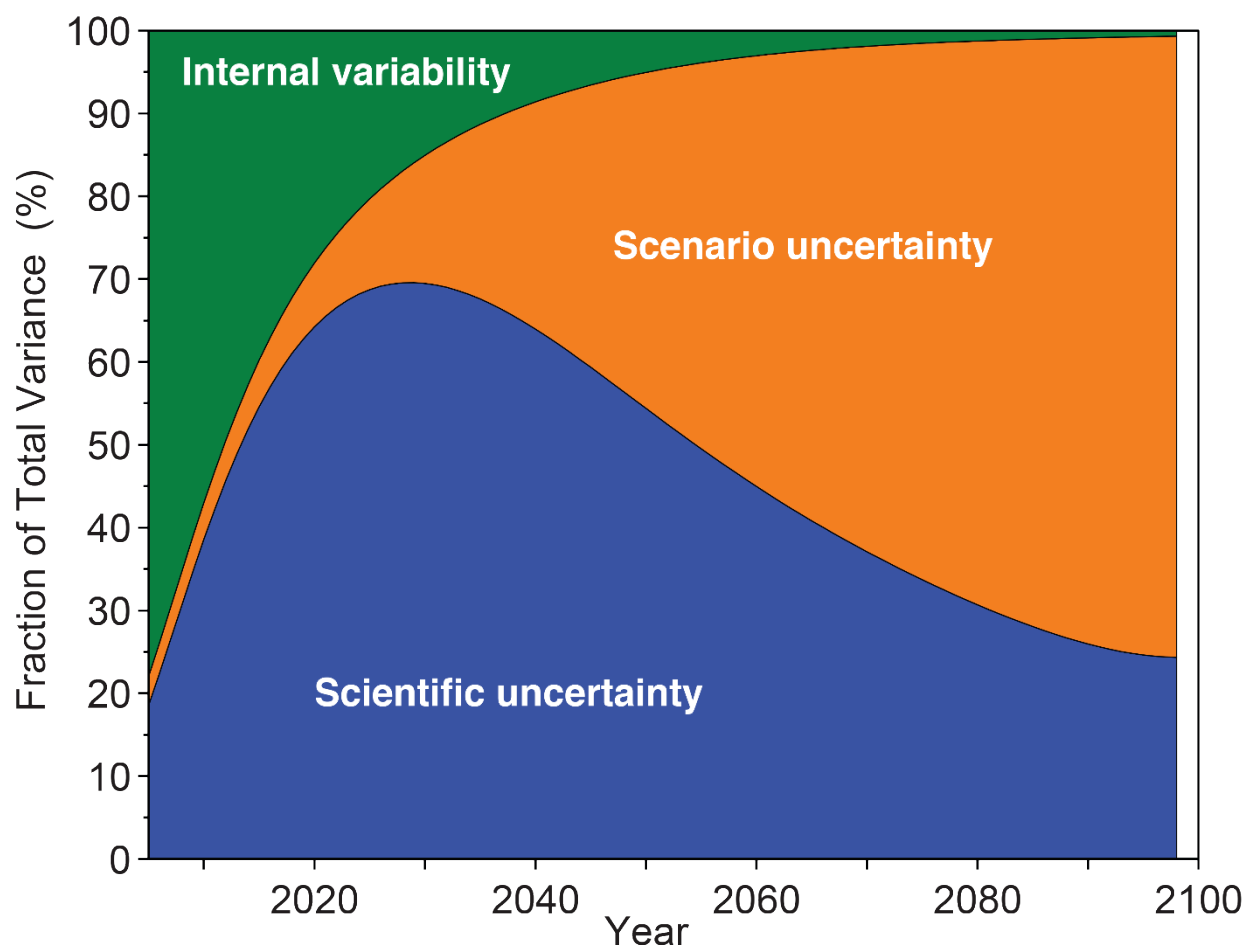


Figure 1. The relative importance of three components of uncertainty in decadal average temperature predictions across the 21st century, expressed in terms of fraction of total uncertainty, for the contiguous United States. Green regions represent uncertainty caused by natural variability of the climate system, blue represents model uncertainty, and orange regions represent human or socioeconomic uncertainty (from Figure 4.5 of Wuebbles et al. [2017], which was based on Hawkins and Sutton [2009]). The relative importance of these uncertainties varies with the climate metric and spatial scale of analysis (Hawkins and Sutton 2009, Rangwala et al. 2021).

considerations of spatial extent and resolution of climate futures). The MACA archive contains output from 20 GCMs for the contiguous United States for both RCPs. We considered all 40 (RCP x GCM) projections plausible representations of the future (Lawrence et al. 2021) that, collectively, represent a broad range of future climates. This use of multiple RCPs and GCMs is in accordance with U.S. Geological Survey (USGS) best practices for using climate models to inform decision-making (Terando et al. 2020) and Department of Interior policy (USDOI 2023).

Climate future selection

CCRP developed climate futures from 40 projections (20 GCMs, 2 RCPs) for a selected time period relevant to a particular planning process. For the products described here (Runyon et al. 2023), we used observations from the GridMET observation dataset (Abatzoglou 2013). Because GridMET was used to train the MACAv2-METDATA downscaling process, we could directly compare historical data to projections without having to perform additional bias corrections. For these products, we used 1979-2012, the reference period used to train the



Figure 2. White Sands National Park relative to cells of gridded climate data. The orange cell is the grid cell selected for climate futures development.

MACA data, to characterize the historical period and the average centered around 2035-2065 (2050) to define a mid-century future planning period. We calculated average annual temperature and precipitation change of each of the 40 projections relative to the historical period, as illustrated in [Figure 3](#).

CCRP used two methods for selecting climate futures: a quadrant-average approach (described below) and an individual-projection approach (Lawrence et al. 2021). The quadrant-average approach used the GCMs within a quadrant to produce the climate futures and was derived from methods pioneered by the Volpe National Transportation Systems Center (Rasmussen et al. 2015). Projections were grouped in the more extreme ends of the temperature and precipitation axes using quantile limits. The mean of each axis designated four quadrants that represent “Warm Wet”, “Hot Wet”, “Warm Dry”, and “Hot Dry” projections. The central tendency, defined by the 25th and 75th percentiles of each metric, was removed. Ensembles of the remaining projections that fell within the four quadrants were then averaged to create four climate futures (two are shown by asterisks in [Figure 3](#)). The individual-projection approach selected a small set of projections that characterized the broadest range of uncertainty over this space. This approach used principal component analysis on the change values (from the 1979-2012 baseline) of temperature and precipitation to select the most divergent projections from principal components 1 and 2 based on the loadings on the first two principal components (circled projections in [Figure 3](#)).

