

Climate and natural hazard analysis for the Mille Lacs Band of Ojibwe

Catherine (Kasia) A. Nikiel and Katherine A. Kurth



Authors

Catherine (Kasia) A. Nikiel¹ and Katherine A. Kurth¹

¹ U.S. Geological Survey National Climate Adaptation Science Center, Reston, Virginia, USA

Acknowledgements

This cooperator report was prepared by the Climate Adaptation Science Centers and published in cooperation with the Alaska Climate Adaptation Science Center in support of the Mille Lacs Band of Ojibwe. We are grateful to members of the Mille Lacs Band of Ojibwe for providing vital input during report development. We also thank peer reviewers for providing feedback including Sara Smith (College of Menominee Nation – Sustainable Development Institute) and Kenneth Blumenfeld (Minnesota Department of Natural Resources – Minnesota State Climatology Office). Finally, we thank Shannon Bayliss for editorial support.

Recommended citation

Nikiel, C. A., & Kurth, K. A. (2026). *Climate and natural hazard analysis for the Mille Lacs Band of Ojibwe*. Climate Adaptation Science Centers: U.S. Geological Survey Cooperative Investigations Report. <https://doi.org/10.21429/n1en-ea66>

Disclaimer

Any use of trade, firm, or product names is for descriptive purposes only and does not imply an endorsement by the U.S. Government.

Table of contents

Table of contents	3
Acronyms	5
Introduction.....	6
Definition of analysis units.....	6
Tools, datasets, and resources.....	12
Observational data	12
Climate projections	13
Limitations.....	15
Historical hazard reports.....	15
Historical and projected climate data	16
Hazards	18
Heat advisories and extreme heat warnings.....	20
Extreme cold warnings	22
Flash floods.....	23
Blizzards.....	24
Winter storms and heavy snow	25
Ice storms	26
Thunderstorm winds	27
Tornadoes.....	28
Hail.....	29
Annual wildfires.....	30
Air quality	30
Ice in and ice out	34
Climate Indicators	35
Annual and seasonal mean daily maximum temperature	36
Annual hot days.....	39
Annual and seasonal average daily mean temperature	44
Annual and seasonal mean daily minimum temperature.....	45
Annual and seasonal total precipitation	46
Freeze days.....	48

Extreme precipitation.....	49
Snow	54
Consecutive dry days and drought.....	58
Climate impacts on hazards.....	62
Flooding.....	62
Winter severity.....	65
Thunderstorm wind.....	67
Tornadoes.....	69
Hail.....	72
Wildfire.....	74
Air quality	75
Ice in and ice out	78
References	82
Appendices	91
Appendix A: additional plots.....	91
Appendix B: Analysis methodology	126
Hazards data retrieval	126
Climate data retrieval.....	127

Acronyms

ACIS – Applied Climate Information System
AQI – Air Quality Index
AQS – Air Quality System
°C – Degrees Celsius
CHaMP – Climate Hazard and Mitigation Planning tool
CoCoRaHS – Community Collaborative Rain, Hail and Snow Network
COOP – Cooperative Observer Program
CMIP – Coupled Model Intercomparison Project
CRIS – U.S. Climate Resilience Information System
EPA – Environmental Protection Agency
°F – Degrees Fahrenheit
FAA – Federal Aviation Administration
FEMA – Federal Emergency Management Agency
GHCN – Global Historical Climatology Network
GHCNd – Global Historical Climatology Network daily
GridMET – Gridded Surface Meteorological dataset (also known as METDATA)
ICAO – International Civil Aviation Organization
IPCC – Intergovernmental Panel on Climate Change
LOCA – Localized Constructed Analogs
MACA – Multivariate Adapted Constructed Analogs
MN ClIMAT – Minnesota Climate Mapping and Analysis Tool
MRCC – Midwest Regional Climate Center
NCEI – NOAA National Centers for Environmental Information
nClimDiv – NOAA NCEI’s U.S. Climate Divisional Dataset
nClimGrid – NOAA NCEI’s U.S. Climate Gridded Dataset
NO₂ – Nitrogen dioxide
NOAA – National Oceanic and Atmospheric Administration
NWSLI – National Weather Service Local Identifier
PM_{2.5} – Fine particulate matter
RAPT – FEMA Resilience Analysis and Planning Tool
RCC – NOAA Regional Climate Center
RCP – Representative Concentration Pathway
SPEI – Standardized Precipitation-Evapotranspiration Index
SSP – Shared Socioeconomic Pathway
U.S. – United States
USDM – U.S. Drought Monitor
USGS – United States Geological Survey
WBAN – Weather Bureau Army Navy
WFO DLH – Duluth Weather Forecast Office
WFO MPX – Twin Cities/Chanhassen Weather Forecast Office
WMO – World Meteorological Organization

Introduction

Understanding potential changes in the frequency and severity of climate-related hazards is critical for supporting long-term strategic planning and community resilience for the Mille Lacs Band of Ojibwe. Federal Emergency Management Agency (FEMA)-approved Hazard Mitigation Plans are one tool the Tribal Nation uses to identify, assess, and reduce risks associated with changing conditions. However, obtaining the climate information needed for the Hazard Mitigation Plan can be challenging due to time constraints, the large number of tools and datasets, and barriers to data accessibility.

At the Tribal Nation's request, the Climate Adaptation Technical Services team from the U.S. Geological Survey National Climate Adaptation Science Center provided data, visualizations, and supporting resources to inform their Hazard Mitigation Plan update, which is due to FEMA in mid-2027. This report creates a foundation for updating previously included information and incorporating future climate projections for the first time, with a focus on near-term planning needs. Designed as a non-interpretive resource, this report supports ongoing data acquisition and informed decision-making.

Specific outputs from this effort include (1) historical hazards and climate conditions data and visualizations, (2) future climate projection data and visualizations, (3) a synthesis of scientific literature describing potential climate change impacts on hazards, and (4) guidance on tools, datasets, and resources to support future updates.

Definition of analysis units

Data and resources within this report are focused on six Minnesota counties of high priority to the Tribal Nation including Aitkin, Crow Wing, Kanabec, Mille Lacs, Morrison, and Pine. Given the similarity in climate across these counties, analysis is largely presented for the combined six-county region (Figures 1, 2, and 3). Additionally, some data are provided for relevant weather stations including Milaca (Mille Lacs County), Mora (Kanabec County), Sandy Lake Dam Libby (Aitkin County), and Pine River Dam and Brainerd (Crow Wing County; Figure 1 and Table 1). Weather stations were selected based on (1) location in the six-county region and (2) having a record spanning from at least 1950 to present for both precipitation and temperature. Weather stations were selected using the filtering tool available in the cli-MATE tool from the Midwest Regional Climate Center (MRCC; MRCC, 2026a). The cli-MATE tool considers weather stations across many network types (Weather Bureau Army Navy [WBAN]; Cooperative Observer Program [COOP]; Federal Aviation Administration [FAA]; World Meteorological Organization [WMO]; International Civil Aviation Organization [ICAO]; Global Historical Climatology Network [GHCN]; National Weather Service Local Identifier [NWSLI]; Regional Climate Centers [RCC]; ThreadEx; and Community Collaborative Rain, Hail and Snow Network [CoCoRaHS])

Weather Stations and Study Area Counties

Central Minnesota

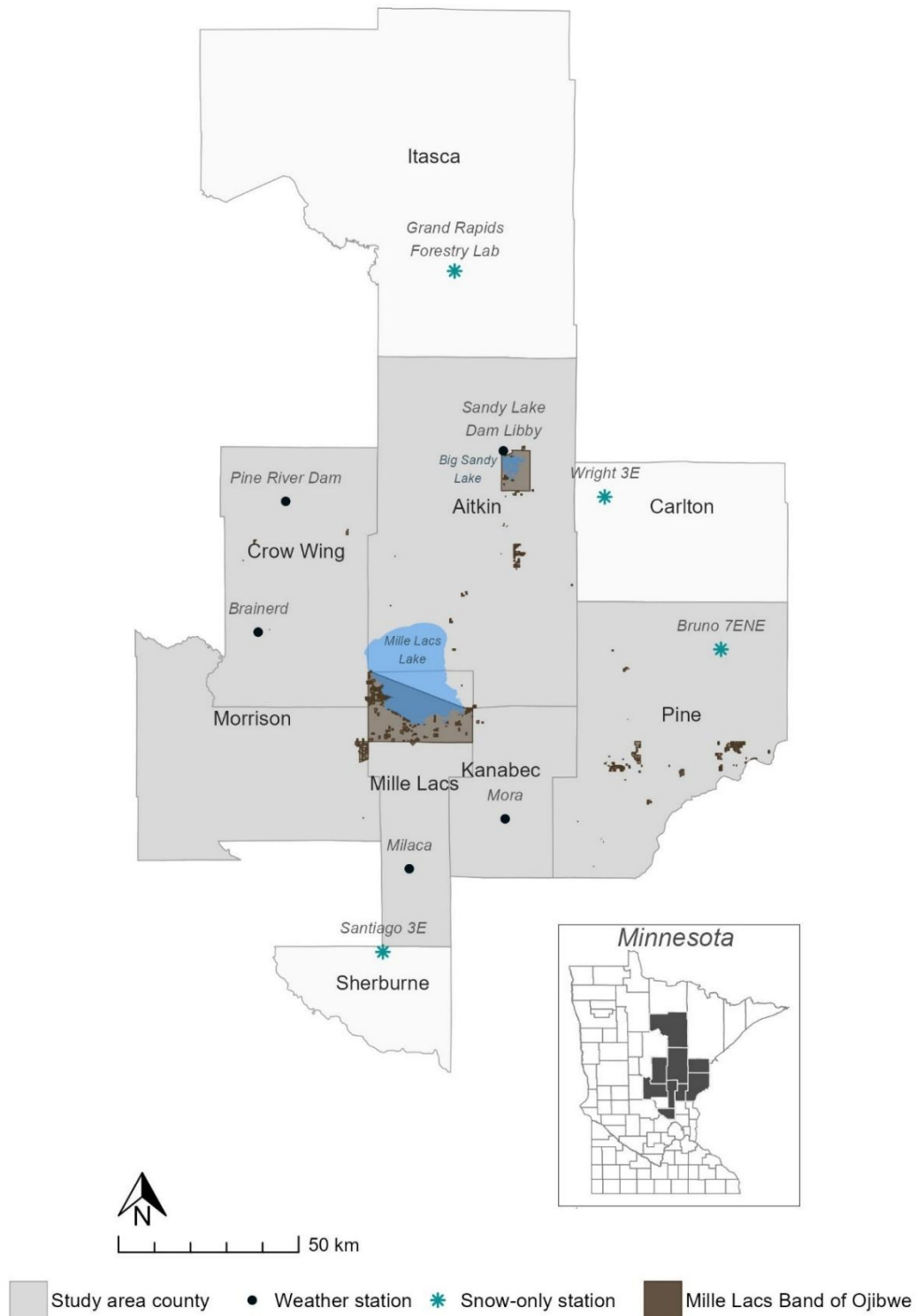


Figure 1. Counties, weather stations, and snow-only stations within the study area in central Minnesota.

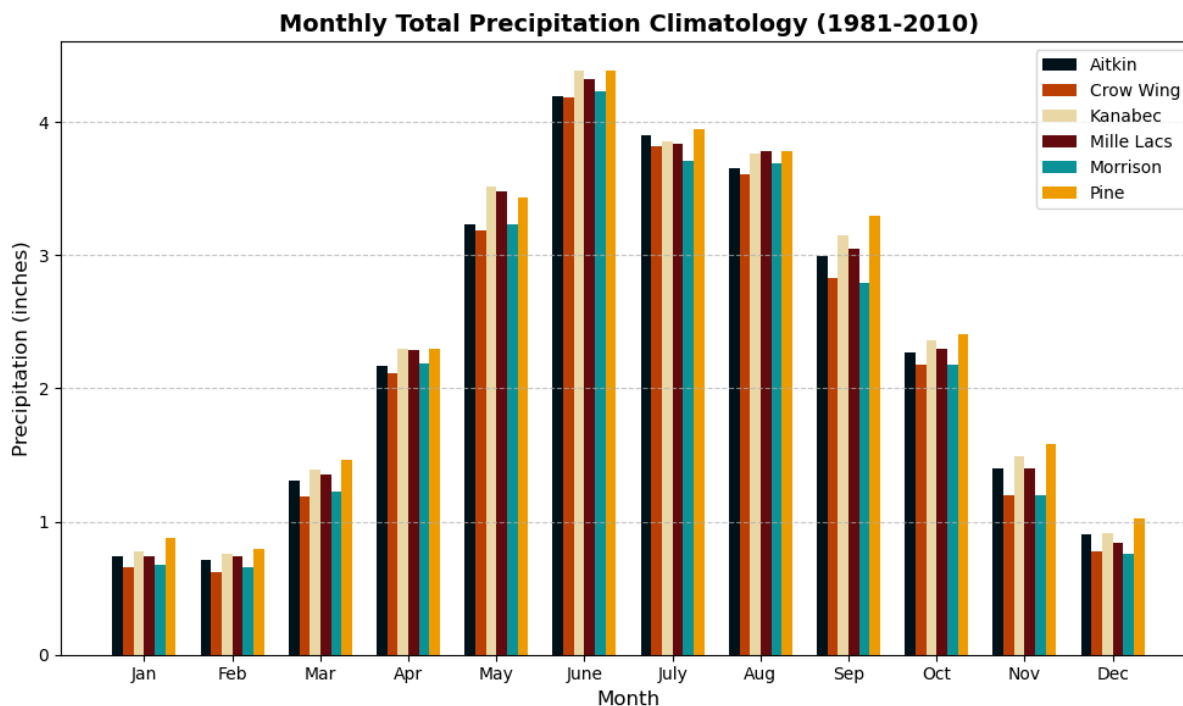


Figure 2: Annual climatology of average monthly precipitation totals for 1981–2010 within six Minnesota counties using the National Oceanic and Atmospheric Administration National Centers for Environmental Information (NOAA NCEI) nClimGrid-monthly historical dataset.

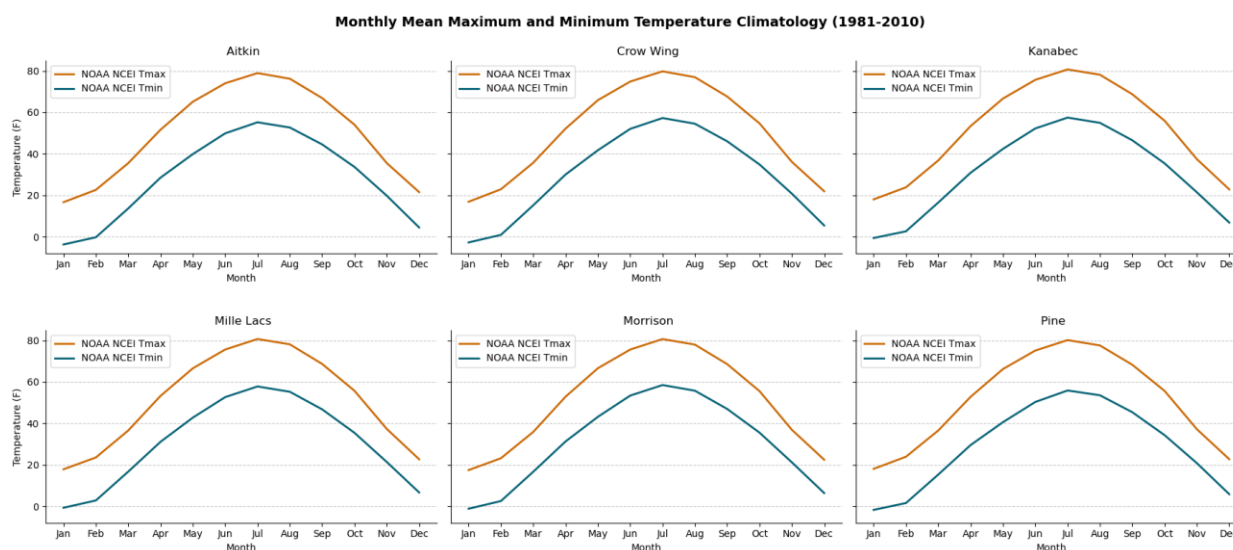


Figure 3: Annual climatology of average monthly mean, maximum, and minimum daily temperature for 1981–2010 within six Minnesota counties using the NOAA NCEI nClimGrid-monthly historical dataset.

Table 1: Table showing station information and period of record for variables. These stations record temperatures as daily minimum and maximum. In cases where the length of record differs between minimum and maximum temperature, the shorter record is reported and marked with an *. The period of record is reported only for the variables used within this report and does not indicate that the station does not record *those* data.

Station	Global Historical Climatology Network (GHCN) ID	Location	Precipitation Record	Temperature Record	Snow Record
Milaca	USC00215392	45.753 N, 93.662 W	1897-02-01–Present	1897-02-01–Present	
Mora	USC00215615	45.878 N, 93.315 W	1904-06-15–Present	1904-06-15–Present	
Brainerd	USC00210939	46.343 N, 94.209 W	1908-01-16–Present	1899-02-01–Present	
Pine River Dam	USC00216547	46.669 N, 94.109 W	1887-03-06–Present	1896-10-01–Present	
Sandy Lake Dam Libby	USC00217460	46.795 N, 93.321 W	1892-08-01–Present	1896-09-01–Present *	
Santiago 3E	USC00217502	45.546 N, 93.757 W			1959-09-14–Present
Grand Rapids Forestry Lab	USC00213303	47.244 N, 93.498 W			1948-07-01–Present
Wright 3E	USC00219173	46.680 N, 92.954 W			1961-07-07–Present
Bruno 7ENE	USC00211074	46.300 N, 92.534 W			1990-09-01–2024-10-09

Additional snow-only stations were included which were selected through the Snowfall Climatology Toolbox from the Midwest Regional Climate Center (MRCC, 2026b). Stations were selected based on (1) their location in or around the six-county region and (2) having at least 30 years of data, with records beginning in 1991 or earlier. The selected snow-only stations included the Grand Rapids Forestry Lab (Itasca County), Santiago 3E (Sherburne County), Bruno 7ENE (Pine County), and Wright 3E (Carlton County; Figure 1 and Table 1).

Stations have variable records and reliability. To prevent including years with substantial missing data, station years were excluded if they had greater than 10% missing days for the period of interest (greater than 36 days for annual metrics, greater than 9 days for seasonal metrics, and greater than 25 days for snow metrics). Some stations had occasional missing years throughout the record while others performed poorly for an extended period (Figures 4–6). Users should note missing data in the station record before using them to assess historical conditions over time.

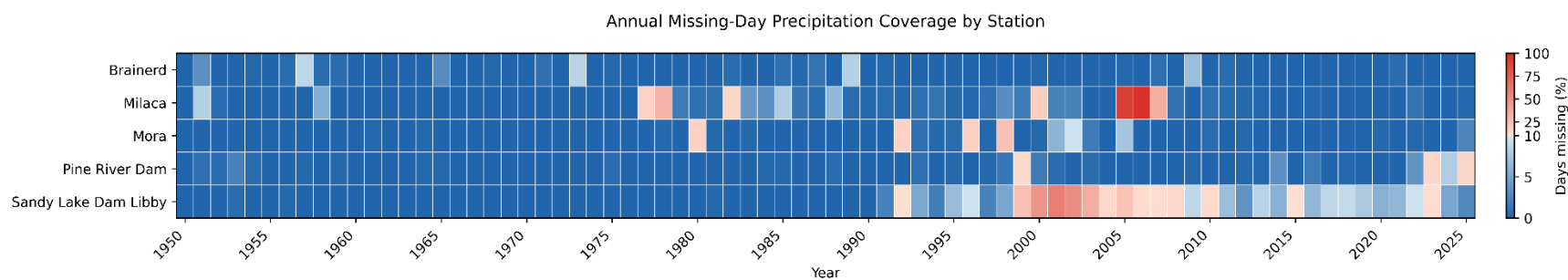


Figure 4: Missing days in Applied Climate Information System (ACIS) station precipitation records from 1950–2025.

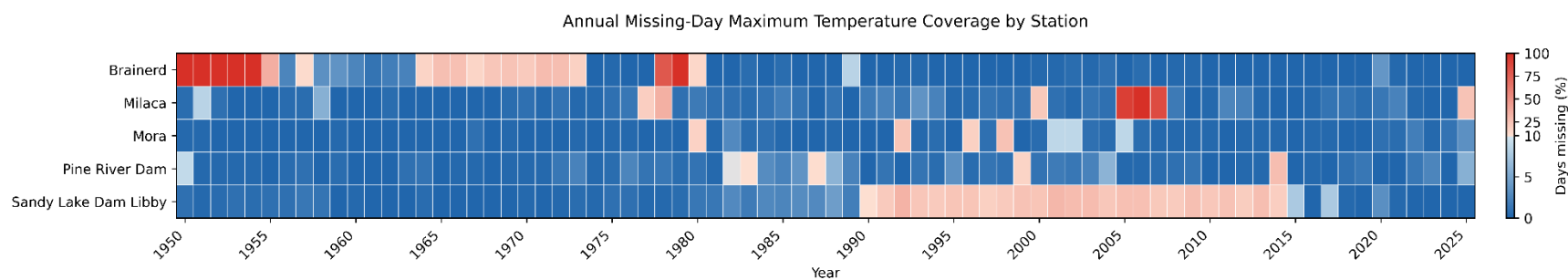


Figure 5: Missing days in ACIS station maximum temperature records from 1950–2025.

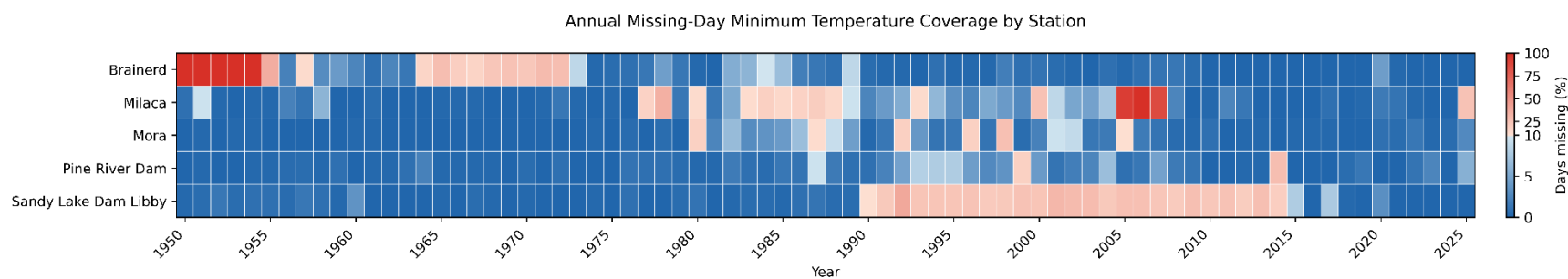


Figure 6: Missing days in ACIS station minimum temperature records from 1950–2025.

Tools, datasets, and resources

A wide range of datasets and online tools are available to help users assess exposure to climate related hazards. However, the variety of available information across different platforms and data formats can make selection and application difficult. A carefully selected set of data sources were utilized for this report and are described within this section to provide context and aid with potential future applications. For more in-depth documentation on how data were obtained and processed see Appendix B: Analysis methodology.

Observational data

Observational data describe the historical climate of a region and are available in a variety of temporal and spatial resolutions depending on the source. When selecting observational data products, it is important to understand differences in data collection methodology and to choose products that are most appropriate for analyzing trends and comparing climate across regions.

NOAA Storm Events Database

The National Oceanic and Atmospheric Administration (NOAA) Storm Events Database provides official and comprehensive records of weather events as entered by NOAA's National Weather Service. It includes over 50 event types, including (1) storms and other weather events that result in fatalities, injuries, or property damage, (2) rare or unusual weather events of special interest, and (3) other significant meteorological events. Records provide details on event magnitude, location, fatalities/injuries, damage, estimated cost, and other relevant information when available. The database contains data from January 1950 through present, though coverage varies by event type (National Weather Service, 2021). While the database is regarded as one of the most comprehensive and reliable sources of severe and significant weather in the United States, there are limitations regarding its use and interpretation (see Limitations: Historical hazard reports section).

NOAA NCEI nClim Products

The NOAA National Centers for Environmental Information (NCEI) has developed several spatially consistent long-term datasets using observations at weather stations in the United States. NOAA NCEI's U.S. Climate Divisional Dataset (nClimDiv) uses data from the NOAA NCEI's U.S. Climate Gridded Dataset (nClimGrid) which is built on the Global Historical Climatology Network daily (GHCNd) station dataset (Menne et al., 2012, Vose et al., 2014a, 2014b, 2014c). nClimDiv is processed to provide a spatially and temporally consistent and complete dataset that is more appropriate for assessing changes in climate over time. In 2018, NOAA NCEI updated the nClimDiv product with county averages (NCEI, 2019). This is the primary observational product used in this analysis due to its long record and consistency. nClimGrid and nClimDiv are available from 1895 through present at a monthly resolution.

Users can access the NOAA NCEI data through the Climate at a Glance tool (NCEI, 2026b). The annual and monthly time series data are also available through the Minnesota Department of

Natural Resources Climate Explorer (Minnesota Department of Natural Resources, n.d. -b). Users should note that the projection data included in the Climate Explorer were not used within this report, instead the more recent modeling in the Minnesota Climate Mapping and Analysis Tool (MN CliMAT) was incorporated. Threshold calculations and other data used in the 5th National Climate Assessment can be accessed through the U.S. Climate Resilience Information System (CRIS; U.S. Federal Government, 2024).

gridMET

GridMET (Gridded Surface Meteorological dataset, also known as METDATA) is a gridded ~4 km observational data product covering the continental United States (Abatzoglou, 2013).