Lawrence et al. (2021) discussed tradeoffs between the two approaches for defining climate futures and where each is most appropriate. The climate future summaries used the quadrant approach for most climate metrics, but the individual-projection approach was used for metrics of extreme events that required additional modeling (e.g., drought return intervals, water balance, extreme precipitation, etc.). Metrics of extreme values are typically associated with highly consequential hazards to park resources and values. The use of single, end-member GCMs to calculate these climate metrics facilitated a more complete characterization of the potential climate risks to parks.

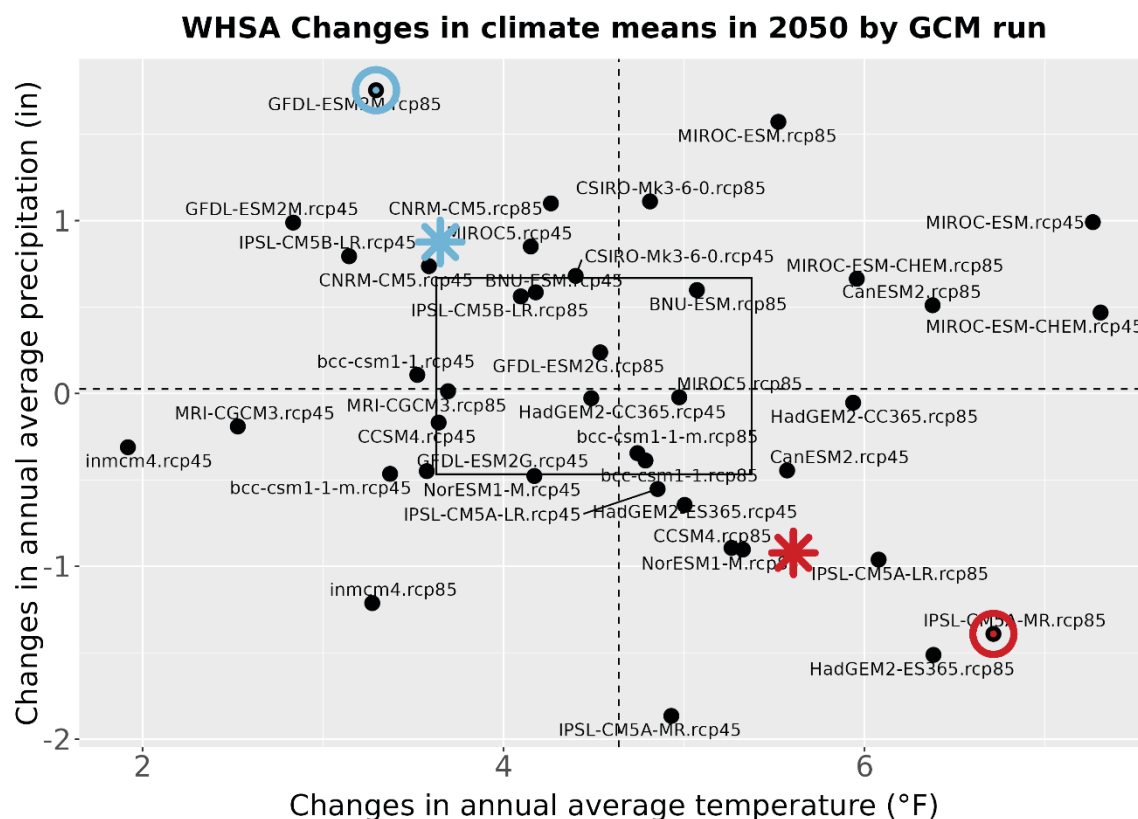


Figure 3. Projections of change in average annual precipitation and temperature (in 2050; 2035–2065), relative to a historical baseline (1979–2012), vary by GCM and RCP, as illustrated by this example from White Sands National Park. For each axis (temperature, precipitation), the mean of all projections is denoted by a dashed line, and the sides of the central box denote the 25th and 75th percentiles, giving a sense of ‘central tendency’. The “warm wet” and “hot dry” climate futures were selected here because they represent a pair of wetter and drier scenarios, with each having distinct implications for resources that can be explored. For each climate future, the average of all projections in those quadrants is represented by an asterisk, and the most extreme projection in the quadrant (i.e., that with the greatest change in precipitation or temperature relative to the average of all projections) is indicated by a circle.

While all projections represent plausible climate futures, some have better skill in representing historical conditions than others. To ensure that individual GCMs selected to represent a climate future have appropriate skill, we used the approach adopted for the U.S. Forest Service 2020 Resource Planning Act (Joyce and Coulson 2020). We used rankings of GCM skill based on 19 performance metrics for three climate regions and applied them to parks within the corresponding regions (Pacific West [PWR], Southwest [SWR], and Southeast [SER]; Rupp et al. 2013, Rupp 2016a, 2016b) ([Appendix 3](#)). We applied an average of model skill across the regions assessed to parks in other regions. Only models that ranked in the top 90% of GCM skill were considered for individual projections.

CCRP typically uses two to four divergent climate futures that bracket the range of climate variation relevant to the resource-management decision of interest (Lawrence et al. 2021). For most resources, we focus on climate futures that represent a “best/worst case” or “most/least change” contrast—typically, climate futures that fall on the diagonally opposite quadrants shown in [Figure 3](#). “Warm wet” and “hot dry” are one set of contrasting climate futures, where warm wet could lead to more precipitation and flood potential, and a hot dry climate future could indicate more drought or conditions conducive to fires. Depending on the resource of interest, these scenarios may have differing impacts. In other situations, the “warm dry” and “hot wet” are the more consequential climate futures (e.g., in the northeastern U.S.).

Climate future impact metrics

CCRP developed climate metrics relevant to resource sensitivities to help managers identify potential resource responses to the divergent climate futures. [Table 1](#) illustrates commonly used metrics and corresponding park resource sensitivities. These metrics are a subset of a broader suite of about 40 metrics including average trends, threshold metrics, water balance metrics, drought characteristics, and extreme precipitation return intervals. A full list of these metrics can be found in [Appendix 1](#), and methods for the calculation of each metric are provided in [Appendix 2](#).

Although multiple approaches exist to calculate or model many of these climate metrics and some approaches may be more appropriate for a given location, the methods we selected for the climate future summaries represent a standardized set that can be used across CONUS. We encourage additional analysis where warranted.

Table 1. Commonly used climate metrics and associated resource sensitivities.

Climate metric	Example sensitivities
Seasonal temperature (maximum, minimum, mean)	Growing seasons or fire-prone seasons; timing of snow melt
Seasonal precipitation	Runoff, spring biomass accumulation, or drought
Extreme heat (days per year over the historical 99th percentile)	Plant, animal, and human stress; stress on cultural resources
Heat index	Staff and visitor safety due to extreme heat
Precipitation return interval (of 24-yr precipitation)	Frequency and volume of large precipitation events, which can cause flooding and erosion
Drought (duration, frequency, severity)	Water security in parks and induce resource stress in plants, animals, and infrastructure.
Climatic water deficit (ecological water availability)	Fire risk, plant growth and condition, and water for runoff and/or groundwater recharge

Conclusion

Here we described the NPS CCRP methods for calculating climate metrics and creating divergent, plausible climate futures used in park-specific climate future summaries. We refined the climate futures methods over the past decade in response to advances in climate and adaptation science and our experiences working with park staff. These metrics and methods have proven valuable in supporting a broad range of park planning and technical evaluations¹, and in helping parks identify vulnerabilities and uncertainties so they can better adapt to climate changes. These methods have been evolving but are now sufficiently stable, efficient, and robust for routine implementation by CCRP and other staff. The CCRP process retains sufficient flexibility to adjust graphics and add evaluations (e.g., drought metrics, heat stress, water balance metrics) as new data and analyses emerge.

The climate future summaries represented here use data and methods that can be applied to and are informative to a broad range of parks. This results in some limitations in appropriate use. Our use of fixed time periods focuses the information on a mid-century future, which is not suitable for all applications, particularly large capital investments or high consequence/expense resource actions. As discussed above, use of analyses from a single grid cell can be inappropriate for parks with a diversity of climates, such as parks with a broad range of elevations (e.g. Figure 9 in Tercek et al. 2021). Changes in climate variability, a principal source of uncertainty in the near-term, are also untreated by use of statistically downscaled climate data, which presumes persistence of historical variability and could therefore lead to near-term climate surprises. The climate futures should be used as “scenarios” of the future, rather than predictions, because projections are considered equally plausible in our construction of climate futures. Although this assumption may not always be warranted, we attempt to remedy it by removing models with poor skill. Advances in climate change science may allow us to further refine the models we consider in climate future construction.

Although climate future summaries are not intended to delve deeply into specific resource responses, we hope they offer a broad view of how climate change could alter aspects of climate relevant to park resources. We aim to “lift all boats” as the threat of climate change rises, so all parks can access this baseline data and incorporate it into their planning processes. If warranted, parks can use this information in further investigations to build sustainable, flexible plans around an uncertain future.

Code and data availability

Code used to create climate future products is available at <https://zenodo.org/records/10253237>. Please contact us for access to data.

¹ See <https://www.nps.gov/subjects/climatechange/scenarioplanning.htm> for examples of development and application of climate futures to aid in park planning.

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Appendix 1. List of climate metrics calculated

The table ([Table 2](#)) lists the standard set of climate metrics used by CCRP to identify potential resource climate impacts. [Appendix 2](#) details calculation methods for each metric. All metrics use the quadrant approach (Lawrence et al. 2021) to characterize climate futures unless denoted with an asterisk (*). Those with an * used the individual model approach.

Table 2. Climate metrics used by CCRP to identify climate impacts.

Parameter	Metric
Averages (annual, monthly, seasonal)	• Average temperature • Average max temperature • Average min temperature • Precipitation • Relative humidity • VPD
Thresholds (days/year over/under)	• Tmax over 95 F • Tmax over 95th • Tmax over 99th • Consec days tmax over 99th • Tmin under 32 F • Tmin under 5th • Consec days tmin under 32 F • Precipitation days • Consec days with precip • Precip over 95th • Precip over 99th • Precip over 1 in • Precip over 2 in • Freeze-thaw cycles • Wet-frost cycles • Growing-degree days • Growing-season length • First green-up day • End growing season • Late-spring frost events • Over “extreme caution” heat index • Over “dangerous” heat index
Water balance (annual, monthly, seasonal)	• Climatic water deficit* • AET* • PET* • Soil moisture* • Runoff* • Snow water equivalent*
Drought	• Timeseries SPEI* • Drought duration* • Drought frequency* • Drought severity* • Drought intensity*
Extreme Precipitation	• Return intervals* • Avg 20-, 50-, 100-yr events*

*Metrics calculated from individual projection climate futures.

Appendix 2. Climate metric calculations

This appendix briefly describes the methods for calculating the future climate metrics identified in [Appendix 1](#). Where needed, citations are provided for detailed descriptions of the metrics, and where specific parameters or other inputs are used, they are described in a paragraph below the metric. For comparison between the historical and future periods, the historical (GridMET 1979-2012) climate is typically included along with the 30-year average of each climate future (MACA, 2035-2065; centered on 2050). Unless noted, all measures are reported in U.S. Customary units (Fahrenheit, inches, etc.).

Averages

Average annual, monthly, seasonal (average maximum temperature, minimum temperature, relative humidity, VPD)

For the period of interest (year, season, month), the mean of the daily values.

Average annual, monthly, seasonal precipitation

Average sum of daily precipitation for the period of analysis (month, year, etc.)

Thresholds

All thresholds are calculated as the number of events (typically days) that exceed an upper or lower threshold value. Examples are days per year over 95 °F (35 °C). Thresholds most relevant to the resources and management differ across park settings and climate zones.

Days/year over 95 °F (35 °C)

Average number of days per year when the maximum daily temperature exceeds 95 °F (35 °C)

Days/year over 95th and 99th percentile historical temperature

Average number of days per year when the maximum daily temperature exceeds the historical 95th and 99th percentile

Consecutive days/year over 99th percentile historical temperature

Average length of consecutive days per year when the maximum daily temperature exceeds the historical 99th percentile

Days/year under 32 °F (0 °C)

Average number of days per year when the minimum daily temperature is below 32 °F (0 °C)

Days/year under 5th percentile historical temperature

Average number of days per year when the minimum daily temperature is below the historical 5th percentile

Consecutive days/year under 5th percentile historical temperature

Average length of consecutive days per year when the minimum daily temperature is below the historical 5th percentile

Days/year with precipitation

Average number of days per year when daily precipitation exceeds 0.05 inches (1.27 mm).