GridMET is available from 1979 through present at daily resolution and is shown in select figures within this report and Appendix A as a comparable observational dataset for the end of the 20th century. These data can be accessed through the UC Merced Climatology Lab and through Climate Toolbox (UC Merced, n.d.-a; Hegewisch & Abatzoglou, 2026). GridMET is used in this analysis because it is the underlying observational training dataset for our primary downscaled climate projections, MACAv2-METDATA.

Weather stations

Surface temperature, precipitation, and snow observations are also available at the individual weather stations that underly the gridded and aggregated products above. Data can be obtained through the Applied Climate Information System (ACIS) which is developed and maintained by the NOAA Regional Climate Centers (RCCs; RCC, 2026). Station data are also hosted on several regional websites, including on the Midwest Regional Climate Center cliMATE Data Portal (MRCC, 2026a). The period of record varies based on the station and may include periods of missing data. Weather stations are shown here to (1) retain consistency with data included in previous versions of the Hazard Mitigation Plan and (2) provide the most site-specific weather information that can be used to validate gridded observations and modeled products and identify any biases.

Climate projections

The Coupled Model Intercomparison Project (CMIP) produces a global ensemble of vetted climate model simulations for use by the international scientific community (Meehl et al., 1997). The most recent generations — CMIP5 and CMIP6 — provide a large ensemble of model simulations but the spatial resolution is coarse, from 50–300 km (Copernicus Climate Change Service, 2021; Lukas and Vano, 2024).

A wide variety of products are available that downscale this coarse resolution information to a scale that is more applicable to regional and local planning. Available datasets differ based on many factors, including the downscaling method and training data used, the model ensemble selected, the emissions scenarios included, the variables available, and their final spatial and temporal resolution (Ekström et al., 2015; Trzaska & Schnarr, 2014). The datasets used in this report are considered high quality and regionally specific (in the case of MN CliMAT), use a

variety of model ensembles and downscaling approaches, and are easily accessible through user-friendly platforms.

Different generations of climate models use different emissions scenarios for projecting future climate. CMIP5 uses Representative Concentration Pathways (RCPs) while CMIP6 uses Shared Socioeconomic Pathways (SSPs; van Vuuren et al., 2011; Meinshausen et al., 2020). Here we show projections from RCP4.5 and RCP8.5 for CMIP5 model ensembles and SSP2-4.5 and SSP5-8.5 for CMIP6 model ensembles. While these emissions scenarios are not identical across generations, they are closely comparable especially at early- and mid-century (Meinshausen et al., 2020). Emissions scenarios are not assigned a probability of how likely one is to occur over another, and it is therefore recommended to assess the impacts of multiple emissions scenarios (Briley et al., 2021a; Terando et al., 2024).

Averages of observations and climate model data are provided for 20–30-year periods, the timeframe recommended for assessing climate changes. This aligns with the World Meteorological Organization’s establishment of a 30-year climate normal that reduces the influence of natural variability (WMO, 2017). All averages are calculated with an awareness of the transition between “historical” and “future” simulations in the modeling ensembles: 2005–2006 in CMIP5 and 2014–2015 in CMIP6.

MACAv2-METDATA

This dataset downscales a 20-member CMIP5 ensemble using the Multivariate Adapted Constructed Analogs (MACA) method which is a high-quality statistical downscaling approach that uses gridMET/METDATA as a training dataset (Abatzoglou & Brown, 2012). Two emissions scenarios (RCP4.5 and RCP8.5) are available for the historical (1950–2005) and future periods (2006–2100) at ~4 km resolution covering the continental United States.

These data can be downloaded as netCDF files from the UC Merced Northwest Knowledge Webpage or visualized and downloaded in other summarized formats from Climate Toolbox (Hegewisch & Abatzoglou, 2026; UC Merced, n.d.-b). This dataset is also included in the U.S. Geological Survey (USGS) National Climate Change Viewer (Alder & Hostetler, 2013). Data are available at daily, monthly, seasonal, and annual time scales depending on the tool and variable. MACAv2-METDATA is the primary climate projection dataset used due to its ease of access relative to other high-quality datasets.

LOCA2

This dataset downscales a 23–27-member (depending on emissions scenario) CMIP6 ensemble using the Localized Constructed Analogs (LOCA) method which is a high-quality statistical downscaling approach that uses the unsplit modified Livneh observational dataset for training (Pierce et al., 2021, 2023). Three emissions scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5) are available for the historical (1950–2014) and future periods (2015–2100) at ~6 km resolution covering the continental United States and portions of Mexico and Canada.

These data can be downloaded as netCDF files through the U.S. Climate Resilience Information System (CRIS) and can be visualized and downloaded in other formats from the USGS National Climate Change Viewer (Alder & Hostetler, 2013; U.S. Federal Government, 2024). Data are available at daily, monthly, seasonal, and annual time scales depending on the tool and variable. Additional thresholds and extremes have been calculated from the daily data for different areas. Here, we use netCDFs that summarize these data by county (Alder, 2025). LOCA2 is used for variables that are not available in MACAv2-METDATA.

Minnesota Climate Mapping and Analysis Tool (MN CliMAT)

This dataset dynamically downscales a six-member CMIP6 ensemble using the Weather Research and Forecasting regional model (Liess et al., 2026). Three emissions scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5) are available for the historical (1995–2014) and three future periods (2040–2059, 2060–2079, and 2080–2099) at 4 km resolution covering Minnesota.

These data can be downloaded as daily and monthly netCDF files through the MN CliMAT website and can be visualized and downloaded in other summarized formats through the online tool (Minnesota Climate Adaptation Partnership, n.d.). Data in the tool are available at monthly, seasonal, and annual scales depending on variable. MN CliMAT is used when available for a local, dynamically downscaled comparison.

Limitations

Historical hazard reports

In this report, we primarily use the NOAA Storm Events Database as an indication of historical hazard occurrence. Although this database is considered one of the most accurate and complete records of severe and significant weather in the United States, a few important considerations relate to reporting criteria, sources, locations, and timing.

First, criteria for some reported events have changed over time (Allen & Tippet, 2015), and the National Weather Service Directive does not explicitly state how these changes are accounted for in storm event data preparation (National Weather Service, 2021). Further, some criteria are based on locally and regionally established criteria (National Weather Service, 2021) which may be difficult to identify and can introduce inconsistencies when comparing across large regions or periods of time.

Additionally, an event must be reported to the National Weather Service to be included in the database which presents several potential biases. The composition of observation sources (e.g., members of the public, storm chasers, trained spotters, government officials, weather and news stations, etc.) has changed over time, and reporting has become easier as telecommunications and internet access has become commonplace (Allen & Tippet, 2015). In areas with higher population densities, the likelihood that an event is observed increases (Potvin et al., 2019; Walker, 2026). For example, a study showed that urban counties had four times more severe wind and hail reports per square mile than nearby rural counties, with

population density explaining approximately half of variation in storm reports density (Walker, 2026). This suggests that reported events may be underestimated in rural areas and has implications for areas where population density increases over time (Potvin et al., 2019; Walker, 2026). Similarly, reports are more common along road networks and areas storm chasers frequent (Potvin et al., 2019; Allen & Tippet, 2015).

Finally, some hazards exhibit persistent increases in reported events beginning at distinct periods, likely associated with several factors including the establishment of the National Severe Storms Forecast Center in 1966 and the National Weather Service modernization in the 1990s (during which the National Severe Storms Forecast Center was renamed the Storm Prediction Center; Allen & Tippet, 2015). Additionally, starting in the early 1990s, the database became more actively maintained, a network of spotters was established, and Doppler radar was rolled out (Allen & Tippet, 2015).

These nonmeteorological factors should be considered when identifying increases in reports and resulting temporal trends. Several approaches can help address these reporting challenges. It may be more reliable to monitor reports for trends after important shifts in criteria (e.g., the rollout of Doppler radar). Evaluating trends in pooled data (e.g., national and annual) is also likely more robust than those identified from localized or fine-temporal scale data (Allen & Tippet, 2015). Statistical corrections can also be applied to account for reporting bias (Potvin et al., 2019). Lastly, using hazard days as a unit of analysis rather than individual reported events may provide a more reliable record (Allen & Tippet, 2015). In this report, we supplement data from the NOAA Storm Events Database with data from weather stations for select hazards. Ultimately, due to interannual variability and bias present within reported data, historical hazard reports alone cannot reliably be used as evidence of climate change (Brooks, 2013).

Historical and projected climate data

Climate data have several sources of uncertainty. In this report we aim to present data in a way that highlights the range of uncertainty in historical and future data across multiple dimensions, stemming from emissions scenarios, model uncertainty, downscaling methodology, and observation methodology.

Climate model simulation uncertainty stems from three main sources: (1) internal variability in the climate system, (2) model process uncertainty, and (3) emissions scenario uncertainty (Lehner et al., 2020). This analysis does not explicitly account for internal variability that is dominant in the short term, such as the influence of high frequency climate oscillations like El Niño. The occurrence of El Niño and La Niña can significantly impact the year-to-year climate of the Midwest (Danco & Martin, 2018; Hoell et al., 2021). This internal variability is best captured by large ensembles where the same model is run under multiple initial conditions and is not available through most downscaled datasets.

Emissions scenario driven uncertainty becomes dominant at the end of the 21st century and is not a major concern for this analysis, though multiple emissions scenarios are still included. Model and process uncertainty is included by presenting the full available model ensemble in each dataset. This ensemble varies by dataset and should be considered when comparing results across datasets. Model ensemble selection should be tied directly to a specific study, system, and impact of interest (Katzenberger et al., 2026).

The choice of downscaling technique can also introduce uncertainty to climate data analysis (Wootten et al., 2017; Wang et al., 2020). Downscaling is the translation of coarse resolution global climate simulations to finer scale products that are more appropriate for regional and local applications (Ekström et al., 2015; Trzaska & Schnarr, 2014). Statistical downscaling uses a statistical relationship between climate variables and observational data that is assumed to persist in the future. Two statistically downscaled datasets are used here: MACAv2-METDATA and LOCA2. High-quality statistical products can capture changes in more climatologically complex regions and at the tails of the distribution (extreme events) rather than just the mean, but they rely on an assumption that physical climate relationships remain stationary (Ekström et al., 2015; Trzaska & Schnarr, 2014). Dynamical downscaling uses a nested numerical model to run a high-resolution regional simulation driven by the coarser global climate simulations at the geographic boundaries (Ekström et al., 2015; Trzaska & Schnarr, 2014). One dynamically downscaled dataset is used here: MN CliMAT. Dynamical products do not rely on a stationarity assumption and may perform better in areas with significant heat, moisture, and momentum fluxes (Notaro et al., 2015; Briley et al., 2021b); additionally, regional models can introduce features that are not included in coarser models such as lakes (Wang et al., 2022; Liess et al., 2026). However, producing dynamical models is significantly more resource-intensive and they often have smaller ensemble sizes (for example, MN CliMAT has an ensemble size of 6 models compared to 20+ models for MACAv2-METDATA and LOCA2).

Historical observations can also have significant uncertainty. This has implications for assessing historical trends and comparing them to climate model projections (Katzenberger et al., 2026). Weather station data can have errors and inconsistencies due to changes in network density, changes in measurement and recording methodology, measurement bias, and station relocations (Groisman & Legates, 1994; Durre et al., 2010; Menne et al., 2012; Svoma & Cervený, 2012; Ribeiro et al., 2016). Gridded and aggregated products such as NOAA NCEI's nClimGrid and nClimDiv and the gridMET/METDATA dataset attempt to document and correct these inconsistencies and sources of uncertainty (Vose et al., 2014a; Daly et al., 2021). Given the limited impact of emissions and model uncertainty in the short term, comparison between historical observations and projected scenarios may be valuable for the next 1–10 years (Terando et al., 2024). However, it is important to remember that climate models are not intended to capture the historical sequence of weather in the past or future; rather, climate model simulations aim to capture the statistical characteristics of weather over a long period of time (i.e., 30-year mean and variability; Katzenberger et al., 2026).

Hazards

Hazardous weather events can occur year-round; however, they typically follow unique seasonal cycles influenced by regional climate conditions. Identifying these cycles and the months of greatest hazard frequency is critical for community preparedness and safety planning. To meet this need, all key hazard events from the NOAA Storm Events Database reported until January 2026 were obtained and the percent of reported hazard events by month were calculated (NCEI, 2026a; Table 2). Distinct seasonal patterns emerged for different hazards, with July having the highest frequency of reported hazard events in central Minnesota. Although, data limitations including imperfect hazard reporting should be considered (see Limitations: Historical hazard reports section).

Table 2. Percent of days (values emphasized with color) with hazard events occurring by month from the start of data collection to January 2026 for Aitkin, Crow Wing, Kanabec, Mille Lacs, Morrison, and Pine counties in Minnesota, as reported in the NOAA Storm Events Database. The total number of reported days and period of record for each hazard type are provided. Current definitions of hazards are in the table footnote, but criteria have changed over time. Because of this, and other dataset limitations including unreported events, careful data interpretation is recommended (see Limitations: Historical hazard reports section).

Hazard	Hazard Occurrence (%) by Month											
	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Blizzard ^a (n=4; 1996–2026)	50	0	0	0	0	0	0	0	0	0	25	25
Extreme Heat ^b (n=5; 1996–2026)	0	0	0	0	0	0	80	20	0	0	0	0
Extreme Cold ^c (n=61; 1996–2026)	52.5	26.2	3.3	0	0	0	0	0	0	0	0	18
Flash Flood ^d (n=37; 1996–2026)	0	0	2.7	10.8	8.1	27	29.7	16.2	2.7	2.7	0	0
Hail ^e (n=314; 1955–2026)	0	0	1.3	3.8	14	22.9	26.1	19.4	10.8	1.3	0.3	0
Heat ^f (n=21; 1996–2026)	0	0	0	0	0	0	71.4	28.6	0	0	0	0
Heavy Snow ^g (n=204; 1996–2026)	11.8	22.1	21.1	9.8	0	0	0	0	0	2.5	10.8	22.1
Ice Storm ^h (n=17; 1996–2026)	35.3	11.8	0	23.5	0	0	0	0	0	0	0	29.4
Thunderstorm Wind ⁱ (n=324; 1955–2026)	0	0	0.3	2.2	8.3	22.5	36.1	20.1	9.3	1.2	0	0
Tornado ^j (n=79; 1950–2026)	0	0	1.3	0	5.1	30.4	36.7	13.9	10.1	2.5	0	0
Winter Storm ^k (n=179; 1996–2026)	10.6	17.9	20.1	15.6	0	0	0	0	0	1.1	11.7	22.9

^aWinter storms that last three hours or more with wind speeds ≥30 knots (35 mph) and falling or blowing snow that reduces visibility to <1/4 mile

^bIssued extreme heat warning

^cIssued extreme cold warning (wind chill ≤-40°F)

^dRapid increases of water into a normally dry area that are potentially life-threatening

^eFalling frozen precipitation in the form of balls or irregular lumps of ice that are ≥0.75 inch in diameter

^fIssued heat advisory

^g≥6 inches of snow within 48 hours

^hIce accretion of ≥0.25 inch

ⁱWinds that (1) occur within 30 minutes of lightning being observed or detected) and (2) wind speeds ≥50 knots (58 mph) or winds of any speed that result in a fatality, injury, or damage

^jReported tornado

^kSnow accumulation of ≥6 inches during a single event, not to exceed 48 hours in length, and accumulation of ≥0.5 inches of sleet or other combinations of winter weather can also be reported as a winter storm event in some areas.

Heat advisories and extreme heat warnings

The National Weather Service uses multiple metrics to issue heat advisories and extreme heat warnings, including heat index, HeatRisk, and wet-bulb globe temperature, as confirmed by J. Moore, a National Weather Service meteorologist in the study area (Minnesota Department of Health, 2025; J. Moore, personal communication, July 21, 2026). Each metric uses different inputs to reflect how hot conditions feel to humans: heat index is a measure that combines air temperature and relative humidity; HeatRisk is a measure that combines weather and health impact factors; and wet-bulb globe temperature is a measure that combines temperature, humidity, wind speed, and solar radiation (Minnesota Department of Health, 2025). Criteria for heat-related advisories and warnings are defined locally/regionally (National Weather Service, 2021) and criteria in place as of summer 2026 are described in Table 3. However, National Weather Service criteria have changed over time, and what these changes are and how they are accounted for in the database is unclear in public documents (National Weather Service, 2021; J. Moore, personal communication, July 21, 2026). Reports of heat-related advisories and warnings were obtained from the NOAA Storm Events Database for the period January 1996 to January 2026 (NCEI, 2026a; Tables 4 and 5). During this period, reported events were recorded most frequently in July followed by August (Table 2). Events that fall outside of the current criteria appear to be included within the database; therefore, any observable trends, or absence of trends, should be interpreted with caution. Gridded observation and weather station data for annual days with a maximum temperature greater than or equal to 90°F, 95°F, 100°F, and 105°F are provided for comparison (Figures A8–A11).

Table 3. National Weather Service local/regional criteria for heat advisories and extreme heat warnings for six Minnesota counties.

Counties	Heat Advisory Criteria	Extreme Heat Warning Criteria	Weather Forecast Office	Source
Kanabec, Mille Lacs, and Morrison	A heat index $\geq 100^{\circ}\text{F}$ and/or a wet-bulb globe temperature of 85°F for ≥ 3 hours	A heat index $\geq 105^{\circ}\text{F}$ or a wet-bulb globe temperature of 87°F for ≥ 3 hours	Twin Cities/Chanhassen Weather Forecast Office (WFO MPX)	(National Weather Service, n.d.-d)
Aitkin, Crow Wing, and Pine	A heat Index $\geq 95^{\circ}\text{F}$ and/or a “Moderate” HeatRisk and/or wet-bulb globe temperature $\geq 79^{\circ}\text{F}$ for ≥ 3 hours (must meet ≥ 2 of the 3 criteria)	A heat Index $\geq 100^{\circ}\text{F}$ and/or a “Moderate” HeatRisk and/or wet-bulb globe temperature $\geq 83^{\circ}\text{F}$ for ≥ 3 hours (must meet ≥ 2 of the 3 criteria)	Duluth Weather Forecast Office (WFO DLH)	(J. Moore, personal communication, July 21, 2026)

Table 4. Number of days with a heat advisory across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a heat advisory.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	0	0	8	8	8	0	8
2005–2009	0	0	2	2	2	0	2
2010–2014	5	5	0	0	0	5	5
2015–2019	1	0	0	0	0	0	1
2020–2024	0	0	0	0	0	0	0
2025	0	0	0	0	0	0	0

Table 5. Number of days with an extreme heat warning across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced an extreme heat warning.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	0	0	0	0	0	0	0
2005–2009	0	0	0	0	0	0	0
2010–2014	0	0	3	3	1	0	3
2015–2019	1	1	0	0	0	1	1
2020–2024	0	0	0	1	0	0	1
2025	0	0	0	0	0	0	0

Extreme cold warnings

As of 2026, extreme cold warnings are issued in central and northern Minnesota if the temperature or wind chill value is less than or equal to -40°F (National Weather Service, n.d.-b; J. Moore, personal communication, July 21, 2026). Wind chill is a measure that combines air temperature and wind speed to reflect how cold conditions feel to humans. However, National Weather Service criteria have changed over time, and public documentation does not clearly describe these changes or explain how they are represented in the database (National Weather Service, 2021; J. Moore, personal communication, July 21, 2026), although events outside of the current criteria appear to be included. Reports of extreme cold warnings were obtained from the NOAA Storm Events Database for the period January 1996 to January 2026 (NCEI, 2026a; Table 6). During this period, over 50% of reported events occurred in January, followed by December, February, and March (Table 2). Annual days with a minimum temperature less than 32°F are provided for comparison from gridded observation and weather station data, respectively (Figure A34).

Table 6. Number of days with an extreme cold warning across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced an extreme cold warning.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	0	0	0	0	0	0	0
2005–2009	11	11	0	0	0	9	11
2010–2014	12	12	9	11	15	11	19
2015–2019	4	4	7	10	13	3	14
2020–2024	8	7	4	2	6	3	12
2025	3	4	2	1	2	1	5

Flash floods

Flash floods are rapid increases of fast-moving water, typically occurring in six or fewer hours, that inundate normally dry areas and often threaten life or property (National Weather Service, 2021). It is unclear whether the criteria for flash floods have changed over time, as public documentation does not describe revisions or explain how they would be reflected in the database (National Weather Service, 2021; J. Moore, personal communication, July 21, 2026). Reported flash flood events were obtained from the NOAA Storm Events Database for the period January 1996 to January 2026 (NCEI, 2026a; Table 7). During this period, most reported events occurred during the spring and summer with over 50% occurring during June and July (Table 2). Additional accounts of historical flash floods are available from the Minnesota Department of Natural Resources (Minnesota Department of Natural Resources, n.d. -a, n.d. -c; Minnesota State Climatology Office, n.d.).

Table 7. Number of days with a reported flash flood across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a flash flood.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	2	2	2	5	6	1	9
2005–2009	1	0	1	2	1	0	3
2010–2014	0	1	0	1	2	4	8
2015–2019	7	3	3	2	2	6	11
2020–2024	1	2	0	0	4	0	5
2025	0	0	0	0	0	0	0

Blizzards

Blizzard events are winter storms that last three or more hours with winds of at least 30 knots (35 mph) and falling or blowing snow that reduces visibility to less than 1/4 mile (National Weather Service, 2021). Criteria for blizzards may have changed over time, but public documentation does not describe any potential changes or how changes may reflect in the database (National Weather Service 2021; J. Moore, personal communication, July 21, 2026). Reported blizzards were obtained from the NOAA Storm Events Database for the period January 1996 to January 2026 (NCEI, 2026a; Table 8). During this period, 50% of reported events occurred in January, 25% in November, and 25% in December (Table 2).

Table 8. Number of days with a reported blizzard across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a blizzard.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	0	0	0	0	0	0	0
2005–2009	0	0	0	0	0	0	0
2010–2014	0	0	0	0	0	0	0
2015–2019	1	0	0	0	0	1	1
2020–2024	1	1	1	1	1	1	1
2025	0	0	0	0	0	0	0

Winter storms and heavy snow

Winter storm events are those in which snow accumulates 6 inches or more during a single event lasting no longer than 48 hours. Accumulation of 1/2 inch or more of sleet is also used as criteria for the Weather Forecast Office Twin Cities/Chanhassen (WFO MPX) which serves Kanabec, Mille Lacs, and Morrison counties. Additionally, a combination of snow, sleet, freezing rain, blowing snow, and/or wind leading to significant impacts can be reported as a winter storm event, at the discretion of the forecaster (National Weather Service, n.d.-d; J. Moore, personal communication, July 21, 2026).

Heavy snow is regionally defined as 6 inches or more within 48 hours (National Weather Service, n.d.-c). While these are the criteria for winter storms and heavy snow as of 2026, criteria may have changed over time and public documents do not clearly document the nature of these changes or their implementation within the database (National Weather Service, n.d.-d; J. Moore, personal communication, July 21, 2026). Reports of winter storms and heavy snow were obtained from the NOAA Storm Events Database during the period January 1996 to January 2026 (NCEI, 2026a; Tables 9 and 10). During this period, reported events occurred between October and April (Table 2). Gridded observation and station data for days with snow depth greater than 6 inches are provided for comparison (Figures A42–A46).

Table 9. Number of days with a reported winter storm event across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a winter storm.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	2	2	21	22	18	2	23
2005–2009	26	25	19	23	23	18	39
2010–2014	0	0	24	25	29	0	33
2015–2019	4	0	15	19	18	5	30
2020–2024	0	2	20	25	23	0	31
2025	0	0	8	6	7	0	11

Table 10. Number of days with a reported heavy snow event across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a heavy snow.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	15	14	0	2	2	20	26
2005–2009	7	3	5	5	5	7	15
2010–2014	29	27	1	1	1	36	48
2015–2019	32	28	1	1	1	23	40
2020–2024	29	29	0	0	0	25	39
2025	13	9	0	0	0	6	13

Ice storms

Ice storm events are reported when there is ice accretion of at least 1/4 inch, defined locally/regionally (National Weather Service n.d., -c; National Weather Service, 2021; J. Moore, personal communication, July 21, 2026). Criteria may have changed over time, but any previous revisions to ice storm criteria or how revisions are reflected in the database are unclear in publicly available documents (National Weather Service n.d., -c; J. Moore, personal communication, July 21, 2026). Reports of ice storms were obtained from the NOAA Storm Events Database during the period January 1996 to January 2026 (NCEI, 2026a; Table 11). During this period, reported events occurred in December, January, February, and April (Table 2). Sleet accumulations are reported separately from ice storm events; however, no sleet events were reported across the six counties. Additional accounts of historical ice storms, including those with less than 1/4 inch of accretion with community impacts, are available from the Minnesota Department of Natural Resources (Boulay, n.d.; Minnesota State Climatology Office, n.d.).