Consecutive days/year with precipitation

Average length of consecutive days per year when daily precipitation exceeds 0.05 inches (1.27 mm).

Days/year over 95/99th percentile historical precipitation

Average number of days per year when precipitation amounts exceed the historical 95/99th percentile. The 95/99th percentile is calculated from days that receive greater than 0.05 inches (1.27 mm) precipitation.

Days/year over 1 and 2 inch precipitation

Average number of days per year when precipitation amounts exceed 1 and 2 inches (25.4 and 50.8 mm).

Freeze-thaw cycles

Average number of freeze-thaw cycles per year, measured as days where the maximum temperature >34 °F (1 °C) and the minimum temperature <28 °F (-2 °C). (Fraser 1959).

Wet-frost cycles

Average number wet-frost cycles per year, measured as days when precipitation exceeds 0.079 inches (2 mm) and average temperature exceeds 32 °F (0 °C) followed immediately by a day when average temperature is below 30.2 °F (-1 °C) (Sabbioni et al. 2010).

Growing season length

The following metrics are calculated as they are defined by CLIMDEX (<https://www.climdex.org/learn/indices/>)

Growing-degree days

Sum of the difference of the average daily temperature and 41 °F (5 °C) for those days when the average daily temperature exceeds 41 °F (5 °C).

Growing season length

Average growing season length, measured in days: the number of days between the start of the first spell of warm days in the first half of the year, and the start of the first spell of cold days in the second half of the year. A spell of warm days is defined as six or more days with mean temperature above 41 °F (5 °C); a spell of cold days is defined as six or more days with a mean temperature below 41 °F (5 °C).

First green-up day

Average green-up date, measured as the start of the first spell of warm days in the first half of the year. A spell of warm days is defined as six or more days with mean temperature above 41 °F (5 °C).

End growing season

Average end of growing season, measured as the first spell of cold days in the second half of the year. A spell of cold days is defined as six or more days with average temperature below 41 °F (5 °C).

Late spring frost events

Late spring frost events, calculated as days with minimum temperatures equal to or below 32 °F (0 °C) after the green-up date (see definition above), but before the summer solstice.

Dangerous heat index days

Average number of days per year when the heat index exceeds the ‘dangerous’ threshold (103°F; OSHA 2019)

The base heat index equation is (NWS 2014):

where

T = temperature in degrees F

$$\begin{aligned} \text{Heat Index} = & -42.379 + (2.04901523 * T) + (10.1433127 * Rh) - (0.22475541 * T * Rh) \\ & - (0.00683783 * T^2) - (0.05481717 * Rh^2) + (0.00122874 * T^2 * Rh) \\ & + (0.00085282 * T * Rh^2) - (0.00000199 * T^2 * Rh^2) \end{aligned}$$

Rh = relative humidity in percent

If $Rh < 13\%$ and $80^\circ\text{F} < T < 112^\circ\text{F}$, adjustment 1 should be subtracted from heat index

If $Rh > 85\%$ and $80^\circ\text{F} < T < 87^\circ\text{F}$, adjustment 2 should be added to heat index

The heat index is assumed to be a measure of instantaneous heat stress from current conditions. However, because available downscaled climate data are only available at daily temporal resolution, we calculate heat index using daily maximum temperature and minimum relative humidity because temperature and relative humidity have an inverse relationship (i.e., the warmest part of the day has the lowest relative humidity; Bonan 2015).

Extreme caution heat index days

Average number of days per year when the heat index exceeds the ‘dangerous’ threshold (90°F ; OSHA 2019)

$$\text{Adjustment 1} = \frac{13 - Rh}{4} * \sqrt{17 - \left| \frac{T - 95}{17} \right|}$$

$$\text{Adjustment 2} = \frac{Rh - 85}{10} * \frac{87 - T}{5}$$

Water balance modeling

Metrics of temperature and precipitation alone fail to account for interactive aspects of climate, soils, and topography that affect water availability for plants and ecosystem processes. Water balance modeling accounts for the interaction of these factors to estimate ecological water availability through time. We used a simple water balance model (Thoma et al., 2020, Tercek et al., 2021) with site-specific parameters (location, elevation, slope, aspect, soils) and meteorological variables from climate futures to evaluate water-related implications of climate changes.

The water balance model partitions precipitation into rain or snow. An adjustment factor, based on relative humidity, was used to account for observed differences in snow dynamics in arid and moist climates (Jennings et al., 2018). Rain and snow melt contribute to soil moisture (water stored in the top meter of soil). Precipitation that exceeds soil storage capacity becomes runoff. Potential evapotranspiration (PET), calculated via the Oudin method (Oudin et al., 2005), is the amount of water that could be evaporated and transpired from a short grass with available energy and unlimited water. This relatively simple method relies on data available for all U.S. parks, and it has been evaluated and used for many park studies (Thoma et al. 2020, Tercek et al. 2023). Actual evapotranspiration (AET), the loss of water from soil via evaporation and transpiration, is limited by soil moisture. Climatic water deficit is the amount of additional water vegetation would use if available, calculated as the difference between PET and AET (Stephenson 1998, Thoma et al. 2020). For site-specific locations with high winds, or where humidity is consistently high, a more complex model that accounts for these variables may provide a somewhat different result.

Key water balance variables are:

Potential evapotranspiration (PET)

Water that could be evaporated and transpired from short grass prairie with unlimited water. Calculated on a daily timestep using the Oudin et al. (2005) equation.

Actual evapotranspiration (AET)

Loss of water from evaporation and transpiration, limited by soil moisture (i.e., by actual water availability).

Climatic water deficit (CWD)

The amount of additional water vegetation would use if available, or an estimation of unmet water need. CWD is calculated as the daily difference between PET and AET.

Soil moisture

The amount of water left in the top meter of soil after precipitation inputs and evaporative outputs, with soil water holding capacity values from the U.S. Natural Resources Conservation Service (Soil Survey Staff, Natural Resources Conservation Service, USDA 2019, Tercek et al. 2021)

Runoff

Runoff is calculated as the surplus water from the soil layer, i.e., when daily inputs–outputs exceeded water holding capacity.