Table 11. Number of days with a reported ice storm across six Minnesota counties, summarized by five-year period (2000–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced an ice storm.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
2000–2004	6	6	0	0	0	4	7
2005–2009	0	0	0	0	0	0	0
2010–2014	3	4	0	0	0	0	4
2015–2019	0	2	0	0	0	0	2
2020–2024	0	0	0	0	0	3	3
2025	0	0	0	0	0	0	0

Thunderstorm winds

Thunderstorm winds are reported when (1) winds occur within 30 minutes of lightning being observed or detected and (2) wind speeds are greater than or equal to 50 knots (58 mph) or winds of any speed result in a fatality, injury, or damage (National Weather Service, 2021). Criteria for thunderstorm winds may have changed over time, but publicly available documentation does not provide sufficient information to determine whether such changes occurred or, if they did, how they are represented in the database (National Weather Service, 2021; J. Moore, personal communication, July 21, 2026). Reported thunderstorm winds were obtained from the NOAA Storm Events Database during the period January 1955 to January 2026 (NCEI, 2026a; Table 12). During this period, reported events occurred from March through October, gradually increasing until peaking in June, July, and August before declining (Table 2). Although the database is considered one of the most complete records of severe and significant weather in the United States, it does not include all relevant events. For example, a derecho that impacted all six counties in the study area occurred on July 4, 1977, but the database only reported the event in Mille Lacs and Pine counties (National Oceanic and Atmospheric Administration, n.d.; NCEI, 2026a).

Table 12. Number of days with reported thunderstorm wind events across six Minnesota counties, summarized by five-year period (1955–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a thunderstorm wind event.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
1955–1959	0	2	0	0	2	0	4
1960–1964	0	0	0	1	1	0	2
1965–1969	0	2	0	0	1	1	4
1970–1974	3	2	0	5	1	1	11
1975–1979	5	3	0	4	6	3	15
1980–1984	1	6	2	3	5	3	17
1985–1989	4	6	4	6	4	5	23
1990–1994	7	4	5	9	6	5	21
1995–1999	13	16	6	8	12	11	35
2000–2004	12	11	10	9	11	9	32
2005–2009	6	14	9	9	15	9	29
2010–2014	10	18	6	14	6	8	39
2015–2019	20	21	5	9	13	12	44
2020–2024	21	18	4	5	11	11	40
2025	4	4	0	1	2	0	8

Tornadoes

Reported tornadoes were obtained from the NOAA Storm Events Database during the period January 1950 to January 2026 (NCEI, 2026a; Table 13). During this period, reported events occurred between March and October (Table 2). June and July had the highest frequency of tornadoes, with each accounting for more than 30% of all tornado reports.

Table 13. Number of days with a reported tornado across six Minnesota counties, summarized by five-year period (1950–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a tornado.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
1950–1954	1	0	0	0	1	0	2
1955–1959	1	0	1	2	0	0	3
1960–1964	0	0	0	0	1	0	1
1965–1969	2	3	1	0	4	1	9
1970–1974	2	6	0	3	1	1	12
1975–1979	2	1	0	0	1	0	4
1980–1984	1	0	1	0	2	0	3
1985–1989	1	3	1	2	1	2	7
1990–1994	2	1	2	1	0	1	5
1995–1999	0	1	1	3	3	1	7
2000–2004	0	1	3	1	3	0	7
2005–2009	0	0	0	0	0	1	1
2010–2014	2	0	0	1	2	2	6
2015–2019	2	1	1	1	1	0	4
2020–2024	2	2	0	0	3	2	7
2025	0	1	0	0	0	0	1

Hail

As of 2026, reported hail events are those that include falling frozen precipitation in the form of balls or irregular lumps of ice that are greater than or equal to 0.75 inch in diameter, any size hail that accumulates approximately 3 inches deep, or any size hail that causes property or crop damage (National Weather Service, 2021). Reported hail events were obtained from the NOAA Storm Events Database during the period January 1955 to January 2026 (NCEI, 2026a; Table 14). During this period, reported events occurred from March through November, with the highest frequency during summer (Table 2). All but one reported event had a recorded hail magnitude of at least 0.75 inches, the exception was a recorded hail event during 1971 with a magnitude of 0 inches. This record was retained because it likely reflected data entry practices at the time rather than an actual hail size measurement. Although days with reported hail events have generally increased within the six counties since 1955, it is important to recognize the nonmeteorological factors that contribute to this trend (see Limitations: Historical hazard reports section).

Table 14. Number of days with reported hail events across six Minnesota counties, summarized by five-year period (1955–2024) and 2025. The Total column represents the total number of unique days during which at least one of the six counties experienced a hail event.

Time Period	Aitkin	Crow Wing	Kanabec	Mille Lacs	Morrison	Pine	Total
1955–1959	0	0	0	0	0	1	1
1960–1964	0	0	0	0	1	0	1
1965–1969	0	0	0	0	1	1	2
1970–1974	1	1	1	1	0	1	5
1975–1979	2	3	3	2	5	2	15
1980–1984	1	5	3	1	3	1	8
1985–1989	4	9	2	5	7	6	21
1990–1994	4	7	0	3	9	4	21
1995–1999	3	16	7	10	18	10	35
2000–2004	4	6	10	9	13	17	33
2005–2009	11	10	4	13	17	6	42
2010–2014	9	16	11	7	11	18	42
2015–2019	19	21	4	10	11	14	48
2020–2024	12	15	6	6	11	14	33
2025	4	3	0	1	0	1	7

Annual wildfires

There are no wildfires reported in the NOAA Storm Events Database for any of the six counties between January 1996 to February 2026 (NCEI, 2026a). Data on smaller-scale wildfires may be available from local sources.

Air quality

The U.S. Air Quality Index (AQI) is a tool developed by the Environmental Protection Agency (EPA) to communicate outdoor air quality and associated public health impacts related to five pollutants: ozone, particulate matter, carbon monoxide, nitrogen dioxide (NO₂), and sulfur dioxide (EPA, 2026c). AQI values are organized into six categories, with higher AQI values corresponding to greater levels of air pollution and health risks (EPA, 2026c; Table 15). To help assess these risks within Minnesota, annual ambient air quality data were obtained from the EPA's Air Quality System (AQS) repository (EPA, 2026b; Table 16).

Table 15. Air Quality Index (AQI) categories with corresponding values and air quality description. Table adapted from EPA (n.d.).

Levels of Concern	Values of Index	Descriptions of Air Quality
Good	0 to 50	Air quality is satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable. However, there may be a risk for some people, particularly those who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is less likely to be affected.
Unhealthy	151 to 200	Some members of the general public may experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: The risk of health effects is increased for everyone.
Hazardous	301 and higher	Health warning of emergency conditions: everyone is more likely to be affected.

The AQS repository stores data from over 10,000 monitors in the United States, 5,000 of which are currently active. Approximately 1/3 of counties in the United States have monitoring data, but not all measure every pollutant or collect data every day. Annual summary data were obtained for counties of interest, when available. However, Morrison, and Pine counties were excluded as only limited data were available between 1995 and 2004, with 100% of monitored days considered within a “Good” AQI level. Although air quality issues in Minnesota were notable at individual stations during 2025 (EPA, 2026a), primarily due to Canadian wildfires, data from this year were excluded as county-level summary data were not yet available at the time of analysis.

To highlight the non-continuous nature of data collection, the tables include the percent of days that data were collected within the time period. Table 17 presents the percent of days during which a given pollutant had the highest AQI value of all measured pollutants. These data should be interpreted with care because a pollutant with the highest AQI value does not necessarily indicate that it was an unhealthy AQI nor that another pollutant did not have a similar AQI value.

Table 16. Air Quality Index (AQI) data for two Minnesota counties, summarized by five-year period (1995–2024). Data Collection Days represent the number of days during which measurements from any monitoring site in the county were reported to the AQS database, those days are also reported as a percent of the total days within the time period. The remaining entries represent the percent of measured days within a given AQI range: Good (0 through 50), Moderate (51 through 100), Unhealthy for Sensitive Groups (101 through 150), Unhealthy (151 through 200), Very Unhealthy (201 through 300), and hazardous (≥ 301).

County	Metric	1995–1999	2000–2004	2005–2009	2010–2014	2015–2019	2020–2024
Crow Wing	Data Collection Days	0	235	1744	1770	1793	1812
Crow Wing	Data Collection Days (%)	0	21.4	95.5	96.9	98.2	99.2
Crow Wing	Good Days (%)	-	89.4	69.4	79.2	85.6	82.4
Crow Wing	Moderate Days (%)	-	9.8	29.6	20.6	14.2	16.8
Crow Wing	Unhealthy for Sensitive Groups Days (%)	-	0.9	0.9	0.2	0.2	0.6
Crow Wing	Unhealthy Days (%)	-	0	0.1	0	0	0.2
Crow Wing	Hazardous Days (%)	-	0	0	0	0	0
Mille Lacs	Data Collection Days	312	1170	1170	1057	1047	952
Mille Lacs	Data Collection Days (%)	28.5	64	64.1	57.9	57.3	52.1
Mille Lacs	Good Days (%)	84.6	77.6	81.4	96.5	95.7	95.5
Mille Lacs	Moderate Days (%)	12.2	21.1	17.5	3.3	4.3	4
Mille Lacs	Unhealthy for Sensitive Groups Days (%)	2.9	1.1	0.9	0.2	0	0.5
Mille Lacs	Unhealthy Days (%)	0.3	0.2	0.2	0	0	0
Mille Lacs	Hazardous Days (%)	0	0	0	0	0	0

Table 17. Air Quality Index (AQI) data for two Minnesota counties, summarized by five-year period (1995–2024). Data Collection Days represent the number of days during which measurements from any monitoring site in the county were reported to the AQS database, those days are also reported as a percent of the total days within the time period. The remaining entries represent the percent of measured days during which the pollutant had the highest AQI value of all measured pollutants.

County	Metric	1995–1999	2000–2004	2005–2009	2010–2014	2015–2019	2020–2024
Crow Wing	Data Collection Days	0	235	1744	1770	1793	1812
Crow Wing	Data Collection Days (%)	0	21.4	95.5	96.9	98.2	99.2
Crow Wing	Days CO (%)	-	0	0	0	0	0
Crow Wing	Days NO ₂ (%)	-	0	0	0	0	0
Crow Wing	Days Ozone (%)	-	76.2	31.4	42.5	41.9	47.6
Crow Wing	Days PM _{2.5} (%)	-	17	68.6	57.5	58.1	52.4
Crow Wing	Days PM ₁₀ (%)	-	6.8	0	0	0	0
Mille Lacs	Data Collection Days	312	1170	1170	1057	1047	952
Mille Lacs	Data Collection Days (%)	28.5	64	64.1	57.9	57.3	52.1
Mille Lacs	Days CO (%)	0	0	0	0	0	0
Mille Lacs	Days NO ₂ (%)	0	0	0	0	0	0
Mille Lacs	Days Ozone (%)	72.8	68.1	68.1	100	100	100
Mille Lacs	Days PM _{2.5} (%)	1.3	30.6	31.9	0	0	0
Mille Lacs	Days PM ₁₀ (%)	26	1.3	0	0	0	0

Ice in and ice out

Date of ice in and ice out as reported by the Minnesota Department of Natural Resources and Minnesota Pollution Control Agency (Minnesota Department of Natural Resources, 2026; Figure 7). The criteria for ice in and ice out can vary by lake but remains consistent over the years. For example, ice out is recorded by citizen observers as the first date the lake is completely free of ice, 90% free, or when it is possible to navigate between designated points. Ice in is recorded by citizen observers as the first date when the entire lake is frozen over and remains covered through the winter. Data were reported non-continuously for Big Sandy Lake (in Aitkin County) from 1930–2026 and for Mille Lacs Lake (in Aitkin, Crow Wing, and Mille Lacs counties) from 1950–2026 (Minnesota Department of Natural Resources, 2026).

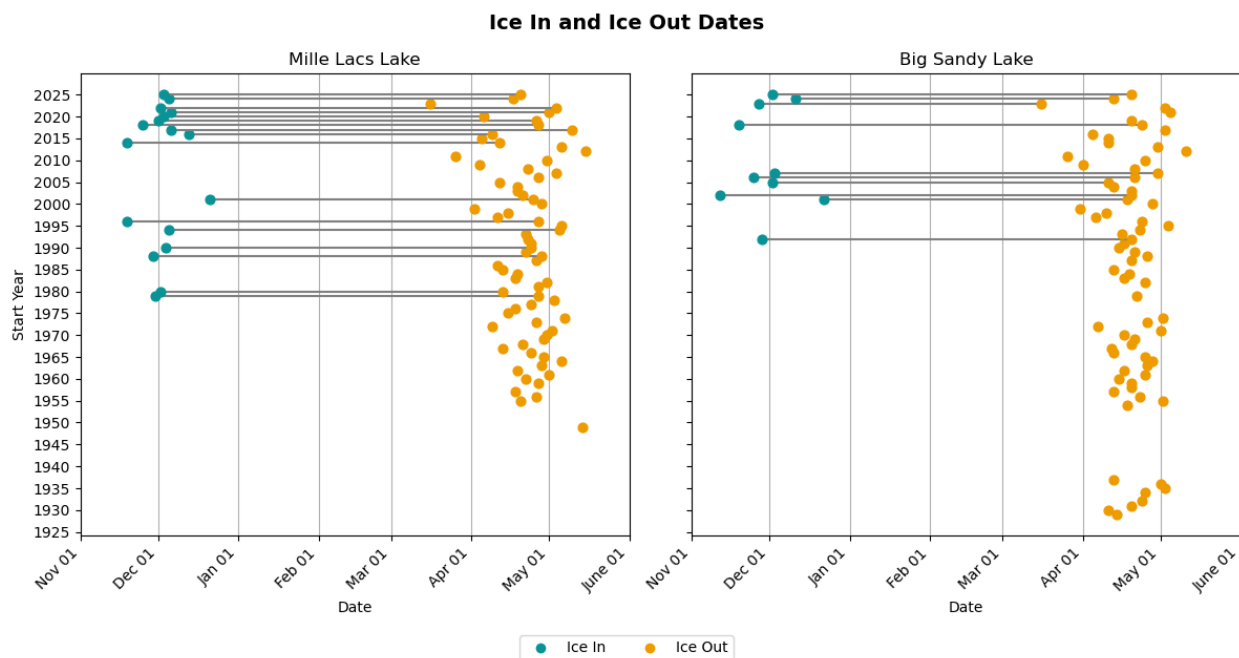


Figure 7. Reported ice in and ice out dates for Big Sandy Lake and Mille Lacs Lake. Winter seasons with both observations are connected by a line representing ice duration.

Climate Indicators

The following analysis shows how period-average climate conditions are projected to change through the mid-21st century over a range of plausible modeling and emissions scenarios. Several sources of information are incorporated to provide cross validation. Differences in datasets are discussed in the Limitations section. Additional analysis and comparisons to weather station data are available in Appendix A.

Data were presented in two main formats: annual timeseries and period average boxplots. To aid in their interpretation, generalized examples and descriptions are provided (Figures 8 and 9). Timeseries plots show the median value (50th percentile—dark lines) across the model ensemble (all included models) as well as the observational data (Figure 8). Shaded regions show the maximum and minimum annual model value across the full ensemble. The same ensemble member will not represent the minimum or maximum value across the entire record (e.g., a given model within the ensemble could represent the minimum value in one year and the maximum value in another). This figure type illustrates the general trend in model projections across the ensemble and between emissions scenarios (distinguished by color) as compared to observational data. No smoothing or moving average is applied to the model values across time. It is important not to interpret individual annual values as a prediction of values for a given year.

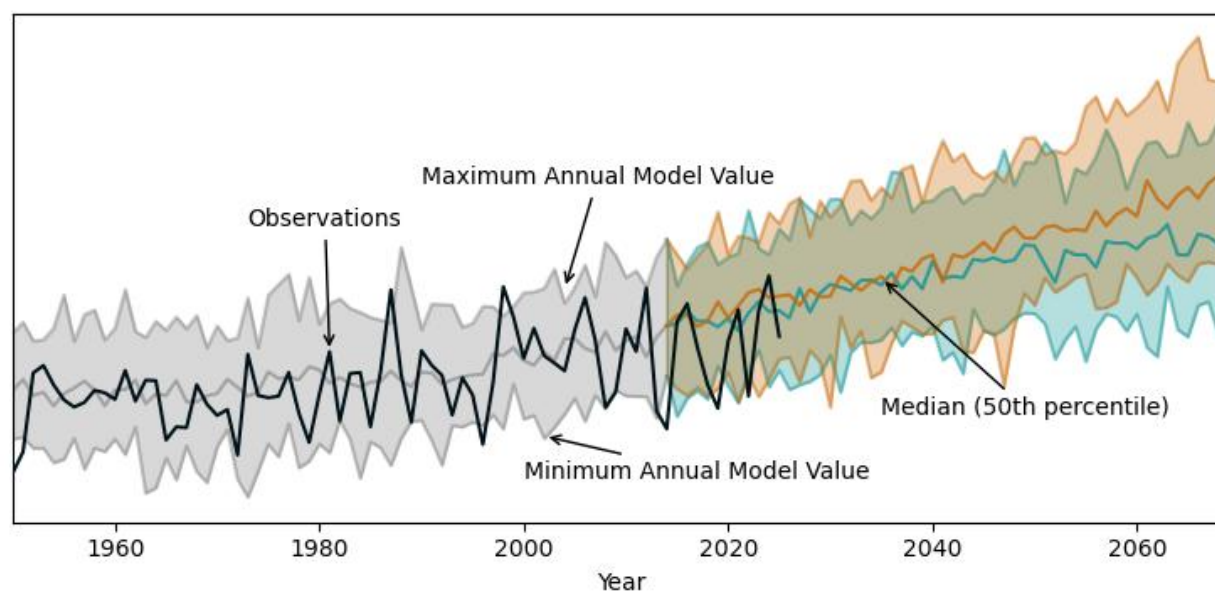


Figure 8. Example of time series plot with all major features labeled.

Boxplots show the median (50th percentile—middle line), 25th percentile (bottom of box), and 75th percentile (top of the box; Figure 9). The whiskers extend to data that fall within $1.5 \times (75\text{th percentile} - 25\text{th percentile, interquartile range [IQR]})$. Open circles show

data points that fall outside this range. Period averages are shown when they are pre-calculated in the given dataset or are calculable based on the period of record.

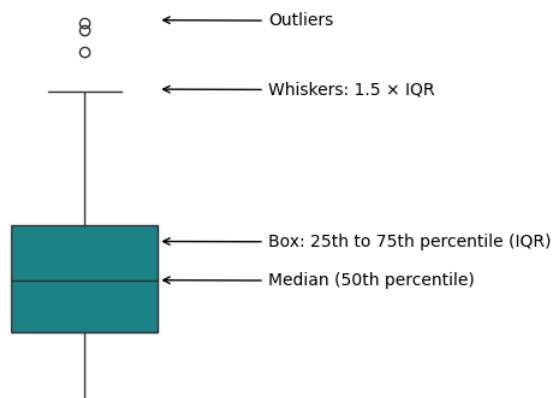


Figure 9. Example of boxplot with all major features labeled. IQR, interquartile range.

Annual and seasonal mean daily maximum temperature

Timeseries plots are provided for both annual (January–December; Figures 10 and 11) and seasonal (summer: June–August; winter: December–February; Figures 12–15) conditions. Annual and seasonal values were calculated using monthly average daily maximum temperature. For the winter season, values were assigned to the year containing January and February (e.g., December 1970–February 1971 was assigned to 1971). Comparisons of gridded observation and station data are shown in Appendix A (Figures A1–A3). Future average annual, summer, and winter maximum temperature is projected to increase in all future time periods and under both the moderate (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emissions scenarios.

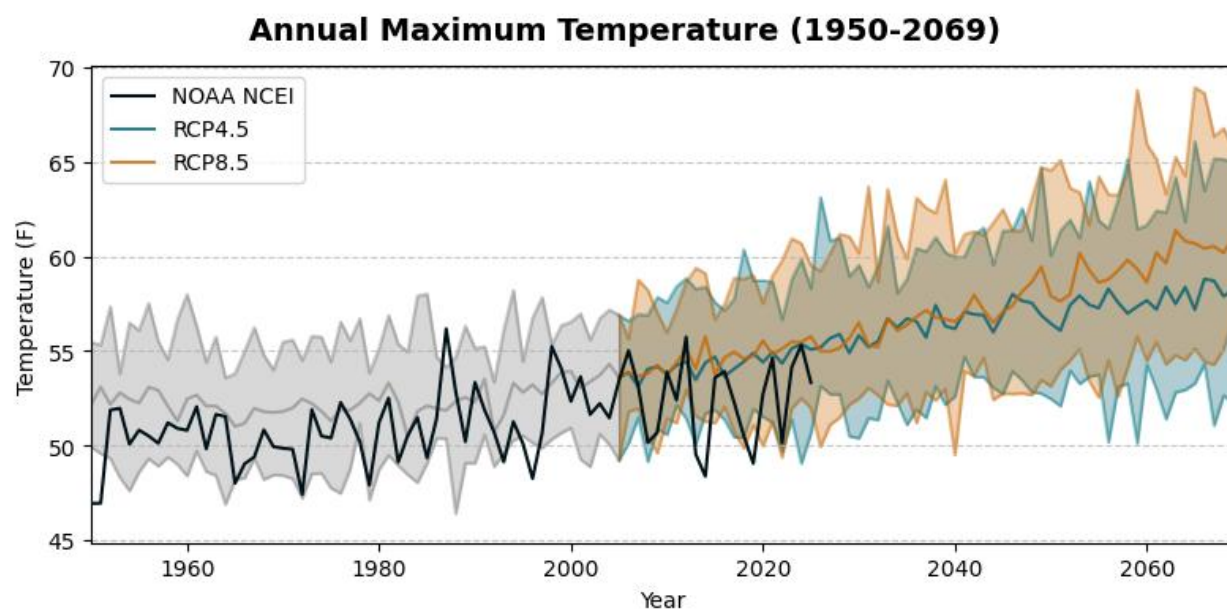


Figure 10. Annual average maximum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

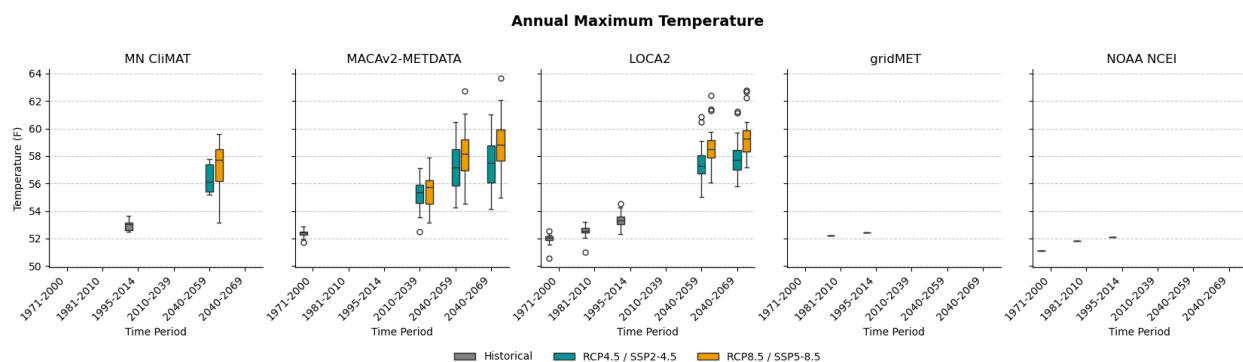


Figure 11. Comparison of period averages of annual average maximum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

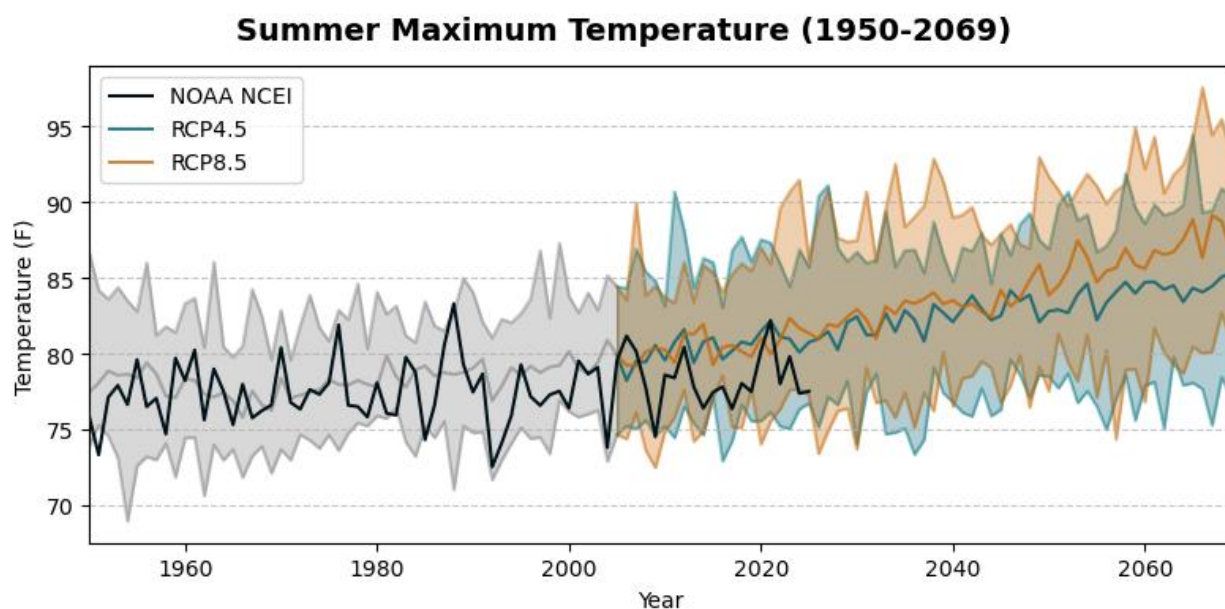


Figure 12. Summer (June–August) average maximum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