Snow water equivalent (SWE)

Amount of snow, as a water equivalent (versus actual snow depth) is estimated using equations from Tercek and Rodman (2016) with temperature coefficients for those equations provided by Jennings et al. (2018).

Extreme events

Characterizing Drought

Standardized Precipitation-Evapotranspiration Index

Standardized Precipitation–Evapotranspiration Index (SPEI) was used to capture characteristics of drought periods. SPEI is a drought index, based on precipitation and potential evapotranspiration (PET), that is used to identify periods that are wetter and drier than average in a given location (Vicente-Serrano and National Center for Atmospheric Research Staff 2015). SPEI is useful when accounting for climate change because it includes temperature effects on evapotranspiration. Monthly SPEI is summarized on a rolling 6-month period (SPEI-6) to represent accumulated drought conditions over an ecologically relevant timescale.

Drought characteristics

CCRP used the R package “SPEI” (Vicente-Serrano et al. 2010, Beguería and Vicente-Serrano 2017) to calculate the indicator and characterized four aspects of a drought event: duration, severity, intensity, and return interval (see [Figure 4](#)). An SPEI value below -0.5 indicates a “drought”, signifying drier than average conditions (Shiau and Shen 2001). A drought event begins when SPEI falls below the threshold and lasts until SPEI returns above the threshold ([Figure 4](#)).

- **Drought duration:** the number of consecutive years a drought lasts;
- **Drought-free interval:** the length of time (in years) between the end of one drought and the start of the next;
- **Drought intensity:** the minimum SPEI value during a drought event (e.g., maximum drought level);
- **Drought severity:** the cumulative SPEI value for the duration of the drought event.

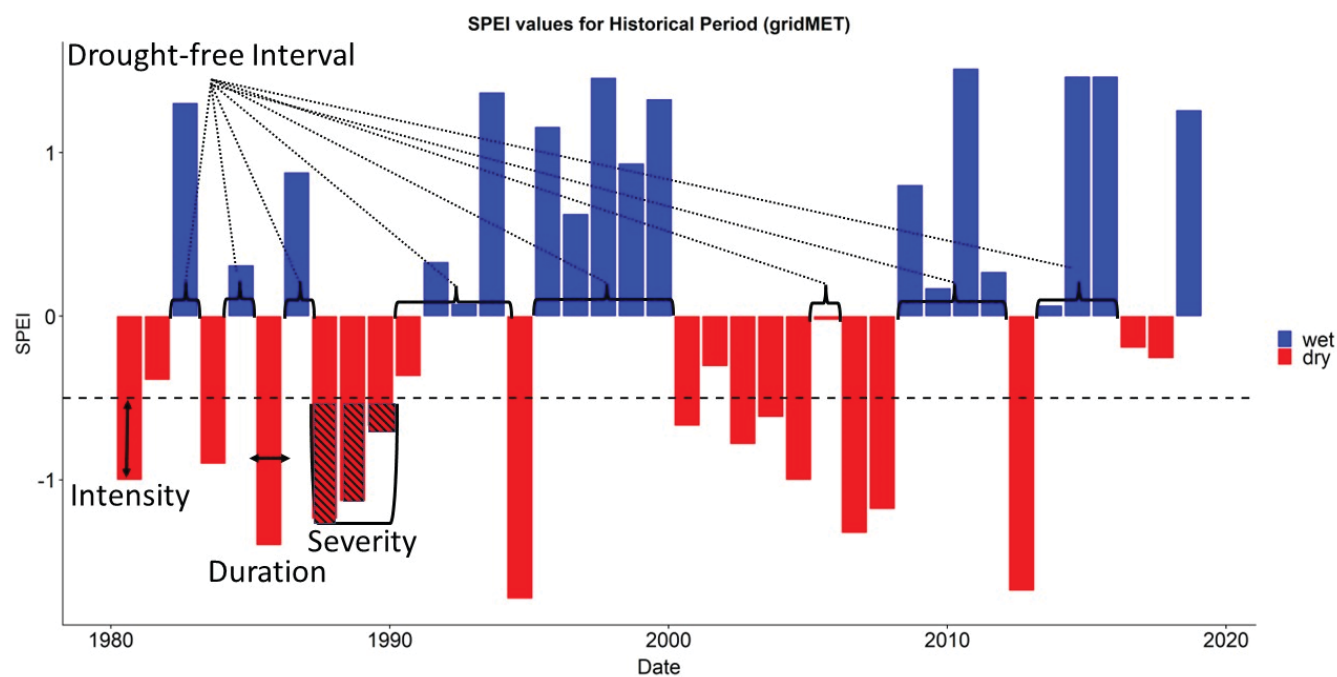


Figure 4. Four drought characteristics were calculated based on discrete drought events. Drought events were defined as years when SPEI-6 fell below a threshold of -0.5. For each period (historical or future), drought events were defined, then drought-free interval, intensity, duration, and severity were averaged for each climate future. These characteristics are illustrated using observed, historical climate data at Wind Cave National Park (gridMET; Abatzoglou 2013).

Extreme Precipitation

24-hour precipitation recurrence intervals

Multiple approaches can be used to estimate potential changes in extreme conditions. Two approaches commonly used are threshold exceedances (frequency of extreme events, characterized by metrics described above) and block maxima (magnitude of event; Katz 2010, Cooley et al. 2019). Tabari (2021) uses the block maxima approach from gridded climate data for both historical and future periods, stating that “extreme value theory shows that block maxima extremes can be approximated most accurately using the generalized extreme value (GEV) distribution.”

The goal of extreme value statistics is often extrapolation (e.g., estimating the magnitude of a 100-year event when only 50 years of data are present). Because extreme events are rare, estimation methods can result in large uncertainties associated with estimated quantities (Cooley et al. 2019). To mitigate these issues, we modeled return periods out to 100 years by fitting the full period of record for the historical period (1979-2012) and future period (2020-2099) to the GEV distribution so that future records required less extrapolation.

The return period is the average time between events and is often used for risk analysis. We calculated return levels following a method similar to those described by Van Dusen et al. (2020).

1. Extract the annual maximum daily precipitation values (block maxima) for the historical period and each climate future and rank the events by magnitude;
2. Estimate the best GEV distribution for each time period by fitting the data to GEV using the R package *extRemes* (Gilleland and Katz 2016). The shape parameters, location (μ), scale (σ) and shape (ε) are estimated using maximum likelihood and shift as a function of precipitation.

where

z = precipitation

σ = shape

μ = location

ε = scale

3. Calculate the return period of a quantile z using:

Where

T = return period in years

From this we have estimates of 1- to 100-year precipitation events and can extract changes in magnitude of a given return as well as how frequently (the probability) that precipitation of a particular magnitude will occur in a given year. One criticism of using block maxima approaches for estimating future climate change is that it cannot account for multiple extreme events that occur close to one another (e.g., first and second highest daily

$$G(z) = \exp \left\{ - \left[1 + \varepsilon \left(\frac{z - \mu}{\sigma} \right) \right]^{\frac{-1}{\varepsilon}} \right\}$$

$$T = \frac{1}{1 - G(z)}$$

precipitation events occurring in the same year). Peaks-over-threshold methods are an alternative approach, accounting for all events over a given threshold, which can be applied when a given threshold is known (Tabari 2021).

Appendix 3. Regional global climate model skill ranking

GCMs have unique quantitative representation of processes that drive climate, leading to differences in accuracy in specific locations or scales. While all CMIP5 GCMs are useful representations of future climate, one method to increase plausibility is to assess the ‘skill’ of GCMs (i.e., model quality and accuracy) by comparing their ability to simulate historical climate to observed climate data. We used the method identified by the U.S. Forest Service for their 2020 Resource Planning Act Assessment (Joyce & Coulson 2020) to rank model skill by region and for all of CONUS.

Historical model rankings developed by Rupp et al. (2013) and Rupp (2016a, b) were used to identify models that poorly captured observed climate using a wide variety of temperature- and precipitation-based metrics¹. These studies applied a consistent methodology across the Pacific Northwest (PWR), Southwest (SWR), and Southeast (SER) regions using MACA downscaled climate data and ranked the models according to their skill ([Table 3](#)). For our analysis, the bottom ten percent were dropped to remove the lowest performing models from consideration of climate futures. Following Joyce et al. 2020, we applied rankings to parks within the corresponding regions and applied an average of model skill across the regions assessed to parks elsewhere in CONUS. Because the regions are not the same size and are only a subset of the country, the average estimate of mean skill will be biased to those areas. This process still does not necessarily ensure reliable future prediction, however, so caution should still be taken when using the climate futures (Snover et al. 2013). Climate futures should be interpreted as representations of future uncertainty, rather than predictive forecasts.

¹ Measures of skill were based on the following metrics for temperature and precipitation: climatological mean of annual value; mean seasonal amplitude; spatial standard deviation of the climatological mean by season; spatial correlation of the observed to modeled climatological mean fields by season; linear time trend of annual values; time series variance for temperature and coefficient of variation for precipitation; persistence measured using the Hurst exponent; strength of ENSO teleconnection in winter; Mean diurnal temperature range by season (Rupp et al. 2013).

Table 3. Ranking of global climate model skill by region (Rupp et al. 2013, Rupp 2016a, 2016b). Analysis performed for the Pacific Northwest (PWR), Southeast (SER), and Southwest (SWR) regions. The average of the model rankings is used for areas in other regions (mean). Lower numbers indicate higher skill.

GCM	PWR Region	SER Region	SWR Region	Mean
bcc-csm1-1.	15	17	19	17
bcc-csm1-1-m.	7	19	9	10
BNU-ESM.	12	11	12	12
CanESM2.	5	13	5	5
CCSM4.	1	4	4	4
CNRM-CM5.	2	1	3	1
CSIRO-Mk3-6-0.	10	6	11	9
GFDL-ESM2G.	17	5	15	13
GFDL-ESM2M.	16	9	14	15
HadGEM2-CC.	4	3	2	3
HadGEM2-ES.	3	2	1	2
inmcm4.	14	10	17	16
IPSL-CM5A-LR.	11	15	10	11
IPSL-CM5A-MR.	6	12	7	8
IPSL-CM5B-LR.	20	14	20	20
MIROC5.	8	8	6	6
MIROC-ESM.	19	20	16	18
MIROC-ESM-CHEM.	18	18	18	19
MRI-CGCM3.	13	16	13	14
NorESM1-M.	9	7	8	7

Appendix 4. Frequently Asked Questions

What is gridded climate data?

Gridded data is a spatial data format that consists of a matrix of cells organized into rows and columns, where each cell contains a value for each grid point across a two-dimensional surface. Gridded climate interpolates all climate station data spatially and temporally, allowing long-term analysis in areas where historical station data may not exist or may be unreliable. Gridded climate data are evaluated and cleaned, allowing analyses for all parks, even those where stations are not present.

Why are you using gridded climate data instead of the station in/near the park for historical trends?

Many parks either do not have stations nearby, or the station-based data require extensive cleaning to address data-quality issues. The algorithms applied to develop gridded historical datasets have already applied the cleaning and corrected for complex geographies. Long-term gridded products that were used for this analysis (Vose et al. 2014; spatially interpolated from the Global Historical Climatology Network [[GHCN](#)]) weight stations with long-term, reliable records more heavily to provide a more accurate record. This dataset uses climatologically aided interpolation to address topographic and network variability and provides monthly precipitation and temperature in a 5x5 km grid, making it suitable for long-term analysis.

Why are historical trends presented since 1970?

We presented climate trends for the whole 20th century as well as since 1970. Although temperatures increased overall during the 20th century, a cooling trend is seen from about 1940 to 1975 resulting from a cooling phenomenon, ‘global dimming’, caused by airborne pollutants (Wild et al. 2007). Industrial activities following World War II, in the absence of pollution control measures, led to a rise in aerosols in the lower atmosphere, which reflected incoming solar energy back into space, leading to cooling. Observations of daily maximum and minimum temperatures during this time show that the ‘global dimming’ masked the warming effects of GHGs. The introduction of pollution control measures (e.g., through the Clean Air Act in the U.S. and other measures taken elsewhere in the world to reduce aerosol loading) reduced aerosol emissions, and gradually the cumulative effect of increasing GHGs started to dominate in the 1970s and warming resumed and accelerated from rising GHG concentrations. More information can be found at [Why did climate cool in the mid-20th Century? \(skepticalscience.com\)](#).

What is ‘downscaling’?