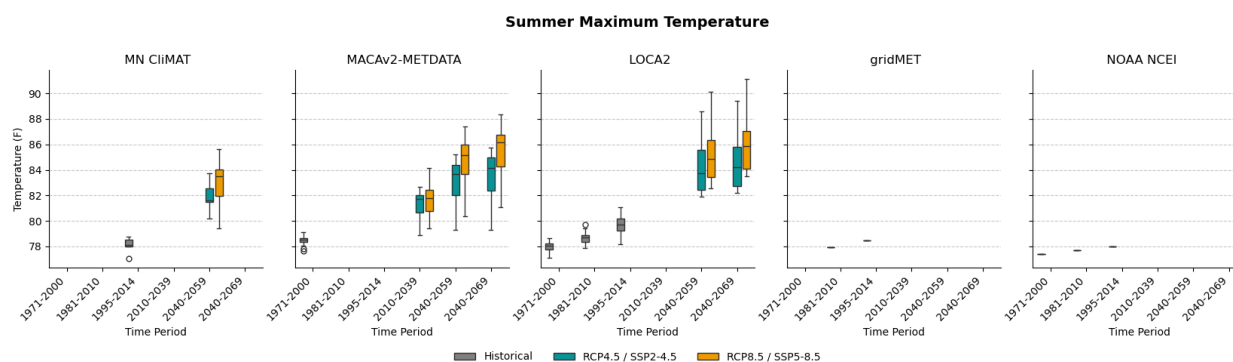


Figure 13. Comparison of period averages of summer (June–August) average maximum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

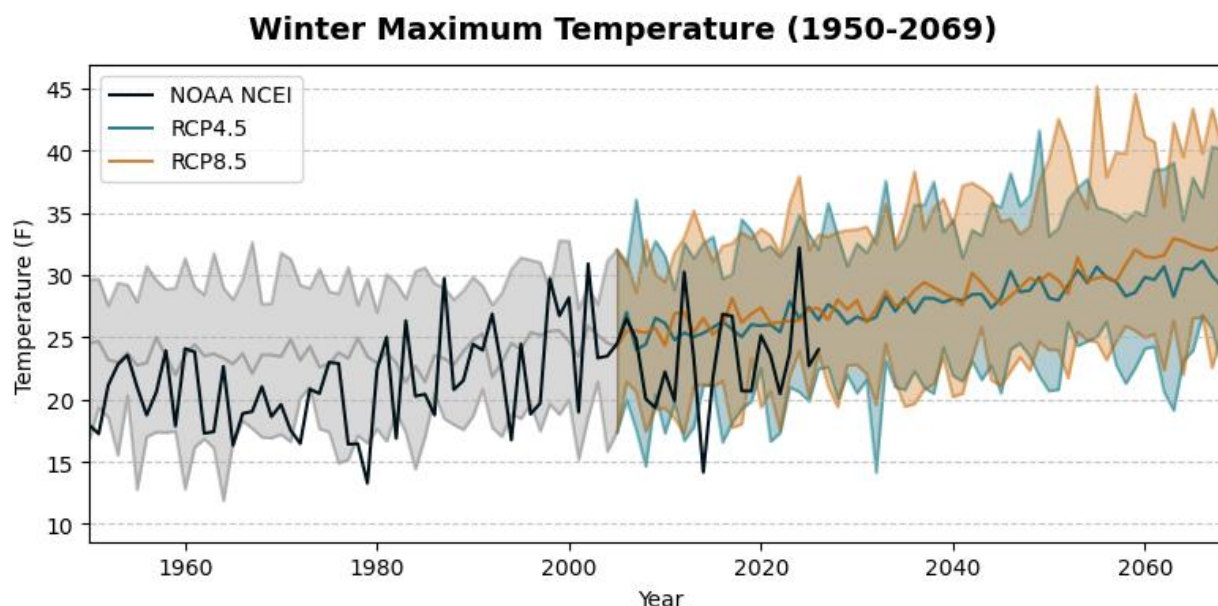


Figure 14. Winter (December–February) average maximum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical ($n=1$).

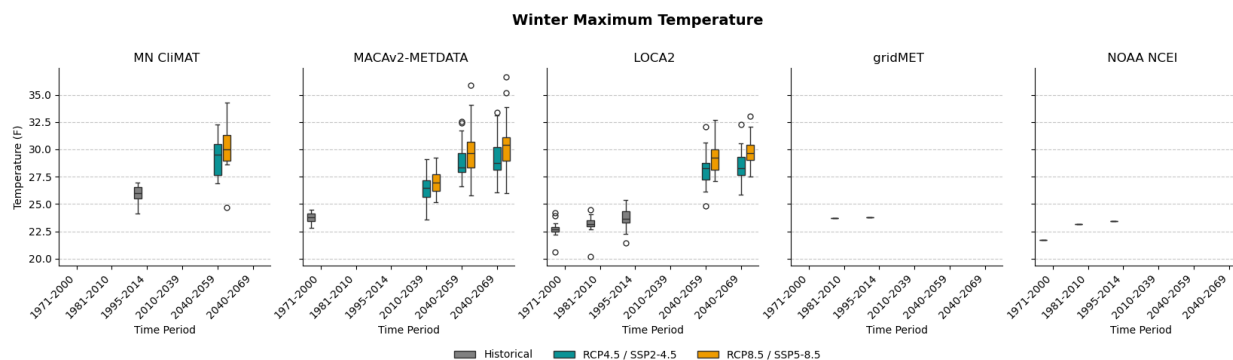


Figure 15. Comparison of period averages of winter (December–February) average maximum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CLiMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CLiMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

Annual hot days

Annual counts of hot days reflect the number of days in which the daily maximum temperature exceeded a specified temperature threshold. Values for days with a maximum temperature greater than or equal to 100°F (Figure 16 and 17) and 105°F (Figure 18 and 19) are shown here. Additional figures for 90°F and 95°F are in Appendix A (Figures A4–A7). Comparisons of gridded observation and station data are shown in Appendix A (Figures A8–A11).

Future average annual number of extremely hot days (days greater than or equal to 100°F and 105°F) is projected to increase in all future time periods and under both the moderate (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emissions scenarios. The model ensembles show a wide range of projections with substantial interannual variability. Additionally, there has been a documented warm bias in extreme temperatures in projection products including LOCA2 (Ulrich, 2023). This bias seems supported by trends and incidence counts in observational data (Figures 16–19 and Figures A8–A11).

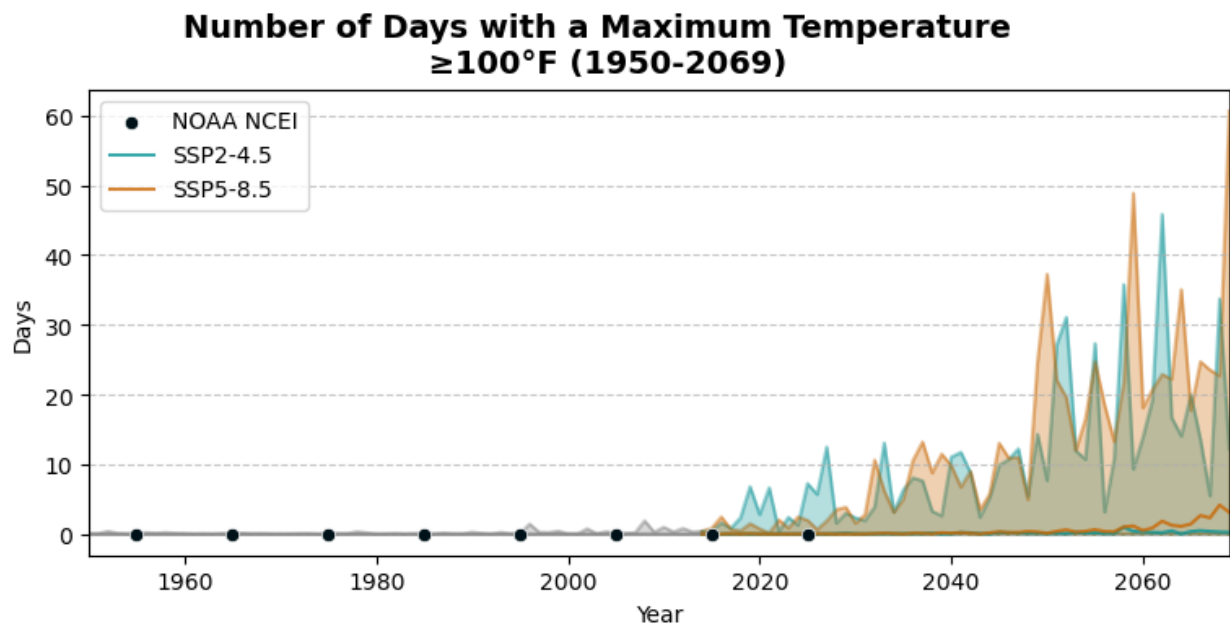


Figure 16. Annual total days with a maximum temperature greater than or equal to 100°F from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

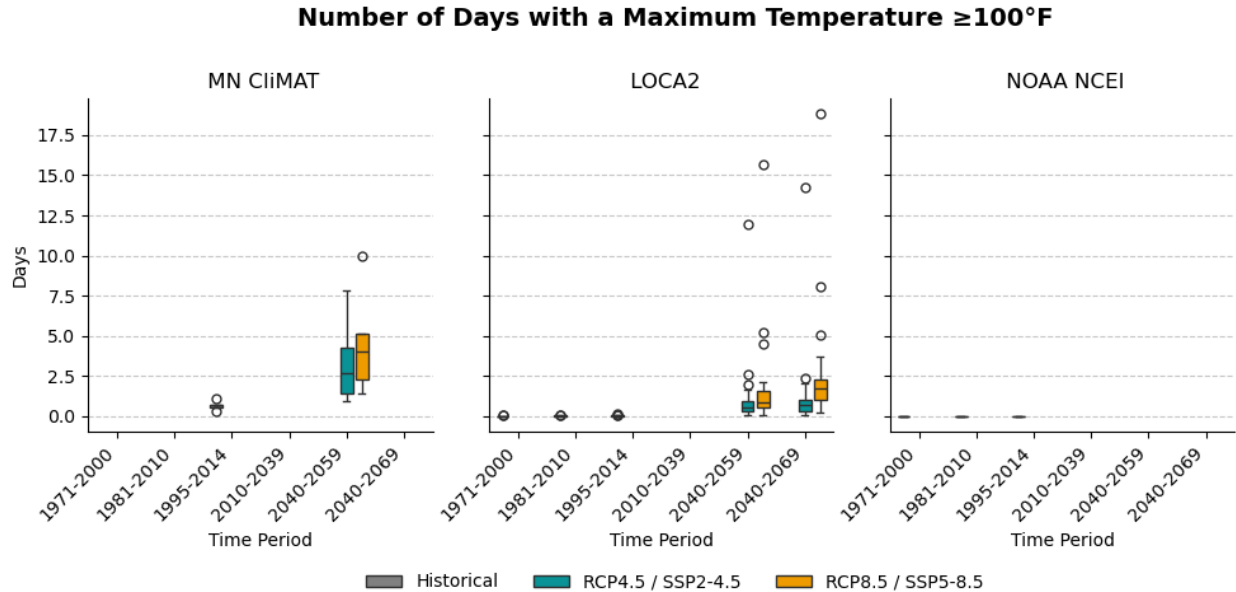


Figure 17. Comparison of period averages of annual total days with a maximum temperature greater than or equal to 100°F across datasets. Note that MN CliMAT data are days greater than 100°F . Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$ and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

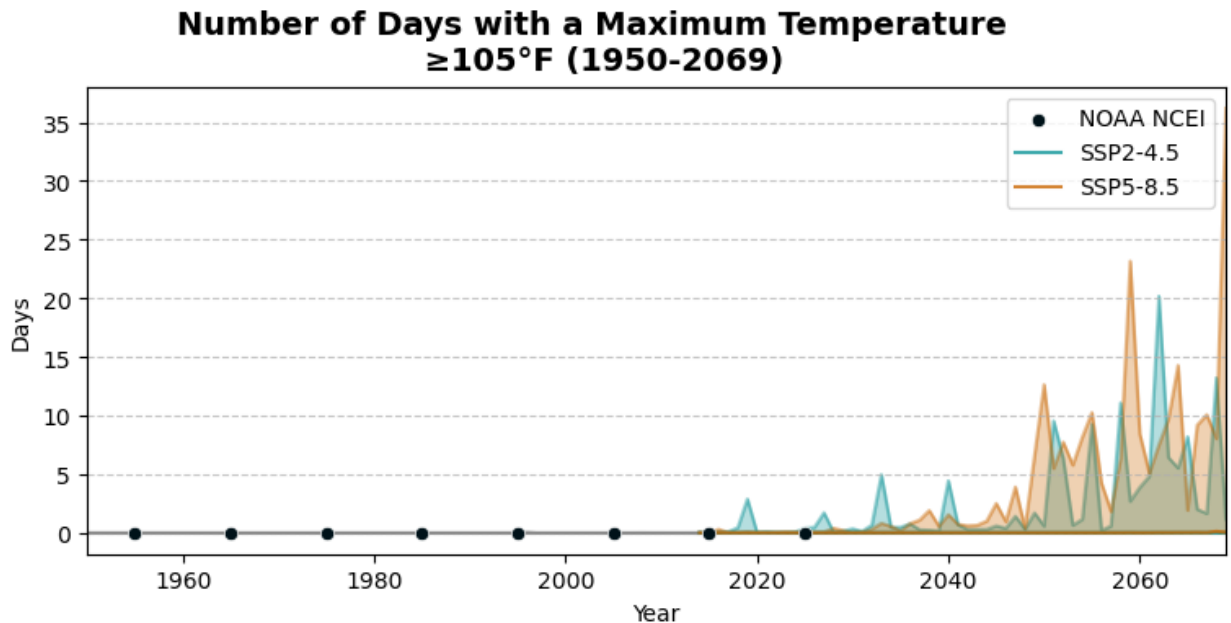


Figure 18. Annual total days with a maximum temperature greater than or equal to 105°F from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

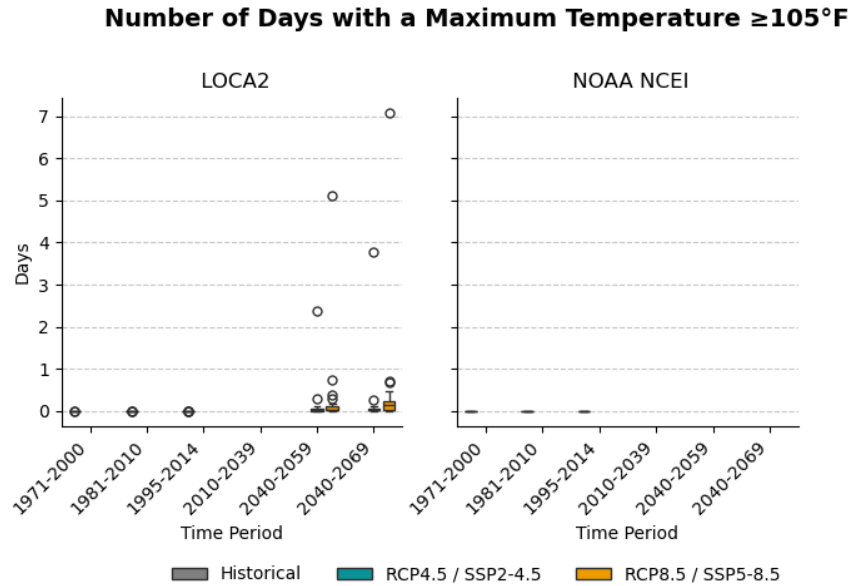


Figure 19. Comparison of period averages of annual total days with a maximum temperature greater than or equal to 105°F across datasets. Boxplots summarize the variation among climate simulations (LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include LOCA2 = SSP.

Several datasets (MACAv2-METDATA and gridMET) show historical and projected values of heat index for days April–October rather than annual maximum temperature days. Values for maximum heat index greater than or equal to 100°F (Figure 20) and 105°F (Figure 21) are shown here. Additional figures for 90°F are in Appendix A (Figure A12).

Heat index incorporates relative humidity and may be a more physiologically relevant metric for human heat stress (Mora et al., 2017; Hondula et al., 2022). In the MACAv2-METDATA and gridMET data, heat index was calculated using the daily maximum temperature and daily minimum relative humidity based on the National Weather Service standard equations (National Weather Service, 2022). This use of daily values does not capture sub-daily extremes which can cause substantial physiological stress and assumes that the daily maximum temperature and daily minimum relative humidity occur at the same time. The National Weather Service also notes that heat index equations were developed for shady conditions with light wind (National Weather Service, n.d.-a).

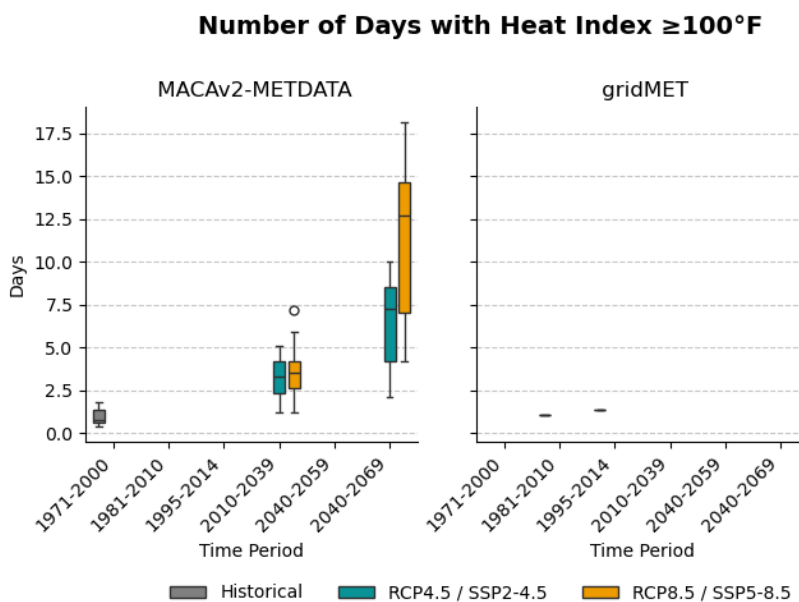


Figure 20. Comparison of period averages of annual total days from April–October with heat index greater than or equal to 100°F across datasets. Boxplots summarize the variation among climate simulations (MACAv2-METDATA $n=20$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MACAv2-METDATA = RCP.

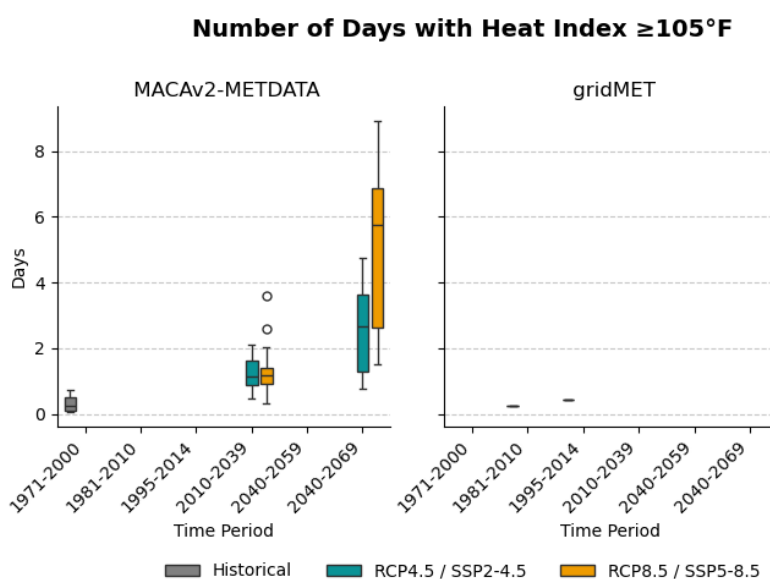


Figure 21. Comparison of period averages of annual total days from April–October with heat index greater than or equal to 105°F across datasets. Boxplots summarize the variation among climate simulations (MACAv2-METDATA $n=20$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MACAv2-METDATA = RCP.

Annual and seasonal average daily mean temperature

Timeseries plots are provided for both annual (January–December; Figures 22 and 23) and seasonal (summer: June–August; winter: December–February) conditions (Figures A13–A16). Annual and seasonal values were calculated using monthly average daily mean temperature. For the winter season, values were assigned to the year containing January and February (e.g., December 1970–February 1971 was assigned to 1971). Comparisons of gridded observation and station data are shown in Appendix A (Figures A17–A19).

Future average annual, summer, and winter mean temperature is projected to increase in all future time periods and under both the moderate (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emissions scenarios. In all future time periods in either emissions scenario, the multi-model ensemble spread of annual mean temperature exceeds the maximum individual model average in the historical period. A similar trend is projected for average summer mean temperature.

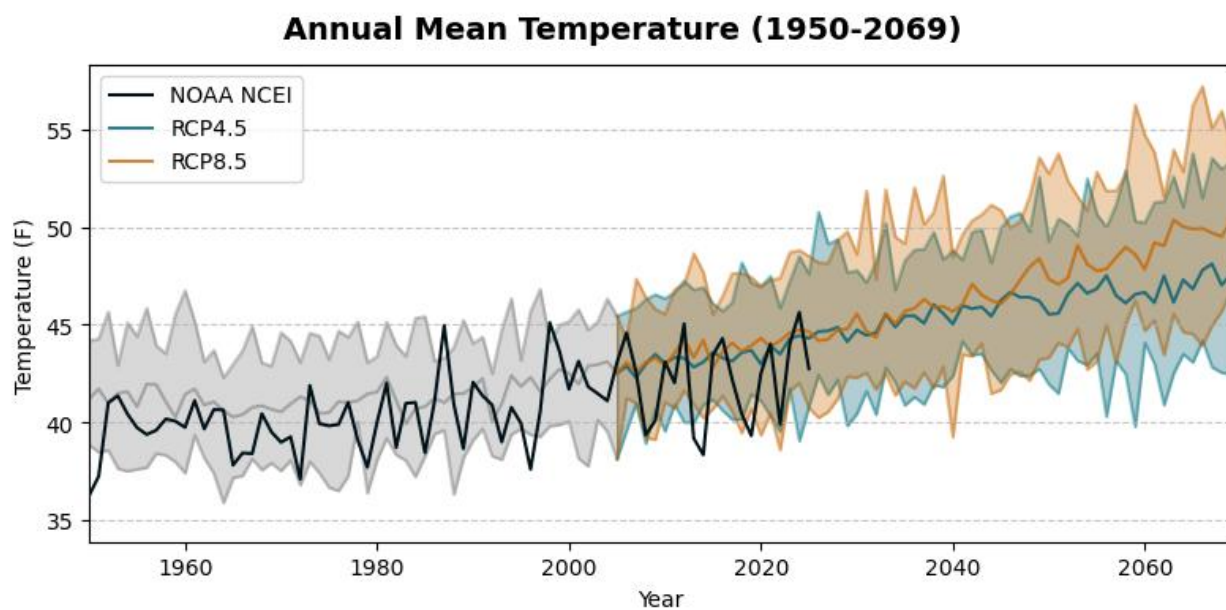


Figure 22. Annual average mean temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

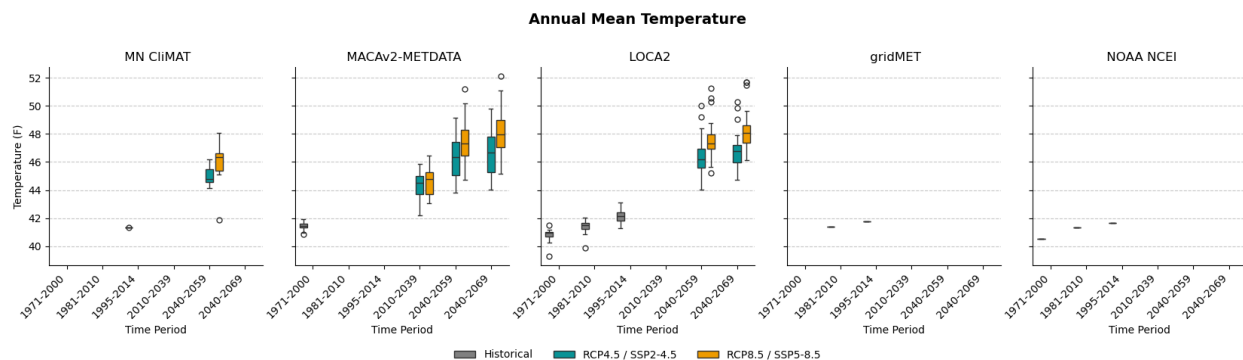


Figure 23. Comparison of period averages of annual average mean temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

Annual and seasonal mean daily minimum temperature

Timeseries plots are provided for both annual (January–December; Figures 24 and 25) and seasonal (summer: June–August; winter: December–February; Figures A20–A23) conditions. Annual and seasonal values were calculated using monthly average daily minimum temperature. For the winter season, values were assigned to the year containing January and February (e.g., December 1970–February 1971 was assigned to 1971). Comparisons of gridded observation and station data are shown in Appendix A (Figures A24–A26).

Future average annual, summer, and winter minimum temperature is projected to increase in all future time periods and under both the moderate (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emissions scenarios. In all future time periods in either emissions scenario the multi-model ensemble spread of annual minimum temperature exceeds the maximum individual model average in the historical period. A similar trend is projected for average summer minimum temperature and average winter minimum temperature (in MACAv2-METDATA and LOCA2 ensembles).