Projections of future climate were derived using global climate models (GCMs) that simulate the earth’s climate. They were designed to capture continental-scale climatological patterns to test the effects of different GHG emissions scenarios on Earth’s climate. Depending on the GCM, a pixel ranges from 1-2 degrees on a side (60-120 miles), making them both too coarse to assess local risk and poorly suited to capture climate patterns in a particular location. Coarse-resolution, global models can be “downscaled” to incorporate finer-scale features and processes that significantly influence local climate (e.g., topography, large water bodies, etc.) so the GCM projections are more useful for granular impact assessments.

There are two main approaches to downscaling, statistical and dynamical, that each have specific methods and tradeoffs (see Lukas et al. 2014 for more details). For these analyses we use statistical methods, which develop a statistical relationship between a GCM and observed data for a historical period, and then applies that model to generate future predictions. Systematic biases in the GCM output must then be corrected by calculating the difference between the historical GCM simulation and fine-scale observations and adjusting the projected GCM output accordingly. Experts have already produced a variety of downscaled projections that are useful as input into impact models for risk assessment, as illustrated in the figure below (see [Figure 5](#)).

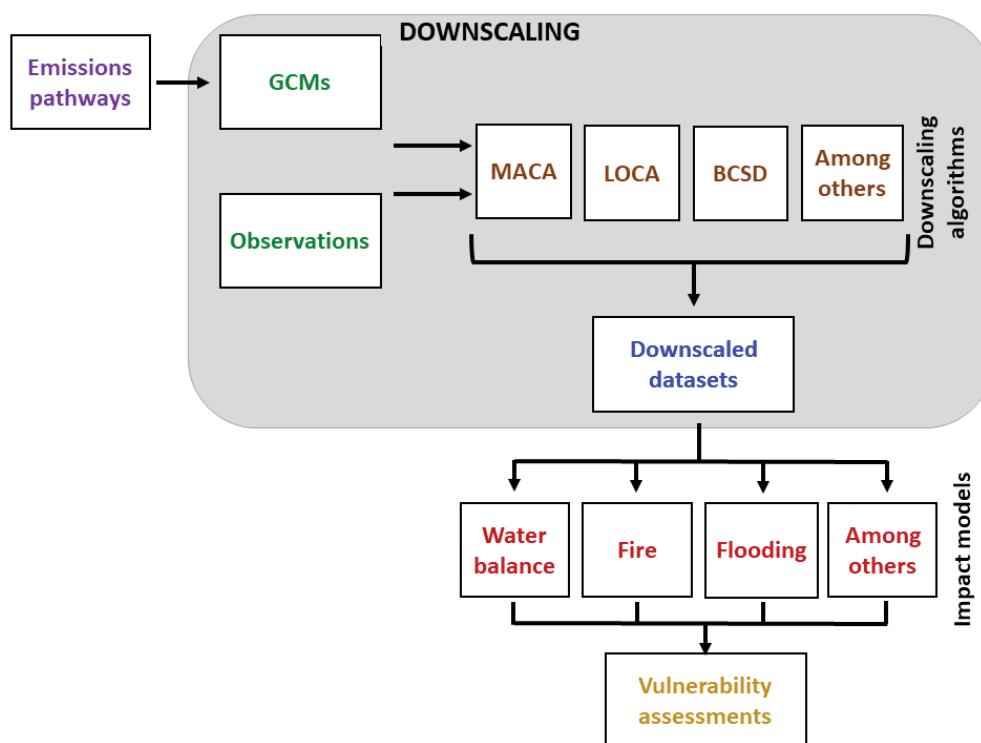


Figure 5. Downscaling is an intermediate climate data processing step that transforms coarse-scale GCM data into a finer scale that is appropriate for assessing local impacts. By combining the GCM output with a reference dataset including historical observations, downscaling creates climate projections that are better suited for use in impact models.

Why are MACA climate data used instead of other downscaled data sets?

There is no single correct downscaling method and other datasets may be more suitable for some applications. However, tradeoffs exist among different climate datasets, and selection of the best climate data for any particular application requires balancing these tradeoffs. We used the Multi-variate Adaptive Constructed Analogs (MACA; MACAv2-METDATA developed by Abatzoglou and Brown [2012] and Abatzoglou [2013]) because it is available for all of CONUS at a fine resolution (4km) with a broad range of global climate models and emissions scenarios. It includes climate metrics that are often useful for evaluating climate impacts at a daily timestep for the whole 21st century. The multi-variate, constructed analogs approach incorporates larger regional patterns and dependence of climate metrics, making it better suited for areas with complex topography, for simulating extreme events, and for capturing hydrological events that are highly important and consequential for parks, relative to other statistical methods (Wooten et al. 2017).

Why are the data for a different location in the park than where my resource is located?

While topography strongly affects local climate (Daly et al. 2008) and many parks may need explicit consideration of topographically rich terrain for specific planning processes (Lawrence et al. 2021), for these analyses, CCRP used climate metric values from a single grid cell, located at the centroid of the park (Figure 2). Experiences from previous engagements with parks (e.g., Schuurman et al. 2019, Runyon et al. 2021, Benjamin et al. 2021) have shown that a single site can be sufficient to evaluate changing trends across a whole park and broadly understanding how climate change may impact park resources. However, at the level of identifying and modeling specific resource responses or impact thresholds, each with unique climate sensitivities, more spatially precise climate information may be warranted to address the climate concerns, balancing tradeoffs between information and complexity (see Lawrence et al. 2021 for considerations of spatial extent and resolution of climate futures).

Why are only two climate futures typically used?

CCRP typically uses two to four divergent climate futures that bracket the range of climate uncertainty relevant to resource-management decisions of interest (Lawrence et al. 2021). For most resources, the objective was to use those that represent contrasting projections. In most instances, the contrasting climate futures were “warm wet” and “hot dry”, where warm wet would generally mean more water availability and a hot dry climate future may mean more drought or fires. Depending on the resource, either could be a best- or worst-case scenario. In limited instances where increasing temperature and precipitation could lead to degradation of cultural resources, “warm dry” and “hot wet” climate futures would be presented.

Why are you not using emissions scenarios as your climate futures?