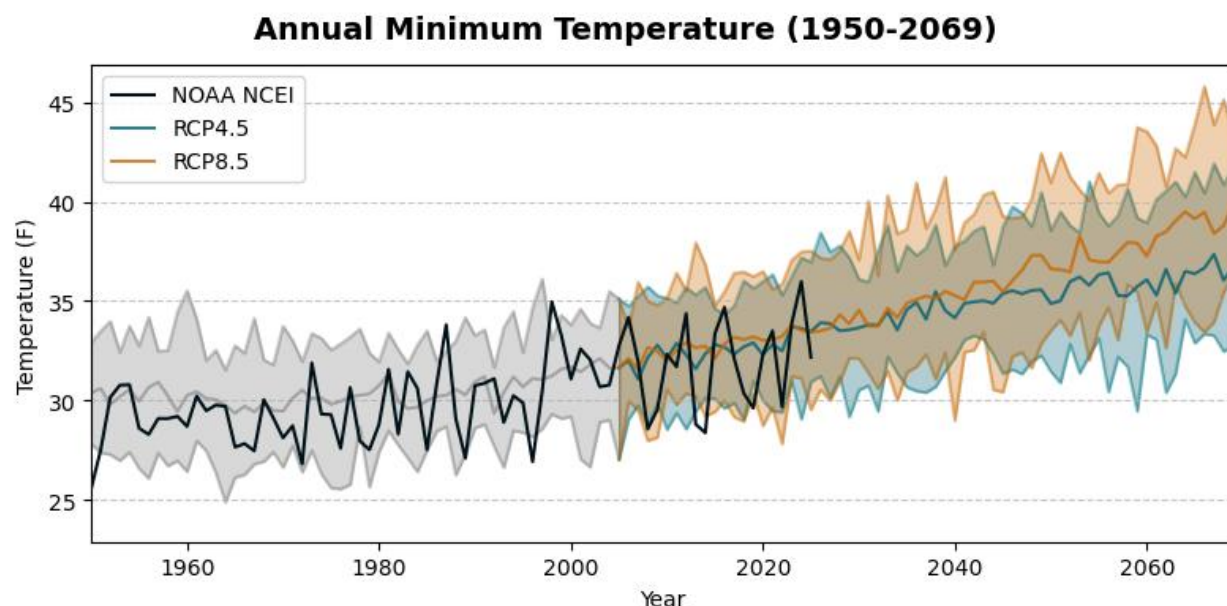


Figure 24. Annual average minimum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

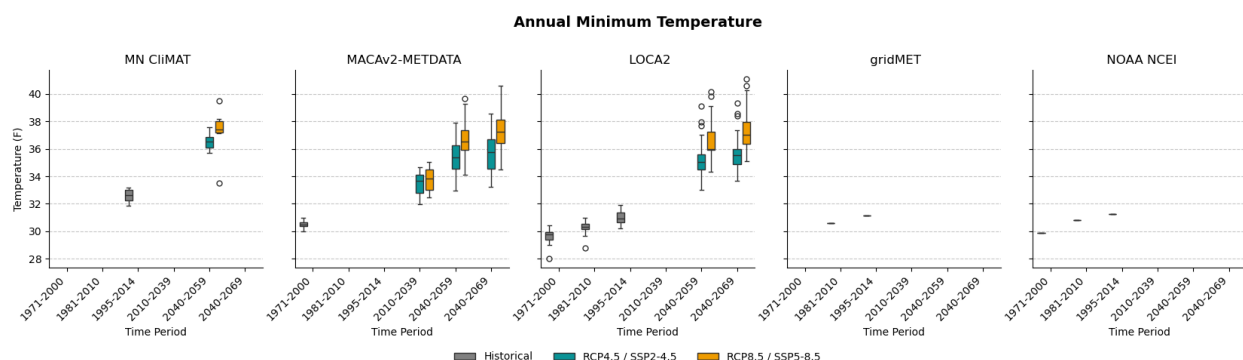


Figure 25. Comparison of period averages of annual average minimum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

Annual and seasonal total precipitation

Annual (January–December; Figures 26–27) and seasonal (summer: June–August; winter: December–February; Figures A27–A30) total precipitation is calculated using monthly total daily precipitation. For the winter season, the year is assigned based on January–February (e.g., December 1970–February 1971 was assigned to 1971). Comparisons of gridded observation and station data are shown in Appendix A (Figures A31–A33).

Precipitation changes are uncertain. Model spread is large enough that changes relative to the historical period cannot be stated with confidence. In general, the annual total multi-model mean shows a small increase from historical to future time periods under both emissions scenarios, but the spread is large. Because each of the included models are plausible, this suggests that the future precipitation amounts could either increase or decrease. The same model spread and uncertainty associated with the annual precipitation is apparent in the summer precipitation projections with the multi-model mean showing a small decrease with large ensemble spread. Winter precipitation shows a stronger increasing trend in precipitation with only a handful of models projecting decreases. This variability in the seasonal projections shows the importance of examining seasonal values as well as annual values.

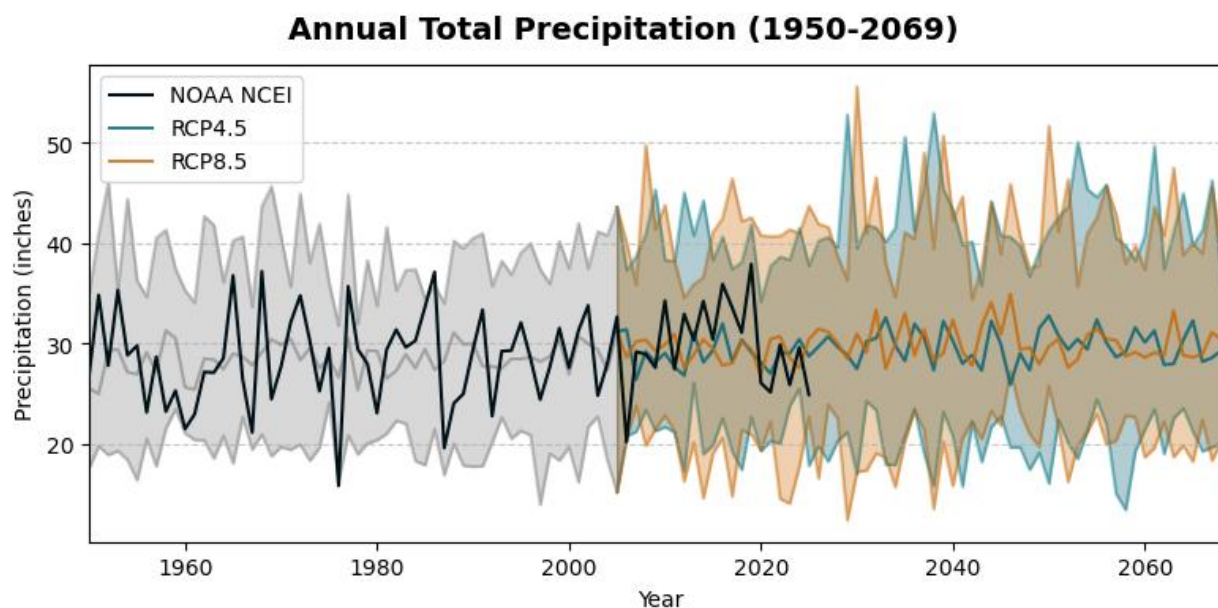


Figure 26. Annual total precipitation from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

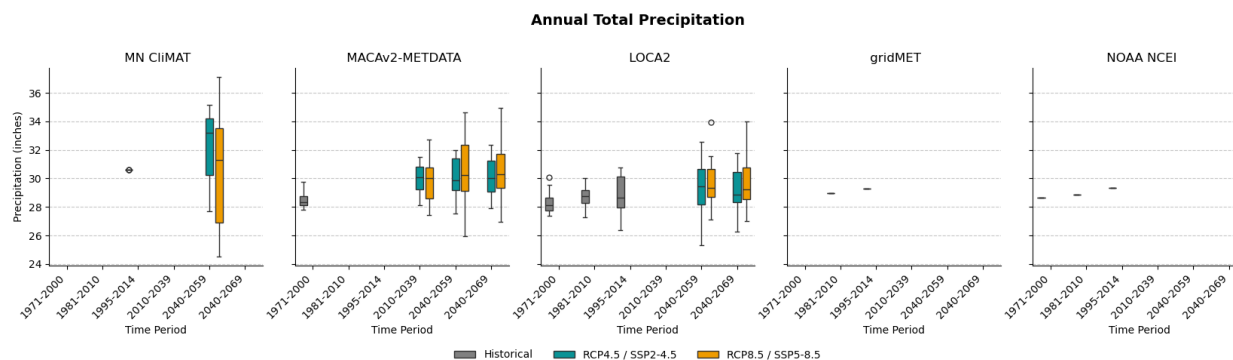


Figure 27. Comparison of period averages of annual total precipitation across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

Freeze days

Annual counts of days with freezing temperatures were calculated using daily minimum temperature (Figures 28 and 29). Comparisons of gridded observation and station data are shown in Appendix A (Figure A34).

Future average annual number of freeze days (days less than 32°F) is projected to decrease in all future time periods and under both the moderate (RCP4.5/SSP2-4.5) and high (RCP8.5/SSP5-8.5) emissions scenarios.

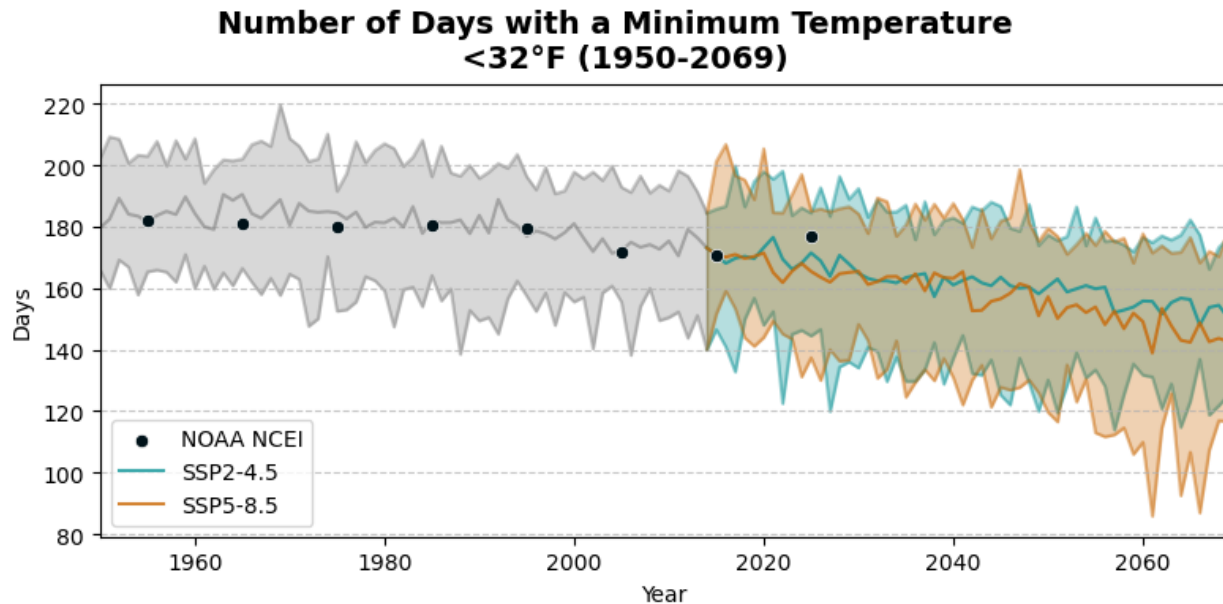


Figure 28. Annual total days with a minimum temperature less than 32°F from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$). NOAA NCEI nClimGrid-monthly values are days with a minimum temperature less than or equal to 32°F.

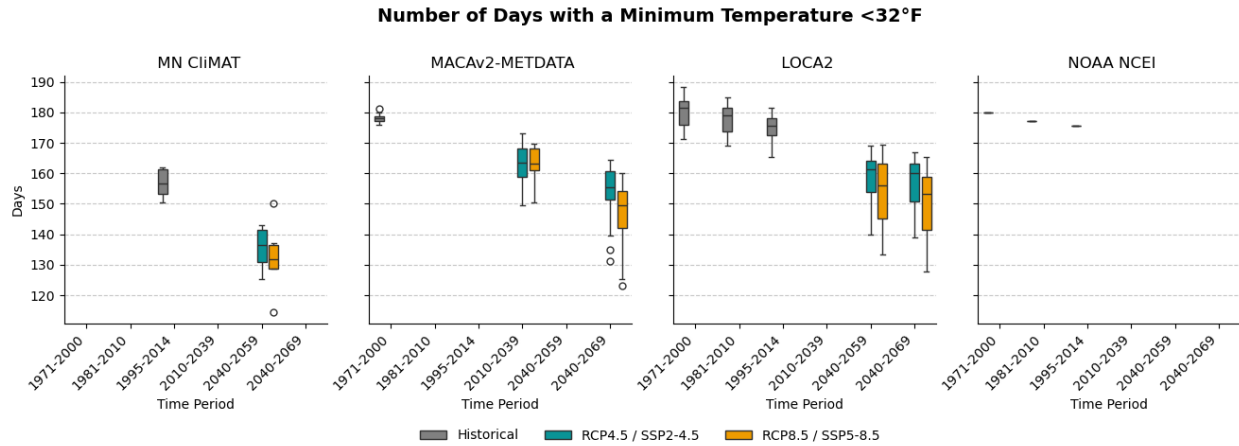


Figure 29. Comparison of period averages of annual total days with a minimum temperature less than 32°F across datasets. NOAA NCEI nClimGrid-monthly values are days with a minimum temperature less than or equal to 32°F. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

Extreme precipitation

Annual counts of days with extreme precipitation were calculated using daily precipitation. Daily thresholds are set at 1 inch (Figures 30 and 31) and 2 inches (Figures 32 and 33). Comparisons of gridded observation and station data are shown in Appendix A (Figures A35 and A36). Additionally, maximum precipitation totals over a 1-day period (Figures 34 and 35) and a 5-day period (Figures 36 and 37) are plotted.

Precipitation changes are uncertain. Model spread is large enough that changes relative to the historical period cannot be stated with confidence. In general, the multi-model mean days with extreme precipitation (greater than 1 inch and greater than 2 inches) show a small increase from historical to future time periods under both emissions scenarios, but the spread is large. Because each of these models are plausible, this spread suggests that precipitation extremes could either increase, decrease, or remain steady. The same model spread and uncertainty associated with the threshold precipitation days exists in the maximum period precipitation data (1-day and 5-day maximum annual precipitation).

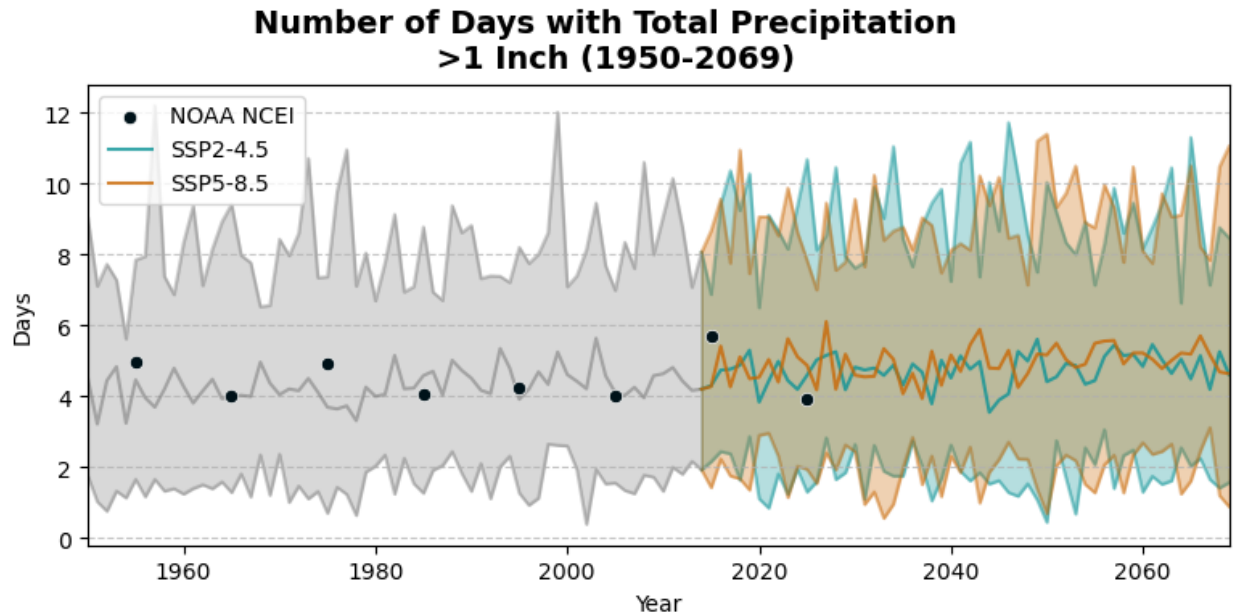


Figure 30. Annual total days with precipitation greater than 1 inch from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$). NOAA NCEI values are days with precipitation greater than or equal to 1 inch.

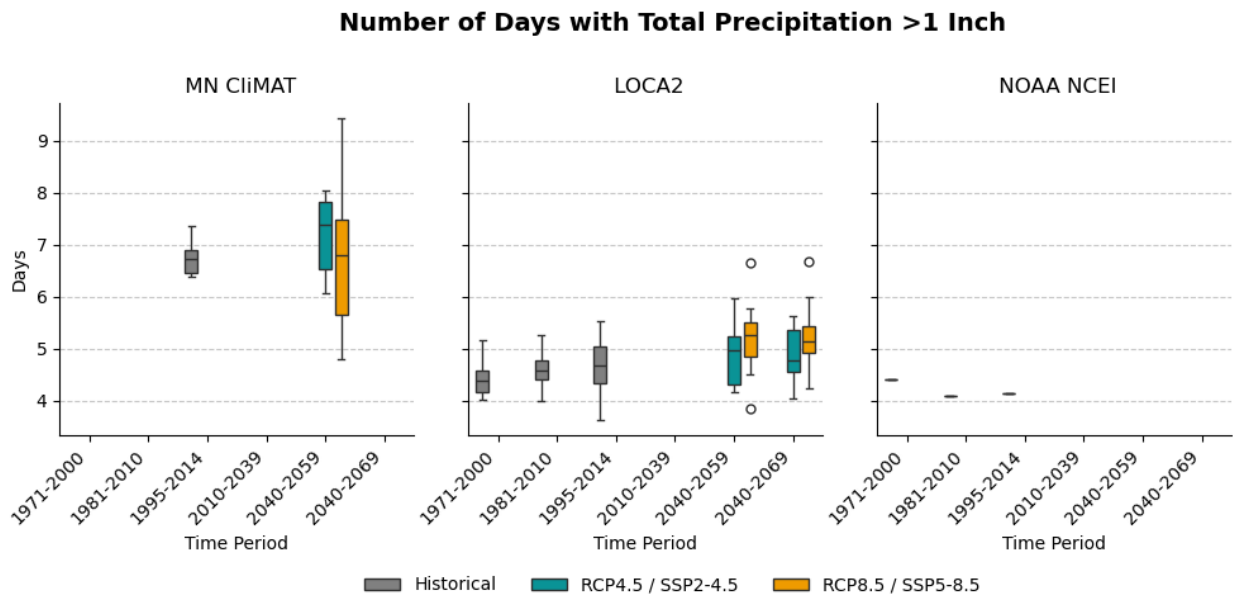


Figure 31. Comparison of period averages of annual total days with precipitation greater than 1 inch across datasets. NOAA NCEI values are days with precipitation greater than or equal to 1 inch. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

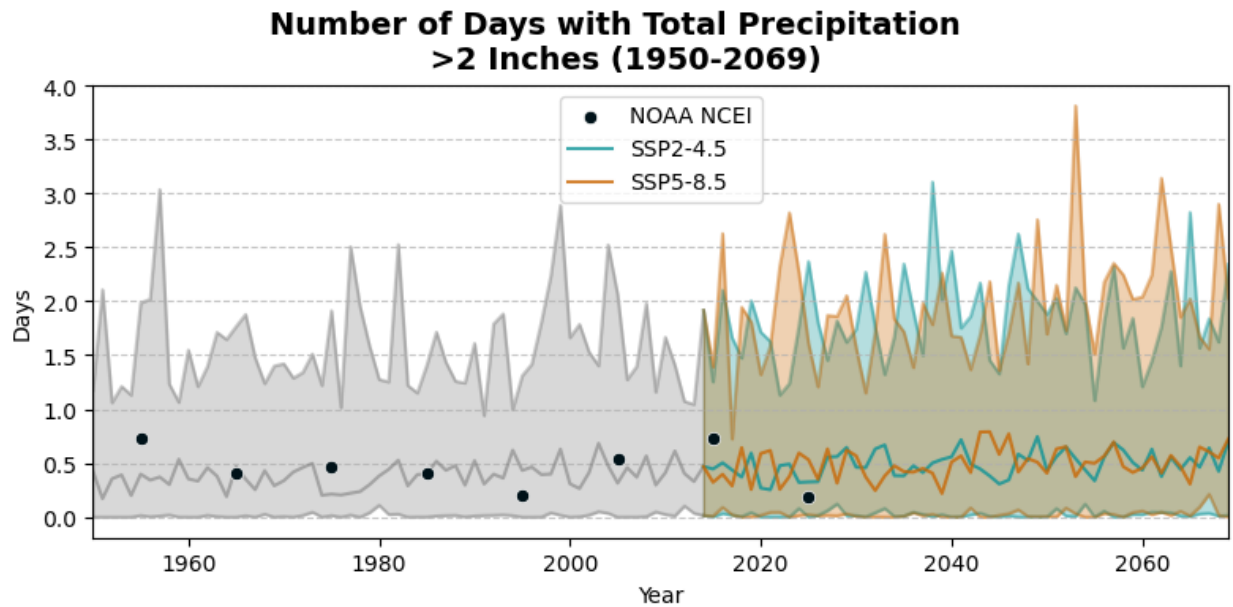


Figure 32. Annual total days with precipitation greater than 2 inches from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$). NOAA NCEI values are days with precipitation greater than or equal to 2 inches.