Managing for uncertainty requires understanding the sources of uncertainty (Hoffman et al. 2015) and explicitly engaging with the uncertainty to identify strategies robust to the widest possible potential range of futures (Lawrence et al. 2021; Brekke et al. 2009). USGS scientists have identified three major sources of uncertainty in climate projections: natural variability, model uncertainty (due to imperfect knowledge of the climate system), and socioeconomic uncertainty (how human actions and decisions affect global GHG emissions) ([Figure 6](#); Terando et al. 2020, Wooten et al. 2017, Hawkins & Sutton 2009). Over the multi-decadal timescale that matters for most NPS decisions (30-50 years), differences between GCMs are the main source of uncertainty and would be missed by using climate futures based solely on emissions scenarios. Emissions-based scenarios are only appropriate for late-21st-century uses but still leave about 30% of the model uncertainty unaccounted for (Lawrence et al. 2021).

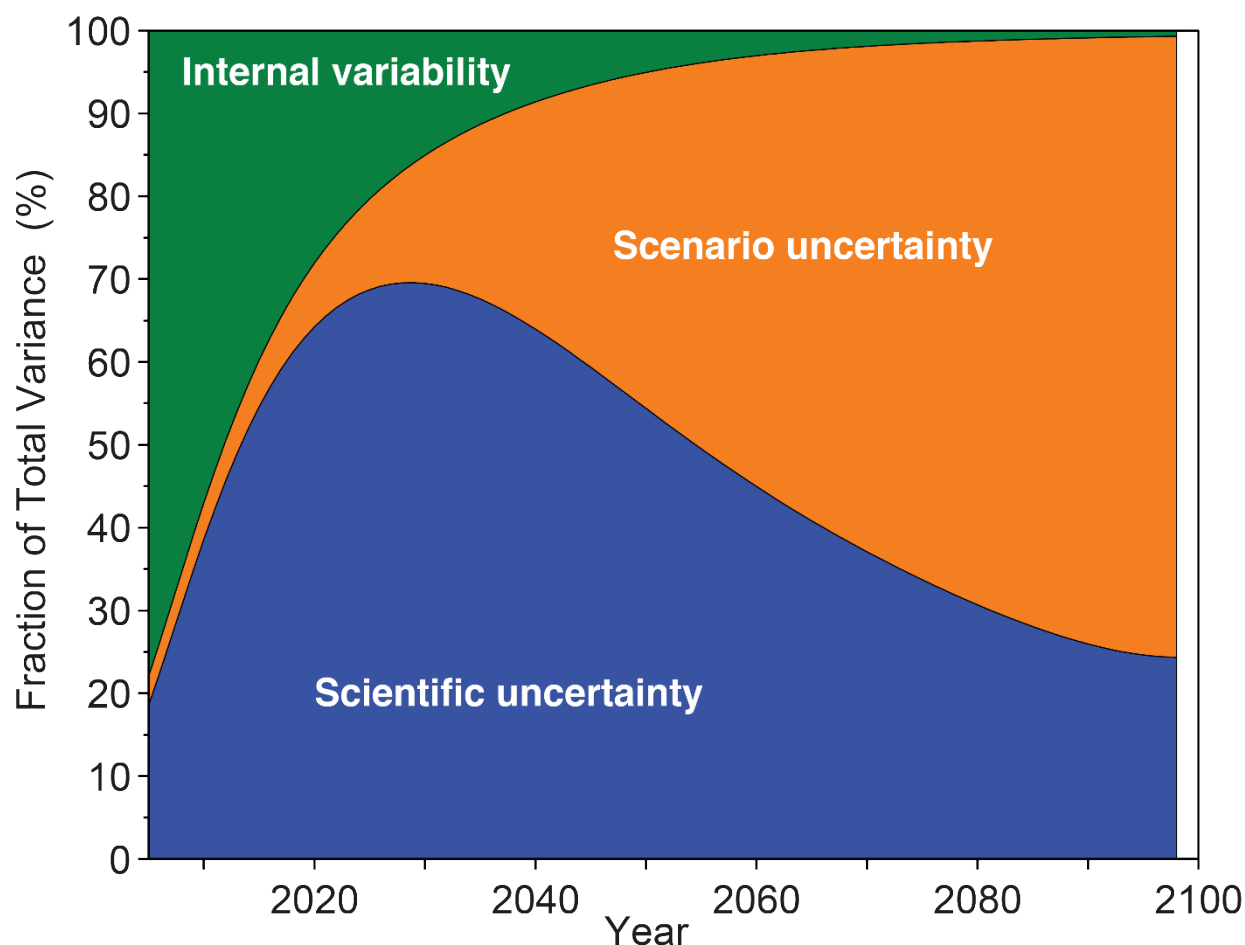


Figure 6. The relative importance of three components of uncertainty in decadal average temperature predictions across the 21st century, expressed in terms of fraction of total uncertainty, for the contiguous United States. Green regions represent uncertainty caused by natural variability of the climate system, blue represents model uncertainty, and orange regions represent human or socioeconomic uncertainty (from Figure 4.5 of Wuebbles et al. [2017], which was based on Hawkins and Sutton [2009]). The relative importance of these uncertainties varies with the climate metric and spatial scale of analysis (Hawkins and Sutton 2009, Rangwala et al. 2021).

Why are you using single models rather than averaging all models?

All projections considered in this study represented plausible realizations of the future. Selecting the best method for characterizing climate futures requires tradeoffs between resources available, decision-making application, and timeframe of the decisions. There are many sources of uncertainty when working with climate data across various timescales (see *Why are you not using emissions scenarios as your climate future?*), and projections derived from individual models helped capture the broadest range of uncertainty across all timescales (see Lawrence et al. 2021 for detailed explanation).

Why is CMIP5 used instead of CMIP6?

This analysis was developed before the release of CMIP6 and was based on careful evaluation of data quality. The number of high-resolution, downscaled CMIP6 products available for the U.S. is limited and there are few studies comparing the skill of each data set. When this information becomes available, the analysis will be updated with newer data sets.

Why are these summaries only produced for CONUS parks?

The geographic extent of these climate future summaries was limited by availability of high-quality, downscaled climate data. We are working to acquire climate data for other regions and will produce summaries for those regions as soon as possible.

How do I get climate futures for my park?

CCRP is producing park-specific climate future summaries for CONUS parks in FY24. Climate information for Alaskan and Pacific Islands parks will follow as data are made available. These summaries present divergent climate futures of key metrics that correspond to resource sensitivities and provide basic interpretation. CCRP has the ‘raw’ climate futures and underlying data as well and can provide the data or assist in further analysis upon request.

For access to climate futures, please submit a technical assistance request through the NPS System for Technical Assistance Requests.

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