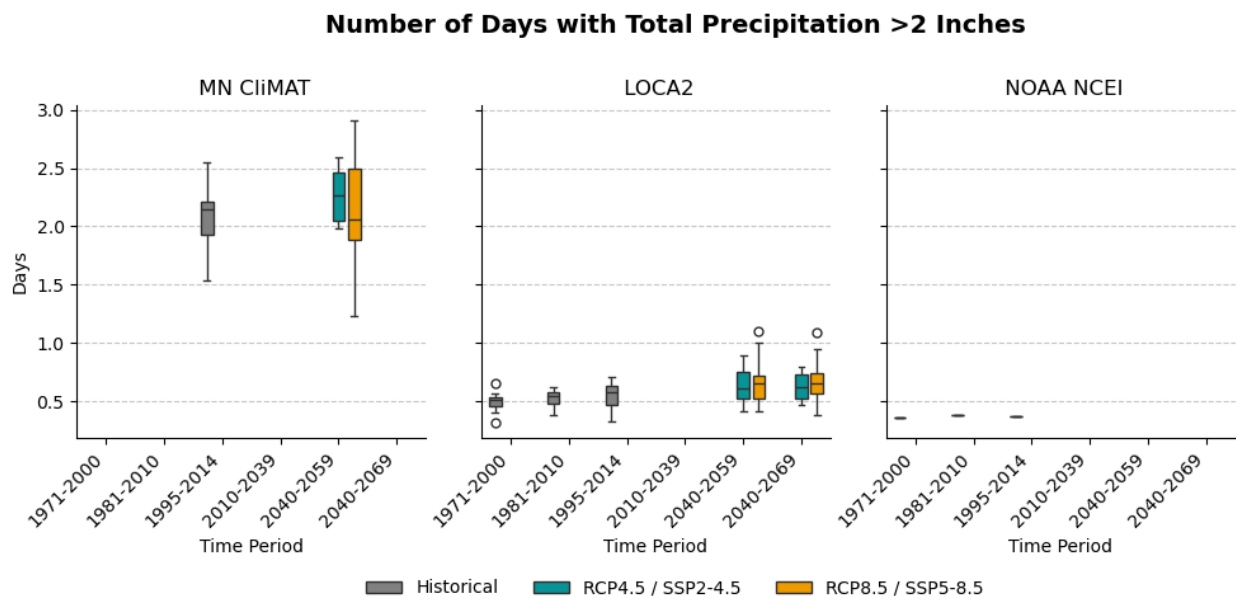


Figure 33. Comparison of period averages of annual total days with precipitation greater than 2 inches across datasets. NOAA NCEI values are days with precipitation greater than or equal to 2 inches. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$ and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

Annual 1-day Maximum Precipitation (1950-2069)

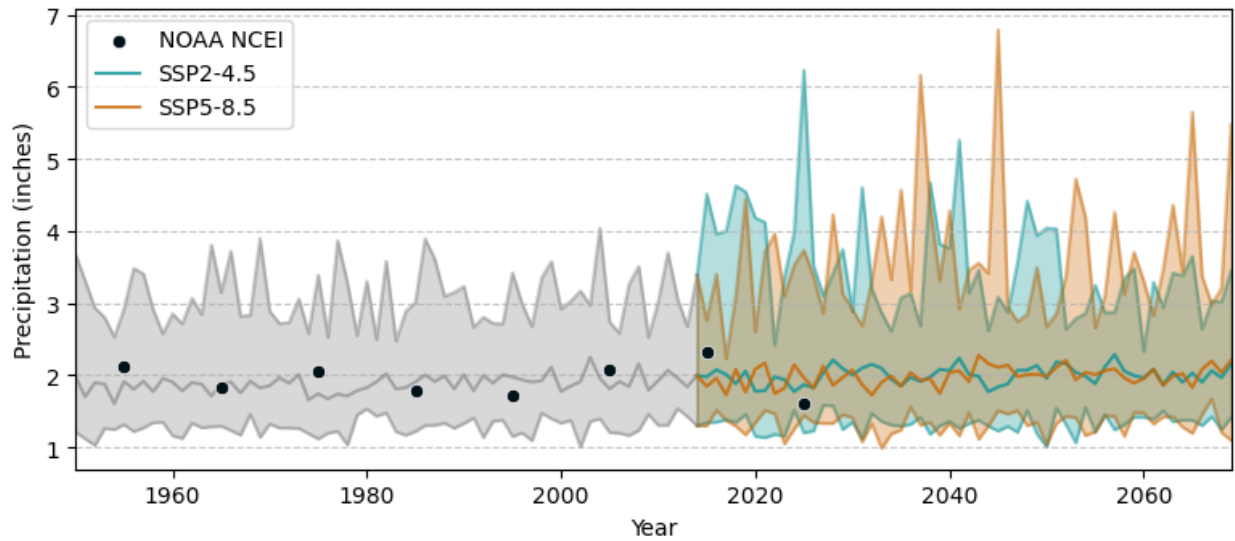


Figure 34. Annual maximum 1-day precipitation 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

Annual 1-day Maximum Precipitation

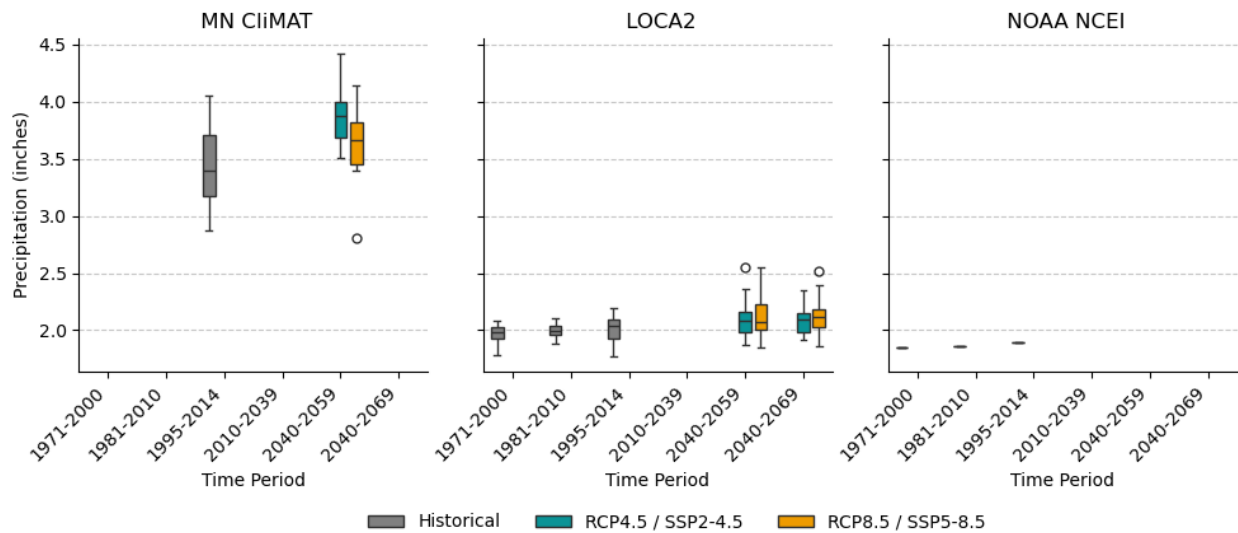


Figure 35. Comparison of period averages of annual maximum 1-day precipitation across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$ and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

Annual 5-day Maximum Precipitation (1950-2069)

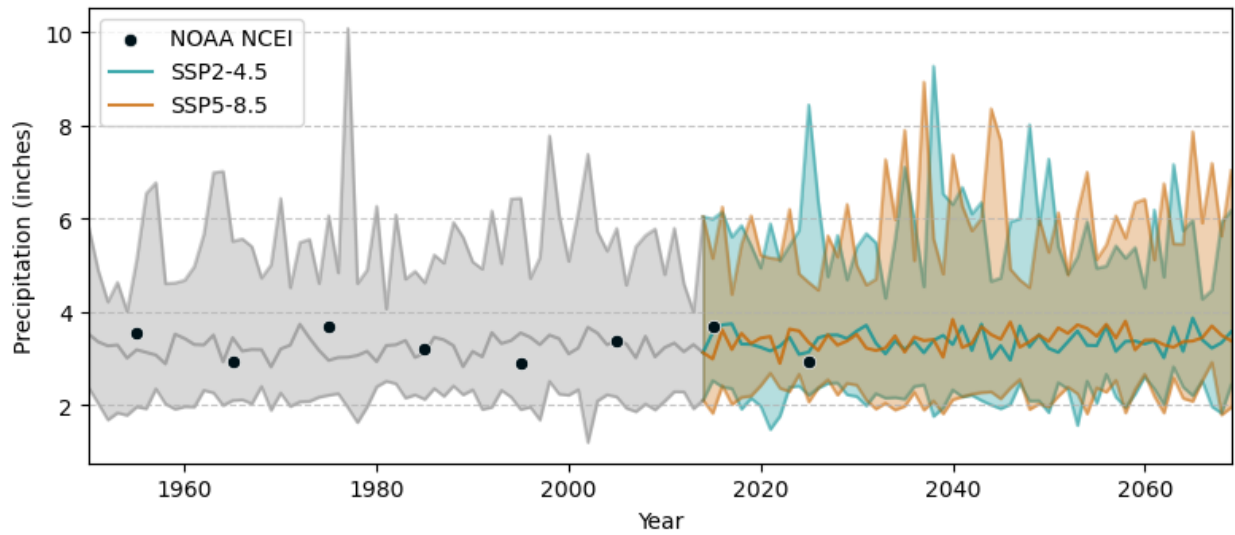


Figure 36. Annual maximum 5-day precipitation 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

Annual 5-day Maximum Precipitation

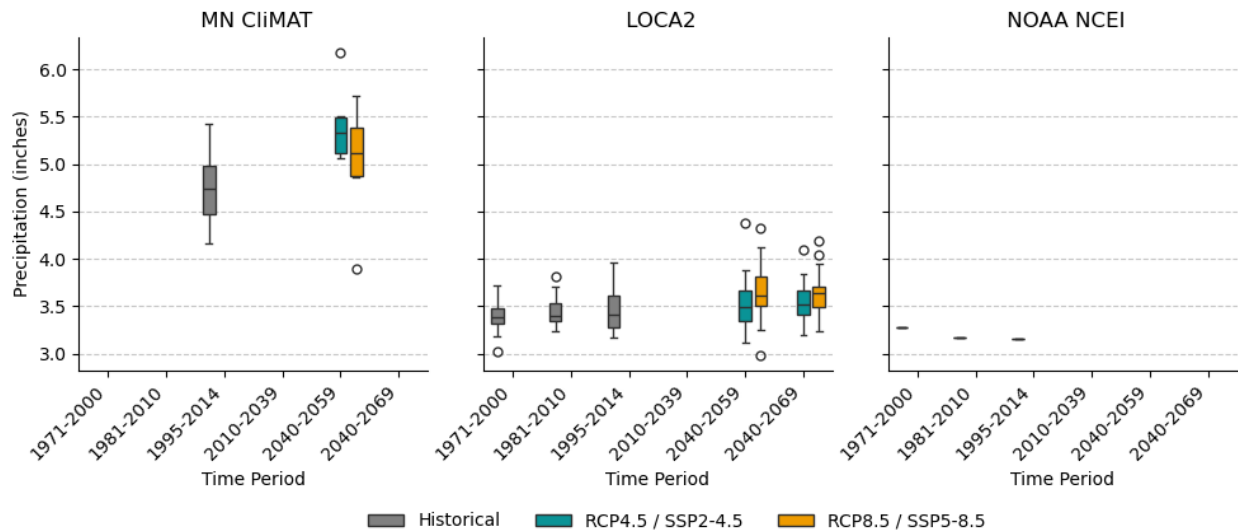


Figure 37. Comparison of period averages of annual maximum 5-day precipitation across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$ and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

Snow

Snow metrics are presented for annual average snow depth (Figures 38–42) and annual total snowfall (Figures 43–46) at select stations for snow year (July–June), with values assigned to the year containing January–June (e.g., July 1970–June 1971 was assigned to 1971). Additional plots for the average number of days with snow depth greater than 1 inch and greater than 6 inches are shown in Appendix A (Figures A37–A46). As an indicator of heavy snow events, Appendix A shows additional station data for snowfall greater than 4 inches in one day (A47–A50). However, users should note the documented bias in snowfall observations including methodological biases in snow to liquid equivalent (Kunkel et al., 2007).

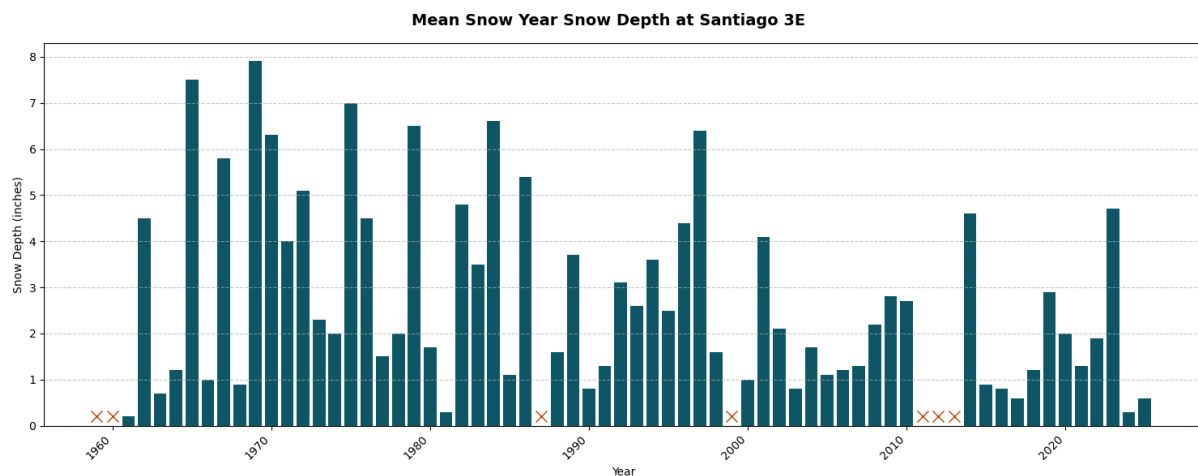
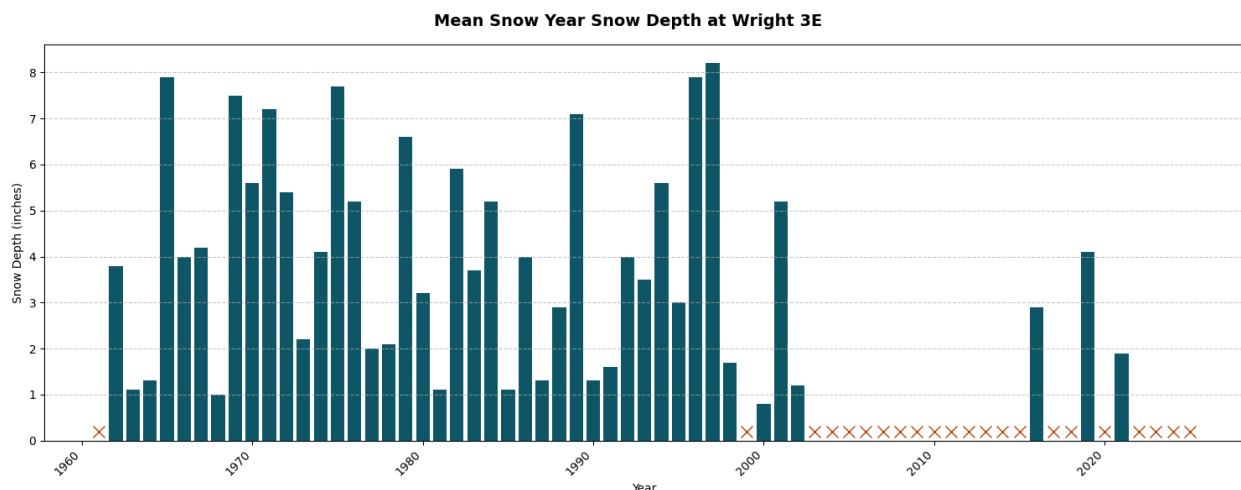


Figure 38. Snow year (July–June) average snow depth at Santiago 3E station in Sherburne County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).



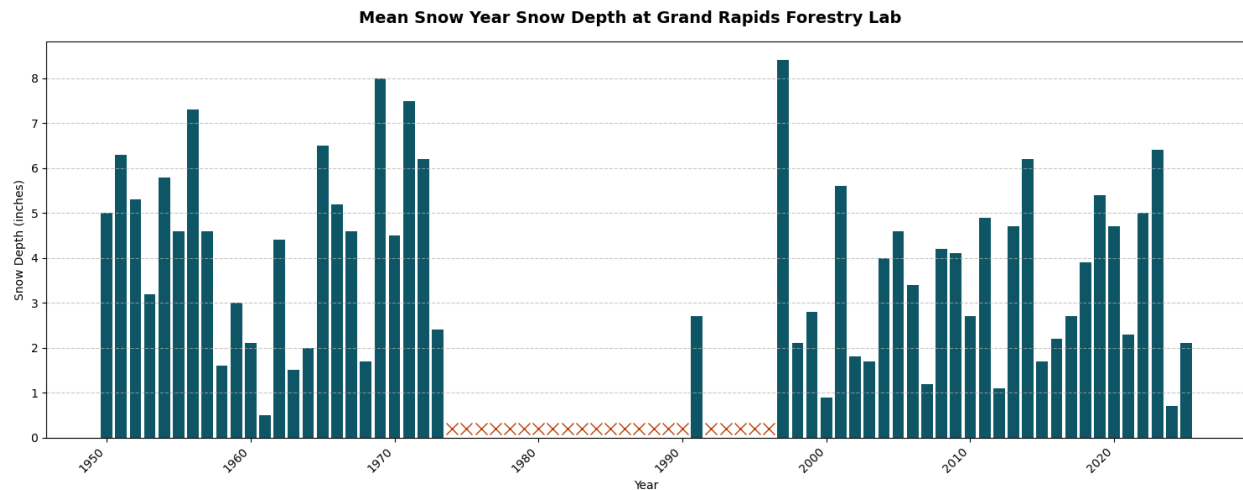


Figure 40. Snow year (July–June) average snow depth at Grand Rapids Forestry Lab station in Itasca County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

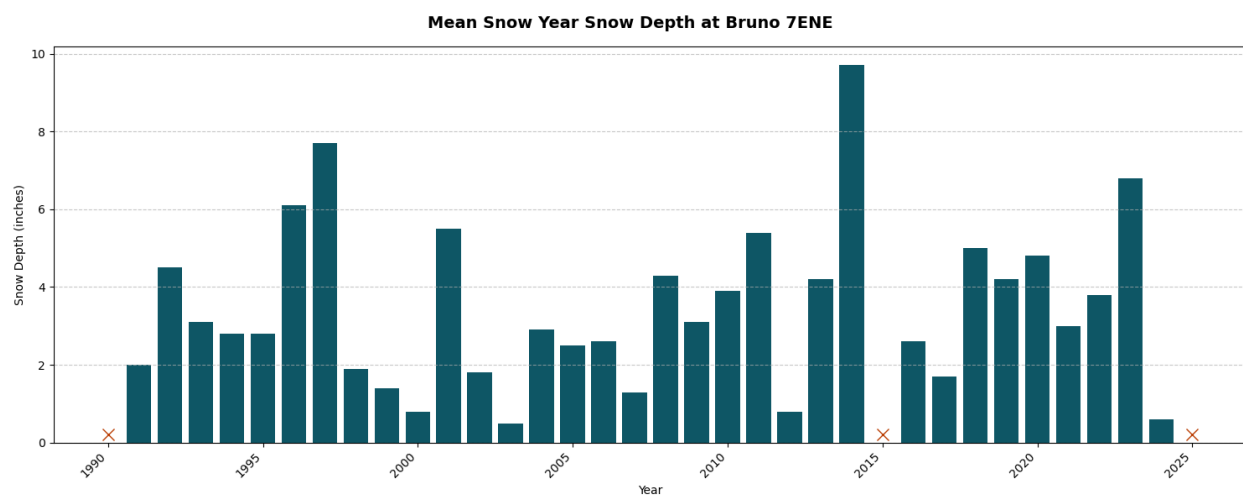


Figure 41. Snow year (July–June) average snow depth at Bruno 7ENE station in Pine County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

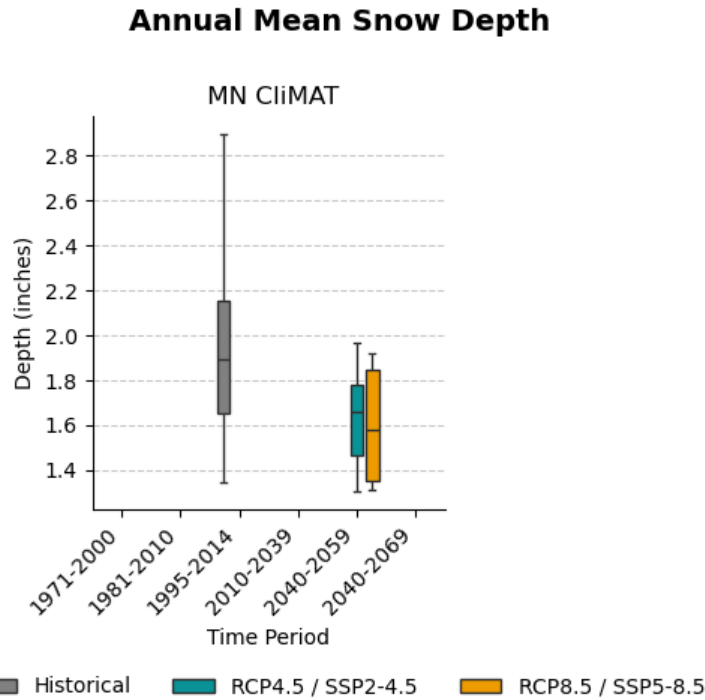


Figure 42. Comparison of period averages of calendar year (January–December) average snow depth in MN CliMAT. Boxplots summarize the variation among climate simulations (MN CliMAT n=6). Emissions scenarios associated with each dataset include MN CliMAT = SSP.

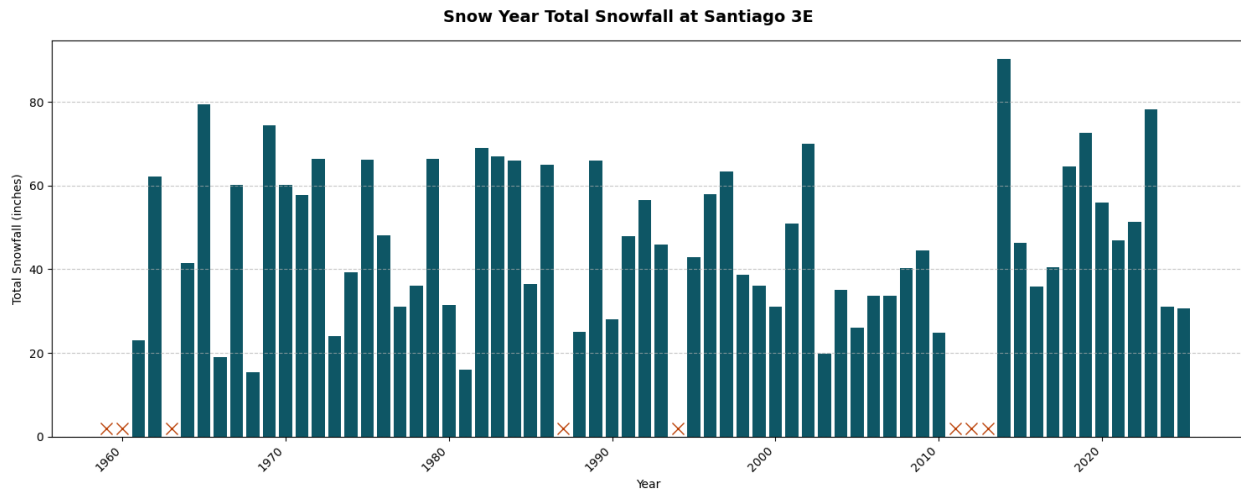


Figure 43. Snow year (July–June) total snowfall at Santiago 3E station in Sherburne County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

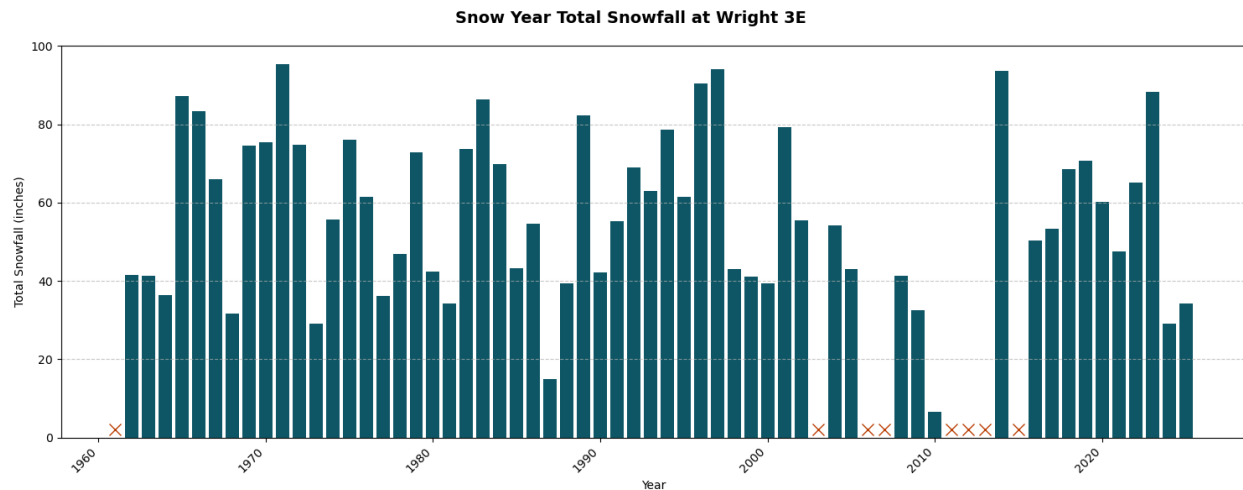


Figure 44. Snow year (July–June) total snowfall at Wright 3E station in Carlton County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

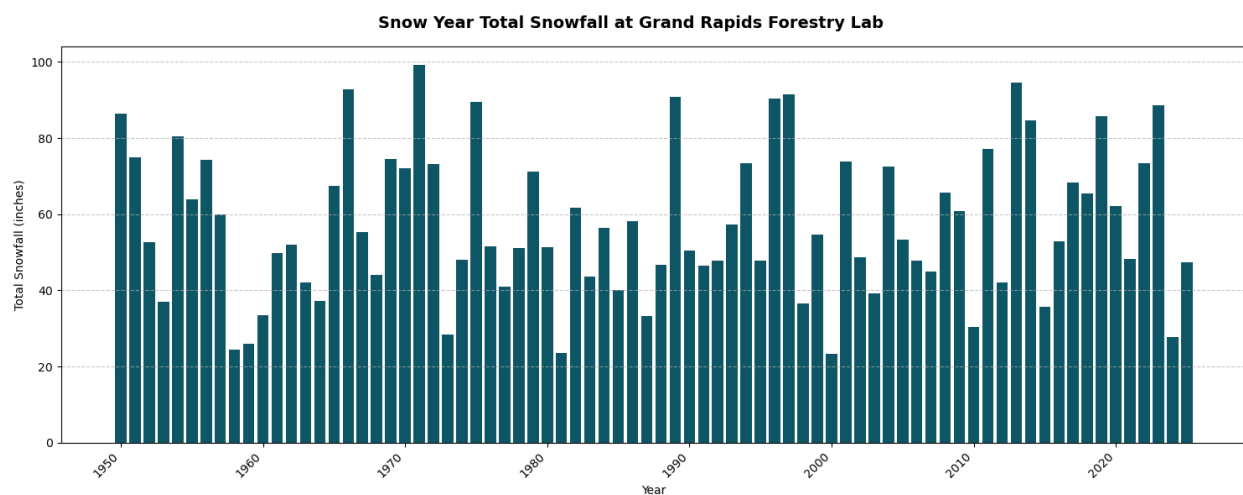


Figure 45. Snow year (July–June) total snowfall at Grand Rapids Forestry Lab station in Itasca County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

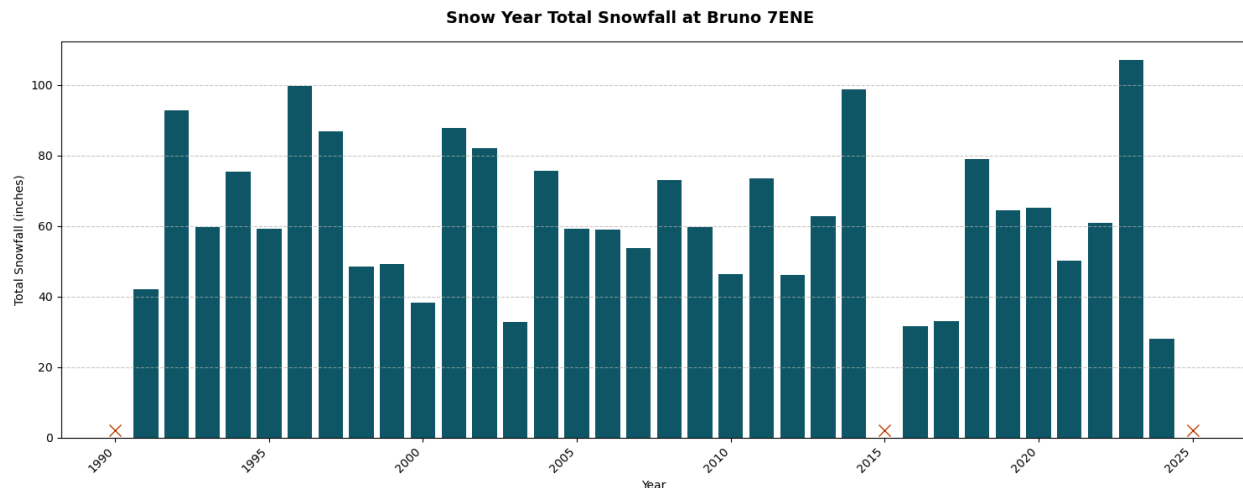


Figure 46. Snow year (July–June) total snowfall at Bruno 7ENE station in Pine County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

Consecutive dry days and drought

Periods of dryness and drought can be identified in many ways and analysis of changes should be anchored to the system that is being impacted. This analysis shows a broadly used and more widely available metric—consecutive dry days—to capture trends in dryness (Figure 47–48). Thresholds applied by different datasets are noted in the captions. If a particular system, impact, and threshold are identified then more complex indexes of drought such as the Standardized Precipitation-Evapotranspiration Index (SPEI) can be used (Vicente-Serrano et al., 2010).

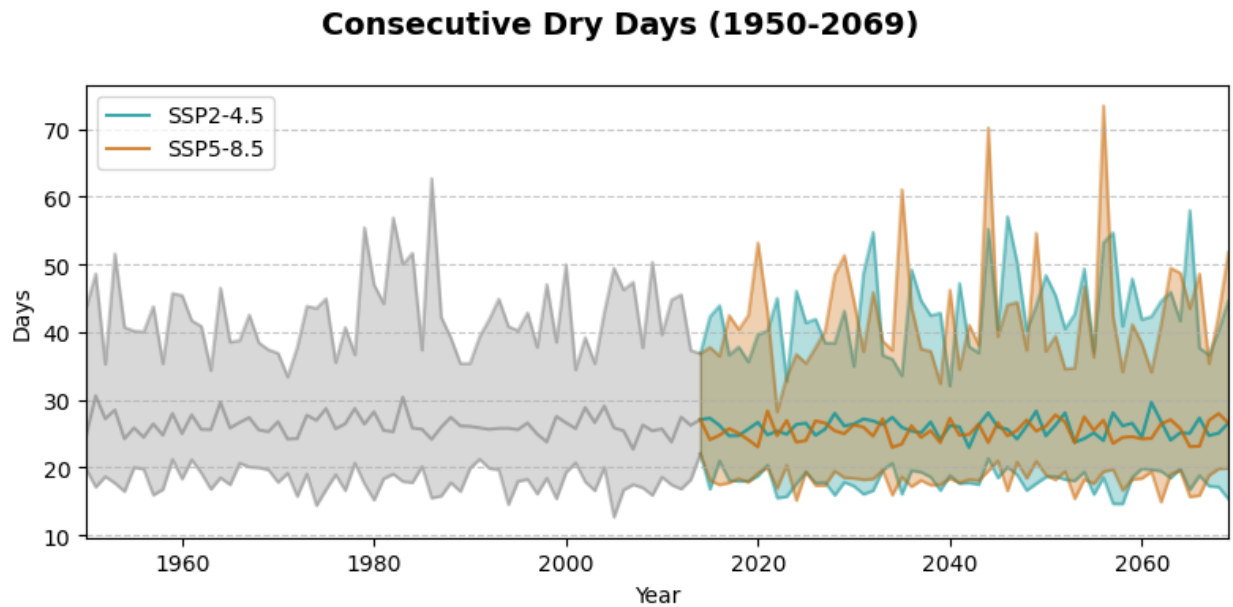


Figure 47. Annual maximum consecutive dry days from 1950–2069 from LOCA2 climate model simulations (n=23).

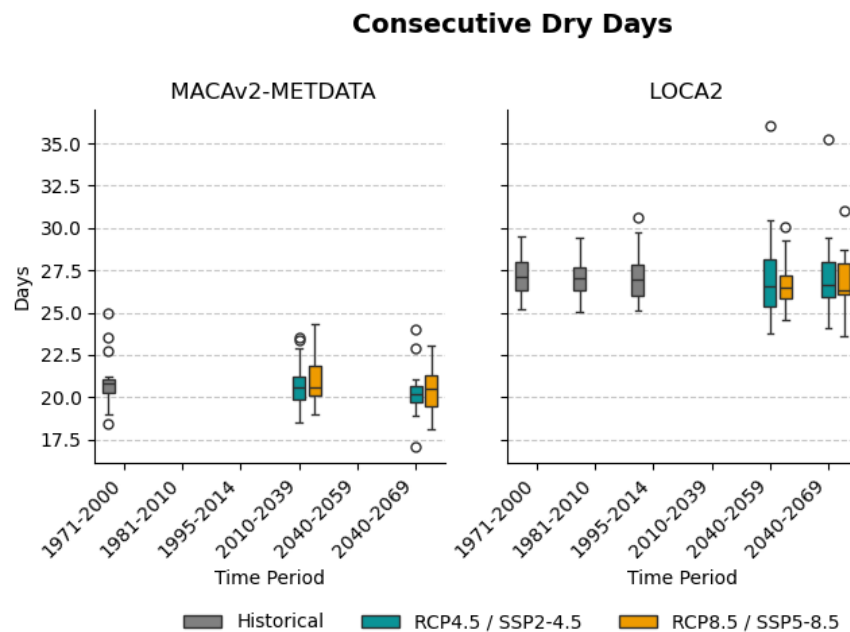


Figure 48. Comparison of period averages of annual maximum consecutive dry days across datasets. MACAv2-METDATA has a dryness threshold of less than 0.2mm of daily precipitation. Boxplots summarize the variation among climate simulations (MACAv2-METDATA n=20 and LOCA2 n=23). Emissions scenarios associated with each dataset include MACAv2-METDATA = RCP and LOCA2 = SSP.

The U.S. Drought Monitor (USDM) is another widely used dataset for the assessment of historical dryness. The USDM is a composite, retrospective index that details recent drought conditions on a weekly basis using a blend of objective indices and expert elicitation (Svoboda et al., 2002; Leeper et al., 2022; Table 18). The USDM uses a convergence of evidence approach and is a combination of physical drought indices, reported impacts, and expert judgement (National Drought Mitigation Center, 2026a). The index record is January 2000 to present (Figures 49–54).

Table 18. Categories and colors associated with the U.S. Drought Monitor (National Drought Mitigation Center, 2026b).

USDM Category	Description
D0	Abnormally Dry – used for areas showing dryness but not yet in drought, or for areas recovering from drought
D1	Moderate Drought
D2	Severe Drought
D3	Extreme Drought
D4	Exceptional Drought

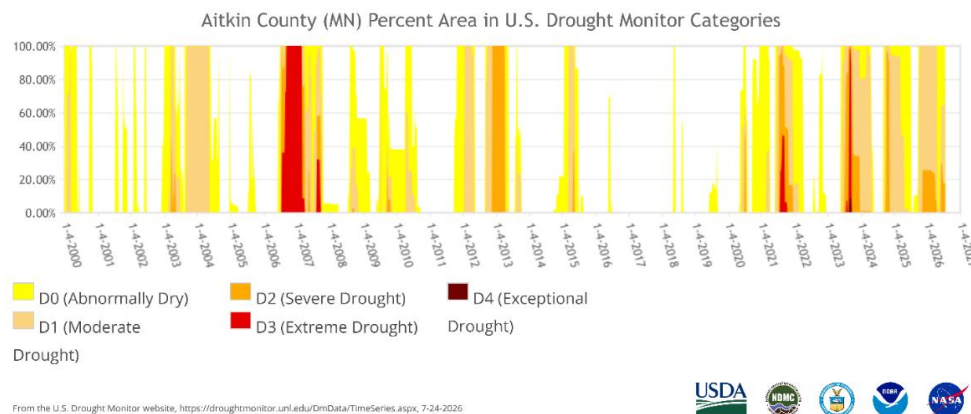


Figure 49. Historical occurrence of weekly Aitkin County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

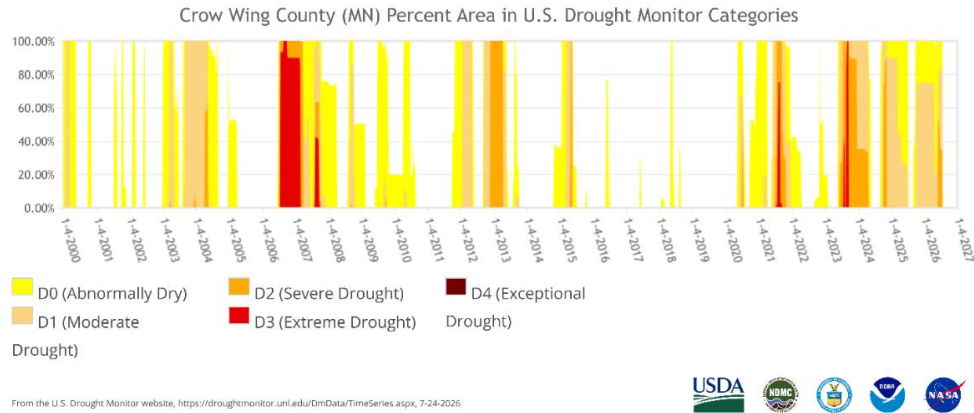


Figure 50. Historical occurrence of weekly Crow Wing County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

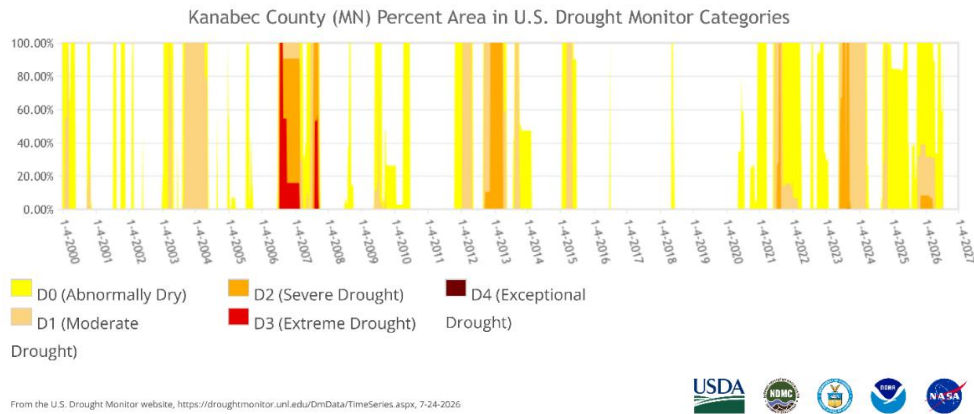


Figure 51. Historical occurrence of weekly Kanabec County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

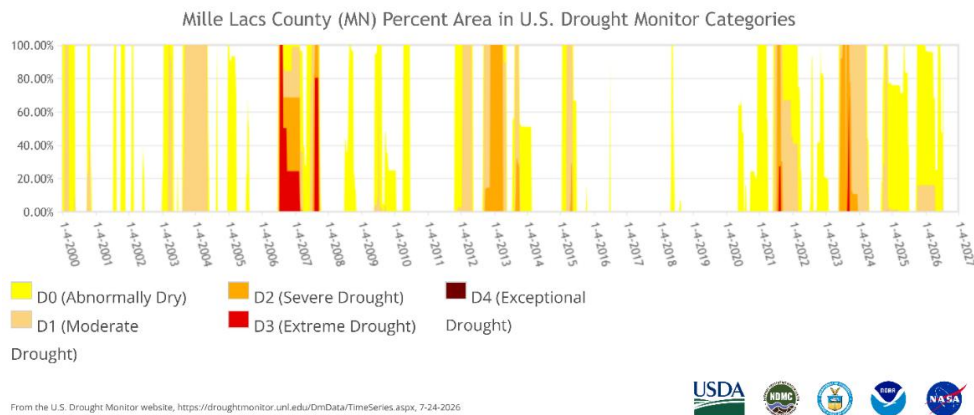


Figure 52. Historical occurrence of weekly Mille Lacs County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

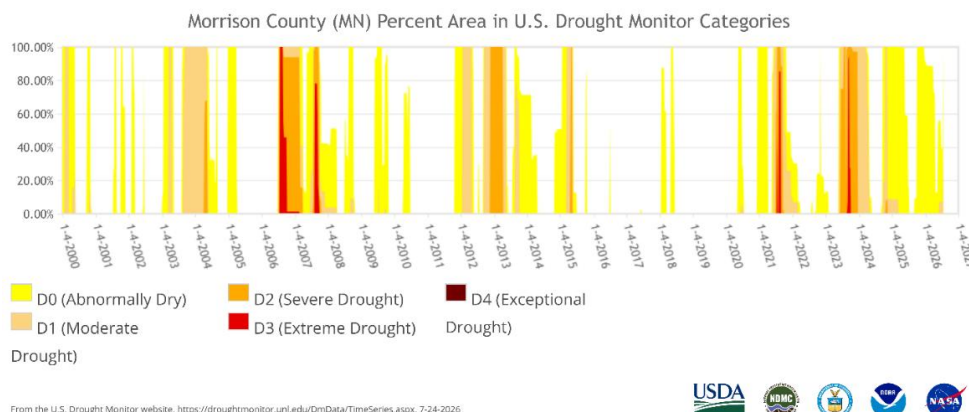


Figure 53. Historical occurrence of weekly Morrison County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

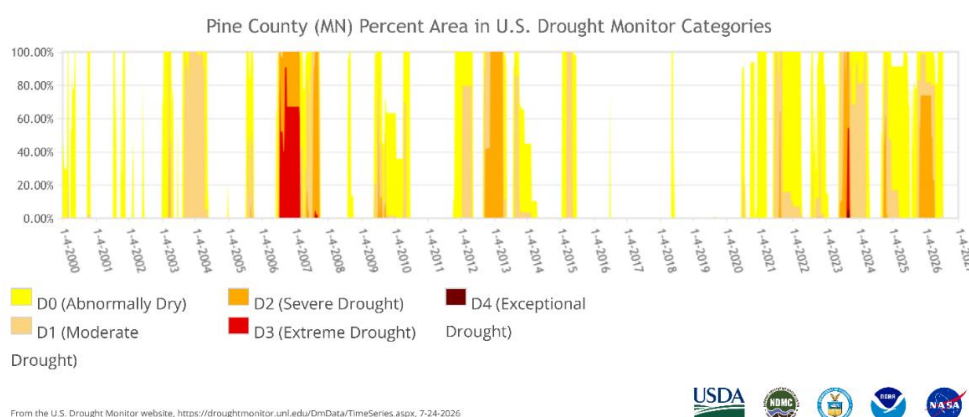


Figure 54. Historical occurrence of weekly Pine County drought area occurrence in the U.S. Drought Monitor from 2000–2026.

Climate impacts on hazards

The ability to quantitatively project future changes in hazards varies considerably, depending on the complexity of the processes involved and the strength of the available evidence. To characterize the current state of the science and the uncertainties surrounding how climate change may affect key hazards, we synthesized the scientific literature and highlighted selected studies and their key findings.

Flooding

Minnesota is projected to have altered precipitation patterns and hydrologic processes. Across the Midwest, average annual precipitation is projected to increase by mid-century, although individual model projections may vary by magnitude, direction (wetter or drier), and spatial distribution (Wilson et al., 2023, p. 24-7). In addition to increases in average precipitation, future climate projections include greater precipitation variability, including

more rapid transitions between precipitation extremes by late-century (Wilson et al., 2023, p. 24-7). Cumulative runoff is also projected to increase annually across much of the Midwest by mid-century, with increases occurring in central Minnesota across all seasons (Wilson et al., 2023, p. 24-27). Lastly, median annual peak streamflow has likely increased in central Minnesota during the few decades preceding 2020 (Williams-Sether & Sanocki, 2025, p. 24) and earlier snowmelt is projected to increase daily maximum spring streamflow (Wilson et al., 2023, p. 24-7).

Trends in streamflow can be used to help inform flood risk, but the relationship between peak flows and flooding also depends on basin characteristics, streamgage record completeness and length, preceding conditions, and other climate considerations (England et al., 2019, p. 11, 18). Similarly, it is often expected that increasing precipitation extremes result in greater flood magnitude and risk. However, observational evidence does not consistently support this simple causal relationship (Sharma et al., 2018). Although extreme precipitation occurrence certainly plays a substantial role in flood risk, other factors such as landscape (i.e., catchment), storm, and prior hydrologic characteristics are also influential (Sharma et al., 2018). Ultimately, the combined projected changes suggest increased flooding susceptibility across Minnesota, although the magnitude and timing of impacts may vary among watersheds and local conditions, and uncertainty remains.

Flooding: Selected studies and key findings

England, J. F., Jr., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas, W. O., Veilleux, A. G., Kiang, J. E., & Mason, R. R., Jr. (2019). *Guidelines for determining flood flow frequency—Bulletin 17C* (Techniques and Methods Book 4, Chap. B5). U.S. Geological Survey.
<https://doi.org/10.3133/tm4B5>

- **Keywords:** streamflow, nonstationarity, flood-frequency analysis
- Relevant quotes:
 - “There are several common issues associated with streamflow data records from gaging stations that may require investigation and treatment by the analyst. These issues include handling of incomplete records, extraordinary floods, and potentially influential low floods (PILFs).” (p. 11)
 - “Physiographic characteristics within a watershed or region, such as mean basin elevation, drainage area, mean annual precipitation, and other physical factors, are useful in estimating regional parameters and in conducting regional flood frequency studies.” (p. 18)

Sharma, A., Wasko, C., & Lettenmaier, D. P. (2018). If precipitation extremes are increasing, why aren't floods? *Water Resources Research*, 54(11), 8545–8551.
<https://doi.org/10.1029/2018WR023749>

- **Keywords:** extreme precipitation, flood magnitude, flood risk
- Relevant quotes:

- “Although simplified, increases in precipitation have been used extensively as the basis for explaining why flooding may increase as temperatures rise with climatic change. However, as extreme precipitation does not always lead to flooding, this argument clearly must be flawed at some level. Across all regions in the contiguous United States the probability of observing extreme discharge given extreme precipitation is much less than unity. Aggregated across all sites only 36% of extreme precipitation events (in a probabilistic sense) lead to a corresponding extreme discharge” (pp. 8545–8546)
- “There is a clear dichotomy between observed increases in precipitation extremes and the lack of corresponding increases in floods, with reduced flood magnitudes observed in many cases. Despite the conceptual arguments we’ve made, there remains a good deal of uncertainty in the relationships between changes in precipitation and flood magnitude across the spectrum of catchment, storm, and antecedent hydrologic conditions. Although changes in flood magnitude are unlikely to be explainable by precipitation changes alone, this has largely been the focus to date in the climate literature. Moving forward, along with a better characterization of changes in floods not directly driven by precipitation increases, we argue for a focus on the complexity of the relationships among the entire suite of variables (including precipitation extremes) that lead to the generation of flood extremes” (p. 8548–8549)

Williams-Sether, T., & Sanocki, C. (2025). *Peak streamflow trends in Minnesota and their relation to changes in climate, water years 1921–2020* (Scientific Investigations Report Nos. 2023–5064–E). U.S. Geological Survey. <https://doi.org/10.3133/sir20235064E>

- **Keywords:** streamflow, nonstationarity, flood-frequency analysis
- Relevant quotes:
 - Figure 11 (p. 24)

Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

- **Keywords:** precipitation, runoff, snowmelt, streamflow, flood risk
- Relevant quotes:
 - "Projections (under low [RCP2.6] to very high [RCP8.5] scenarios) suggest precipitation increases across the Midwest ranging from 8% to 20% by mid-century relative to the previous five decades, with individual model uncertainty regarding the degree, direction (wetter or drier), and regional spatial characteristics. Rapid transitions between precipitation extremes are expected

- to increase across all of the Midwest by late century (2071–2100) compared to historical conditions." (p. 24-7)
- "The amount of precipitation falling in the most intense 1% of events increased significantly (45%) in the Midwest between 1958 and 2021. Under a global warming level of 3.6°F (2°C), extreme precipitation intensity is projected to increase 10%–15%, and perhaps more than 20% in some areas." (p. 24-19)
 - "Projected changes in cumulative local runoff will lead to increased flooding susceptibility in winter and spring" (p. 24-27)
 - "Cumulative runoff is projected to increase annually across the Midwest between 2036 and 2065 compared to 1991–2020 (shown in percent changes). Cumulative runoff increases are expected throughout the region in winter and across all but the northern Great Lakes in spring and southern Midwest in fall. Summer cumulative runoff is projected to be more variable." (p. 24-27)
 - Figure 24.11 (p. 2427)
 - "Future projections suggest further changes in seasonality and increases in variability. Earlier snowmelt is expected to increase daily maximum spring streamflow." (p. 24-27)

Winter severity

In the Midwest, changing climate conditions are resulting in milder winters characterized by decreased snowfall, snow cover, length of snow seasons, frequency of intense snowfall events, ice cover, and persistent cold conditions (Wilson et al., 2023, p. 24-14, 24-26, 24-35). Climate projections indicate that these trends will continue nationwide through the end of the century under a high emissions scenario (SSP5-8.5), with snowfall and the number of snowfall days expected to decrease by more than 50% compared to conditions observed from 1995–2014 (Chen et al., 2020). Minnesota is projected to receive approximately 50–100 cm less snow accumulation annually by the end of century (SSP5-8.5) with snowstorm counts decreasing dramatically in the shoulder months resulting in a shorter winter season (Ashley et al., 2020). However, some climate drivers may lead to opposing changes. For example, aerosol emissions are associated with decreases in temperature and increases in precipitation which can produce more intense snowfall events during the cold season (Chen et al., 2020). Additionally, increases in phenomena such as lake-effect snow may continue to occur (Wilson et al., 2023, 24-26, 24-30). Consequently, although severe winter weather events will take place, Minnesota is projected to have milder, shorter winters with less persistent snow and ice cover (Chen et al., 2020; Wilson et al., 2023, p. 24-14, 24-26, 24-35).

Winter severity: Selected studies and key findings

Ashley, W. S., Haberlie, A. M., & Gensini, V. A. (2020). Reduced frequency and size of late-twenty-first-century snowstorms over North America. *Nature Climate Change*, 10(6), 539–544. <https://doi.org/10.1038/s41558-020-0774-4>

- **Keywords:** snow water equivalent, snowstorms, snow season, pseudo-global warming study

- Relevant quotes:
 - “Seasonal SWE [snow water equivalent] from Minnesota eastward to the Canadian Maritimes is projected to decrease from 50 to 100 mm which, using a simple 10:1 snow-to-liquid ratio, is nearly a decline of 50–100 cm in snow accumulation.”
 - “The most notable changes between the CTRL [control] and PGW [pseudo-global warming] simulations arise during the shoulder-season months; temperatures during these months are marginal for snowfall and the fraction of precipitation falling as snow is especially sensitive to warming due to climate change. Snowstorm counts during October, November and April are projected to decrease 83.5%, 48.4%, and 60.5%, respectively, signalling a robust decrease in future events during the shoulder seasons and a further shortening of the already observed changes in spring snowcover across the Northern Hemisphere. The largest per cent reduction in all metrics is found during October, suggesting that future early season snow events will be nearly eliminated if RCP 8.5 is realized. Monthly swath count decreases of 5.1–12.8% are projected during the core of winter, revealing declines in snowstorms even during the coldest months.”

Chen, H., Sun, J., & Lin, W. (2020). Anthropogenic influence would increase intense snowfall events over parts of the Northern Hemisphere in the future. *Environmental Research Letters*, 15(11), Article 114022. <https://doi.org/10.1088/1748-9326/abbc93>

- **Keywords:** snowfall, intense snowfall, snowfall days, attribution
- Relevant quotes:
 - “By the end of this century (2081–2100), annual snowfall and snowfall days are expected to significantly decrease with a high confidence level across the lands of the Northern Hemisphere (figure 4), especially over the mid-latitude regions, including southern Europe, southern China, Japan, and USA, in which snowfall and snowfall days will decrease by at least 50% under the SSP5-8.5 scenario compared to the current state (1995–2014).”
 - “Relatively strong responses of intense snowfalls to anthropogenic influence are expected across the Northern Hemisphere (figure 3). The occurrence probability of intense snowfalls is found to obviously increase with climate warming in ALL forcing simulations, especially over regions of most parts of Asia, North America, and Greenland, in which FARs [fraction of attributable risks] are estimated to increase by at least 10%, possibly even exceeding 20%. Thus, the increased anthropogenic activity in the past decades is partly responsible for the increase in intense snowfall events over these regions.”
 - “In contrast, we can see the increasing probability of snowfall in response to AER [aerosol] forcing across the Northern Hemisphere, especially over the mid-latitude regions. This is closely connected to the cloud effects of AERs that generally leads to a decrease in temperature. Furthermore, increasing AER

emissions has also increased the occurrence probability of intense precipitation events, or more specifically, intense snowfall events during the cold season.”

Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

- **Keywords:** snowfall, intense snowfall, snowfall days, lake-effect snow, ice cover, persistent cold
- Relevant quotes:
 - “Warming has shortened the length of persistent cold conditions and decreased snow cover in the Upper Midwest.” (24-14)
 - “Observed decreases in the length of winter have reduced snowfall across the Midwest, with negative impacts for snow-dependent winter tourism for the Midwest and Great Lakes. By the end of the century, projections indicate reductions in snowstorm frequency and size and snow-water equivalent totals; shorter snow seasons; and fewer intense snowfall events.” (24-26)
 - “Observed changes in hydrology include increases in the variability of lake levels, evaporation, and water temperatures, along with more intense precipitation, including lake-effect snow, and shorter duration of snow and ice cover.” (24-26)
 - “The Great Lakes have witnessed significant water-level variability over the last several decades, with low water levels from 1998 to 2013 and high-water levels since 2015. This variability is due in part to changes in the seasonality and intensity of precipitation (including lake-effect snow), warmer lake temperatures, lake evaporation, and loss of ice cover.” (24-30)
 - “Overall, there is unequivocal evidence that Midwestern ecosystems have been and will continue to be affected by landscape change, and many studies link changes in the functioning of these systems to rising temperatures and reduced snow and ice cover. There is strong evidence that these climatic factors have been changing in the Midwest.” (24-35)

Thunderstorm wind

Climate change is projected to increase the frequency and severity of straight-line winds (or non-tornadic thunderstorm winds) across the central United States (Prein, 2023). Evidence suggests that these damaging wind events intensified in the central United States by 13% per 1°C rise in temperature (~7% per 1°F) during summers over the past 40 years (1980–2020), nearly double what theoretical considerations would have suggested (Prein, 2023). Additionally, during this period the geographic area impacted by straight-line winds increased nearly five-fold (Prein, 2023). Warming temperatures can lead to an increase in moisture

availability and convective available potential energy, leading to more intense convective storms. However, warming may also lead to troposphere stabilization and decreased wind shear, potentially counteracting this projected intensification (Prein, 2023). These conflicting elements, in conjunction with the complex large- and local-scale features that influence wind in general, make projecting the impact of climate change challenging (Prein, 2023; Klink, 2002).

Historical observations from Minnesota illustrate this complexity: weather stations in the state generally exhibited a modest decline in mean annual surface wind speeds from the early 1960s to the mid-1990s (Klink, 2002). However, the data also showed complicated patterns in annual wind speed distributions and substantial year-to-year variability (Klink, 2002). Overall, there is low confidence in clear trends for past severe thunderstorm winds (IPCC, 2023, p. 1594). While there is high confidence that climate changes support future increases in the frequency and severity of thunderstorms that include high winds, the magnitude of these increases are less certain (IPCC, 2023, p. 1594)

Thunderstorm wind: Selected studies and key findings

Intergovernmental Panel on Climate Change (IPCC). (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II, and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H. Lee & J. Romero, Eds.).

<https://doi.org/10.59327/IPCC/AR6-9789291691647>

- **Keywords:** thunderstorms, wind, climate projections
- Relevant quotes:
 - “...there is low confidence in past trends for hail and severe thunderstorm winds. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (high confidence), but there is low confidence in the details of the projected increase” (p. 1594)

Klink, K. (2002). Trends and interannual variability of wind speed distributions in Minnesota. *Journal of Climate*, 15(22), 3311–3317. [https://doi.org/10.1175/1520-0442\(2002\)015<3311:TAIVOW>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<3311:TAIVOW>2.0.CO;2)

- **Keywords:** wind, historical observations
- Relevant quotes:
 - “Wind is an inherently noisy variable that reflects both large-scale and local-scale features, but the seven sites within and surrounding Minnesota show some common characteristics. Least squares regression shows that, at most stations, mean annual wind speeds have decreased over the period of record (roughly, the early 1960s to the mid-1990s). Annual distributions of mean daily wind speeds, however, show a more complex pattern.”

- “Though wind has been observed and recorded for centuries, the lack of long-term digital wind data and sufficiently detailed station histories are significant problems for investigations of wind variability over climatological timescales. In addition, much is still unknown about the relationships between the near-surface wind field (both speed and direction) and other parts of the climate system, such as temperature and humidity.”
- “All of the sites also showed marked interannual variability in the shape and central tendency of wind speed distributions. Trends and variability in wind speeds at these sites are likely due to forcing at both large scales (cyclone and anticyclone activity) and small scales (urbanization, land cover, topography).”

Prein, A. F. (2023). Thunderstorm straight line winds intensify with climate change. *Nature Climate Change*, 13(12), 1353–1359. <https://doi.org/10.1038/s41558-023-01852-9>

- **Keywords:** straight-line winds, convective storms
- Relevant quotes:
 - “Climate change impacts on SLWs [straight line winds] have long been elusive. Combining multiple lines of evidence from kilometre-scale modelling, observational records and theoretical considerations robustly shows that climate change increases the frequency and intensity of SLWs.”
 - “Here, focusing on the central USA, a global hot spot for SLWs, I use observations, high-resolution modelling and theoretical considerations to show that SLWs have intensified over the past 40 years. Theoretical considerations suggest that SLWs should intensify at a rate of $\sim 7.5\% \text{ }^{\circ}\text{C}^{-1}$, yet the observed rates show a more pronounced increase of $\sim 13\% \text{ }^{\circ}\text{C}^{-1}$. The simulation results indicate a 4.8 ± 1.2 -fold increase in the geographical extent affected by SLWs during the study period...during JJA...over the past 40 years...meaning that much larger areas in the central USA are experiencing extreme SLWs nowadays than in the 1980s.”
 - “Convective storms are expected to intensify under progressive warming, mainly due to an increase in moisture availability and subsequent increases in convective available potential energy (CAPE). However, increases in convective inhibition, a stabilization of the troposphere due to larger warming at higher levels, and decreases in wind shear might counteract the expected intensification. The complex interactions of multiple processes across a large variety of scales, observational challenges and model inabilities to simulate convection realistically make assessing climate change impacts on severe convective storms extremely difficult.”

Tornadoes

Assessing current and projected changes in tornado activity remains challenging because observations of tornado events and the complex atmospheric conditions associated with them are incomplete. Projections of future tornado activity are also limited by the difficulty of

representing small-scale, short-lived severe weather events and the complex processes that lead to their development (Marvel et al., 2023, p. 2-20). Generally, the average annual number of tornadoes nationwide appears to have remained relatively constant. However, evidence suggests there have been increases in tornado outbreak frequency, tornado intensity, and fall tornado activity, as well as an eastward shift in the area known as Tornado Alley (Marvel et al., 2023, p. 2-20). Large thunderstorm clusters capable of producing tornadoes have also become more frequent and longer lasting over the past two decades (Marvel et al., 2023, p. 2-20).

Projections under future emissions scenarios include robust and consistent shifts in the components that influence severe convective storm development, including thermodynamic instability, convective inhibition, and vertical wind shear (Roufa et al., 2026). As a result, projections for severe convective storms associated with tornadoes include a longer severe weather season, increased frequency of severe convective storm days, particularly during spring and summer, and a continued eastward shift of activity. In Minnesota, these changes are more pronounced under a high-emissions scenario (RCP8.5) by the end of the century compared to under a moderate emissions scenario (RCP4.5) by mid-century (Roufa et al., 2026). Modeling studies also suggest that future warming may increase the intensity of some tornado-producing storms occurring outside the traditional severe weather season (Woods et al., 2023). However, climate change may have competing effects by both inhibiting storm development and strengthening the storms that do form (Trapp & Hoogewind, 2016). As a result, there is high confidence that changes in climate are increasing the frequency and severity of thunderstorms that include tornadoes, but specific insights into projected increases in tornado frequency are less certain (IPCC, 2023, p. 1594).

Tornadoes: Selected studies and key findings

Intergovernmental Panel on Climate Change (IPCC). (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II, and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H. Lee & J. Romero, Eds.).
<https://doi.org/10.59327/IPCC/AR6-9789291691647>

- **Keywords:** tornado, thunderstorm
- Relevant quote:
 - “Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (high confidence), but there is low confidence in the details of the projected increase.” (p. 1594)

Marvel, K., Su, W., Delgado, R., Aarons, S., Chatterjee, A., Garcia, M. E., Hausfather, Z., Hayhoe, K., Hence, D. A., Jewett, E. B., Robel, A., Singh, D., Tripathi, A., & Vose, R. S. (2023). Chapter 2: Climate trends. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock, (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program.
<https://doi.org/10.7930/NCA5.2023.CH2>

- **Keywords:** tornado, thunderstorm
- Relevant quotes:
 - “Changes in smaller-scale, short-lived severe weather such as tornadoes and thunderstorms are more difficult to assess, and direct observations of those events and the conditions associated with them are incomplete. While the average annual number of tornadoes appears to have remained relatively constant, there is evidence that tornado outbreaks have become more frequent, that tornado power has increased, that tornado activity is increasing in the fall, and that "Tornado Alley" has shifted eastward. The complexes of thunderstorms that bring substantial precipitation to the central United States during the warm season have become more frequent and longer-lasting over the past two decades.” (p. 2-20)

Roufa, C. M., Ashley, W. S., Haberlie, A. M., Corner, J. M., Hawthorne, K. T., Moeller, L. K., Gensini, V. A., & Michaelis, A. C. (2026). Projected mid- and late-century changes in severe convective storms across the United States from dynamically downscaled climate simulations. *International Journal of Climatology*, Article e70475.

<https://doi.org/10.1002/joc.70475>

- **Keywords:** severe convective storms, tornado
- Relevant quotes:
 - “Fundamental ingredients that support the development and sustenance of SCS [severe convective storms] broadly support the observed and projected spatiotemporal changes in synthetic SCS activity. Among these ingredients, thermodynamic instability, CIN [convective inhibition] and vertical wind shear show robust and consistent shifts under future emissions scenarios, providing some physical context for the projected SCS changes described above.”
 - “In response to enhanced greenhouse forcing and related changes in fundamental severe storm ingredients, projected synthetic SCS [severe convective storms] activity exhibits spatiotemporal changes relative to the historical baseline, including lengthening of the severe season, increases in the overall frequency of SCS days and an eastward shift of event frequency maxima. In addition to changes in mean frequency, results illustrate enhanced variability and increases in relatively high-activity days across all future epochs, driven by more frequent spring and early summer occurrences.”
 - Figure 7
 - Figure 8

Trapp, R. J., & Hoogewind, K. A. (2016). The realization of extreme tornadic storm events under future anthropogenic climate change. *Journal of Climate*, 29(14), 5251–5265.

<https://doi.org/10.1175/JCLI-D-15-0623.1>

- **Keywords:** tornado, pseudo-global warming study

- Relevant quote:
 - “...the combined effects of increased convective inhibition (CIN) and decreased parcel lifting under PGW [pseudo global warming] led to a failure of convection initiation in many of the experiments. Those experiments that had sufficient matching between the CIN and lifting tended to generate stronger convective updrafts than CTRL [control simulations]”

Woods, M. J., Trapp, R. J., & Mallinson, H. M. (2023). The impact of human-induced climate change on future tornado intensity as revealed through multi-scale modeling. *Geophysical Research Letters*, 50(15), Article e2023GL104796. <https://doi.org/10.1029/2023GL104796>

- **Keywords:** tornado, pseudo-global warming study
- Relevant quote:
 - “...the tornadic-storm and associated vortex of the COOL [cool-season] event experiences consistent and robust increases in intensity in an ensemble of imposed climate-change experiments...These results have implications on future tornadoes forming outside of climatologically favored seasons.”

Hail

Assessing trends in hail events is challenging due to observer bias, limited data, and changing observation systems (Marvel et al., 2023, p. 2-20). Additionally, hail is difficult to observe and model due to its small scale, relative rarity, and complexity in underlying atmospheric drivers (Raupach et al., 2021). Despite these limitations, evidence supports that climate change affects the environmental conditions favorable for hail formation and properties (Raupach et al., 2021), and those associated with large hail production (greater than 2 inches in diameter) have increased in frequency in the central United States (Marvel et al., 2023, p. 2-20). Consistent with this evidence, climate model projections show robust and consistent shifts in the atmospheric components associated with severe convective storms that can produce hail, including thermodynamic instability, convective inhibition, and vertical wind shear (Roufa et al., 2026). These shifts are projected to lengthen the severe weather season, increase the frequency of severe convective storm days, particularly during spring and summer, and continue the eastward shift in severe storm activity. In Minnesota, these projected changes are more pronounced under a high-emissions scenario (RCP8.5) by the end of the century (2085 to 2100) than under a moderate-emissions scenario (RCP4.5) by mid-century (2040 to 2055; Roufa et al., 2026).

However, changes in the conditions that support hail formation may not translate directly into changes in hail occurrence. While hail severity may increase as favorable environments become more common, some studies indicate hailstorm frequency may decrease in the United States (Raupach et al., 2021). Consequently, the impact of climate change on current and future hailstorms remains highly uncertain (Raupach et al., 2021).

Hail: Selected studies and key findings

Marvel, K., Su, W., Delgado, R., Aarons, S., Chatterjee, A., Garcia, M. E., Hausfather, Z., Hayhoe, K., Hence, D. A., Jewett, E. B., Robel, A., Singh, D., Tripathi, A., & Vose, R. S. (2023). Chapter 2: Climate trends. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock, (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH2>

- **Keywords:** hail, observational records
- Relevant quotes:
 - Direct observational records for these hazards are largely insufficient for identifying trends due to factors including observer biases, limited length of the record, and changes in the observing systems. However, days with environmental conditions conducive to producing large hail (greater than 2 inches in diameter) have become more frequent over the central US.” (p. 2-20)

Raupach, T. H., Martius, O., Allen, J. T., Kunz, M., Lasher-Trapp, S., Mohr, S., Rasmussen, K. L., Trapp, R. J., & Zhang, Q. (2021). The effects of climate change on hailstorms. *Nature Reviews Earth & Environment*, 2(3), 213–226. <https://doi.org/10.1038/s43017-020-00133-9>

- **Keywords:** hail, literature review
- Relevant quotes:
 - “As a result of anthropogenic warming, it is generally anticipated that low-level moisture and convective instability will increase, raising hailstorm likelihood and enabling the formation of larger hailstones; the melting height will rise, enhancing hail melt and increasing the average size of surviving hailstones; and vertical wind shear will decrease overall, with limited influence on the overall hailstorm activity, owing to a predominance of other factors.”
 - “Observations and modelling lead to the general expectation that hailstorm frequency will increase in Australia and Europe, but decrease in East Asia and North America, while hail severity will increase in most regions.”
 - “Owing to a dearth of long-term observations, as well as incomplete process understanding and limited convection-permitting modelling studies, current and future climate change effects on hailstorms remain highly uncertain.”
 - “Efforts to understand the effects of climate change on hail are complicated by the small scale and relative rarity of hailstorms, which make hail hard to observe and model.”

Roufa, C. M., Ashley, W. S., Haberlie, A. M., Corner, J. M., Hawthorne, K. T., Moeller, L. K., Gensini, V. A., & Michaelis, A. C. (2026). Projected mid- and late-century changes in severe convective storms across the United States from dynamically downscaled climate simulations. *International Journal of Climatology*, Article e70475. <https://doi.org/10.1002/joc.70475>

- **Keywords:** severe convective storms, hail
- Relevant quotes:
 - “Fundamental ingredients that support the development and sustenance of SCS [severe convective storms] broadly support the observed and projected spatiotemporal changes in synthetic SCS activity. Among these ingredients, thermodynamic instability, CIN [convective inhibition], and vertical wind shear show robust and consistent shifts under future emissions scenarios, providing some physical context for the projected SCS changes described above.”
 - “In response to enhanced greenhouse forcing and related changes in fundamental severe storm ingredients, projected synthetic SCS [severe convective storms] activity exhibits spatiotemporal changes relative to the historical baseline, including lengthening of the severe season, increases in the overall frequency of SCS days and an eastward shift of event frequency maxima. In addition to changes in mean frequency, results illustrate enhanced variability and increases in relatively high-activity days across all future epochs, driven by more frequent spring and early summer occurrences.”
 - Figure 7
 - Figure 8

Wildfire

Fire weather occurs when high temperatures, low humidity, low rainfall, and high winds combine to increase the risk of wildfires (Jones et al., 2020). Climate change is resulting in higher temperatures and more frequent and severe heatwaves and droughts, making these conditions more common. However, shifts in rainfall patterns can complicate fire weather trends, and reductions in fire weather are possible in some regions (Jones et al., 2020). Overall, rising temperatures are increasing wildfire risk for Midwestern forests (Wilson et al., 2023, 24–14). While fire probability in Minnesota has historically been low, it is projected to increase by approximately 25–75% from the historical baseline by mid-century (2040–2069), making it one of the regions with the largest increases in the United States (Gao et al., 2021).

Wildfire: Selected studies and key findings

Gao, P., Terando, A. J., Kupfer, J. A., Varner, J. M., Stambaugh, M. C., Lei, T. L., & Hiers, J. K. (2021). Robust projections of future fire probability for the conterminous United States. *Science of The Total Environment*, 789(1), Article 147872. <https://doi.org/10.1016/j.scitotenv.2021.147872>

- **Keywords:** wildfire risk, climate projections
- Relevant quotes:
 - “In pyromes across the Upper Great Lakes (Minnesota, Wisconsin, Michigan), fire probabilities are historically low (0.05–0.07) but are projected to increase to 0.11–0.14 by the end of the century (Fig. 2). While these absolute changes might seem small, they represent a nearly 120% increase in fire probability from the

historical baseline, which is among the highest percentage increases projected nationally.”

- Figure 3

Jones, M. W., Smith, A., Betts, R., Canadell, J. G., Prentice, I. C., & Le Quéré, C. (2020). Climate change increases the risk of wildfires. *Tyndall Centre for Climate Change Research*. <http://www.jstor.org/stable/resrep51248>

- **Keywords:** wildfire risk, climate change, review
- Relevant quotes:
 - “Fire weather refers to periods with a high likelihood of fire due to a combination of high temperatures, low humidity, low rainfall and often high winds. Rising global temperatures and more frequent heatwaves and associated droughts increase the likelihood of wildfire by promoting hot and dry conditions which are conducive to fire weather. Changes in rainfall and its seasonality complicate trends in fire weather, and so reductions in fire weather are possible in some regions”

Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

- **Keywords:** wildfire risk, temperature
- Relevant quotes:
 - “Increasing temperatures are projected to increase wildfire risks to Midwestern forests.” (p. 24-14)

Air quality

Climate change, human activities, and air quality are closely interconnected. Many activities that generate greenhouse gases also emit air pollutants, and several of these pollutants have direct impacts on the climate (IPCC, 2021, p. 895). This results in complex interactions and feedback loops between air quality and climate change.

Although some pollutants, such as nitrogen dioxide and fine particulate matter (PM_{2.5}), have declined in the United States in recent decades due to emissions controls and air quality regulations, climate change is generally expected to counteract some of these improvements and reduce air quality, with specific trends varying by pollutant and region (IPCC, 2021, p. 839; West et al., 2023, p. 14-5-9).

For example, higher temperatures accelerate the production of ground-level ozone (West et al., 2023, p. 14-7; Wilson et al., 2023, p. 24-17). Under a high-emissions scenario, increased ground-level ozone due to warming is expected to result in higher ozone-attributable death

rates in the Midwest and Great Plains than the rest of the country (Wilson et al., 2023, p. 24-17). Heat waves, stagnant air, and wildfire can also increase the accumulation of fine particulate matter (West et al., 2023, p. 14-7) and increases in wildfire-related particulate matter have been associated with higher rates of intensive care unit admissions in the Midwest (Wilson et al., 2023, p. 24-18). Additionally, increasing spring and fall temperatures have been linked to higher pollen concentrations, which contribute to worsening allergies, asthma, and other respiratory illnesses (Wilson et al., 2023, p. 24-18). In parts of Minnesota, pollen concentrations have increased in recent decades and continued projected increases are expected to lead to more emergency room visits in the Midwest (West et al., 2023, p. 14-15; Wilson et al., 2023, p. 24-18).

Air quality: Selected studies and key findings

Intergovernmental Panel on Climate Change (IPCC). (2021). Climate change 2021: The physical science basis. Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou, Eds.). Cambridge University Press. <https://doi.org/10.1017/9781009157896>

- **Keywords:** air quality, greenhouse gases
- Relevant quotes:
 - “Climate change and air quality are intimately linked. Many of the human activities that produce long-lived greenhouse gases also emit air pollutants, and many of these air pollutants are also ‘short-lived climate forcers’ that affect the climate. Therefore, many options for improving air quality may also serve to limit climate change and vice versa. However, some options for improving air quality cause additional climate warming, and some actions that address climate change can worsen air quality” (p. 895)
 - “The AR5 reported NO₂ decreases by 30–50% in Europe and North America... Extension of this analysis covering the time period up to 2015 reveals that NO₂ has continued to decline over the USA, Western Europe and Japan because of effective fossil fuel NO_x emissions controls, although this rate of decline has slowed down post-2011.” (p. 839)

West, J. J., Nolte, C. G., Bell, M. L., Fiore, A. M., Georgopoulos, P. G., Hess, J. J., Mickley, L. J., O’Neill, S. M., Pierce, J. R., Pinder, R. W., Pusede, S., Shindell, D. T., & Wilson, S. M. (2023). Chapter 14: Air quality. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH14>

- **Keywords:** air quality, wildfire smoke, public health
- Relevant quotes:

- “Climate change is projected to worsen air quality in many US regions (*medium confidence*), thereby harming human health and increasing premature death (*very likely, high confidence*). Extreme heat events, which can lead to high concentrations of air pollution, are projected to increase in severity and frequency (*very likely, very high confidence*), and the risk of exposure to airborne dust and wildfire smoke will increase with warmer and drier conditions in some regions (*very likely, high confidence*). Reducing air pollution concentrations will unequivocally help protect human health in a changing climate.” (p. 14-5)
- The response of ozone and PM_{2.5} to climate change—and their associated impacts on health—will vary regionally, reflecting the net balance of several complex chemical, meteorological, and small-scale processes, which vary spatially and over time. Across the Midwest and Northeast, year-round ozone is expected to increase by 2035 under a very high scenario (RCP8.5)...Projecting future PM_{2.5} is complicated, as different types of PM_{2.5} are expected to respond differently to changing climate.” (p. 14-6)
- “Wildfires emit gases and fine particles that are harmful to human health, contributing to premature mortality, asthma, and other health problems (*very high confidence*). Climate change is contributing to increases in the frequency and severity of wildfires, thereby worsening air quality in many regions of the contiguous US and Alaska (*likely, high confidence*)...Wildfires are projected to increase in many regions over the coming century. Smoke pollutants emitted by wildfires negatively impact human health, visibility, and solar energy generation. Wildland fires are the largest contributors to PM_{2.5} concentrations in some parts of the western US and impact air quality across the US. These concentrations could increase, particularly in the western US, by the end of the century, offsetting improvements from reduced human-caused air pollutant emissions. Wildfires emit PM_{2.5} and other air pollutants, including volatile organic compounds (VOCs), nitrogen oxides (which contribute to ozone generation in plumes), and toxic gaseous and particulate species.” (p. 14-9)
- Figure 14.1
- Figure 14.2
- Figure 14.6

Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

- **Keywords:** air quality, ozone, wildfire smoke, public health
- Relevant quotes:

- “Rising temperatures can increase the production of ground-level ozone and particulate matter. Exposure to these air pollutants can cause or worsen cardiovascular and respiratory illnesses and lead to premature death. Future warming under a very high scenario (RCP8.5) is projected to increase exposure to ground-level ozone by midcentury, with higher ozone-attributable death rates in counties in the Midwest and Great Plains than in the rest of the United States.” (p. 24-17)
- “Wildfire smoke from both local and distant sources poses a threat to human health by aggravating cardiovascular and respiratory conditions such as heart arrhythmias and asthma. A study of hospital admissions across the US between 2006 and 2015 found that an increase of 10 micrograms per cubic meter in wildfire-related particulate matter in a hospital’s zip code was associated with a nearly 3% increase in probability of an intensive-care-unit admission. Compared to other US census areas, this association was most consistent across Midwestern zip codes. This may be due to the larger population in this region compared to other study regions or the lack of personal protective behaviors. Based on very high (RCP8.5) and intermediate (RCP4.5) future climate projections, many Midwest counties will experience increased exposure to wildfire smoke.” (p. 24-18)
- “Increasing spring and fall temperatures are leading to rising pollen counts, which can worsen allergies, asthma, and other respiratory conditions. By 2050, increased oak pollen is projected to lead to a 7% annual increase in asthma-related emergency room visits for the Midwest under a very high scenario (RCP8.5) compared to 2% under an intermediate scenario (RCP4.5). Notably, when sensitive individuals are simultaneously exposed to allergens and air pollutants, respiratory reactions can become more severe. Black, Hispanic, and Indigenous populations tend to be disproportionately exposed to air pollution and have the highest rates of asthma and asthma-related deaths and hospitalizations in the United States.” (p. 24-18)

Ice in and ice out

Rising winter air temperatures are impacting lake ice conditions in Minnesota (Wilson et al., 2023, p. 24-14). Lakes are generally freezing later in the year and thawing earlier in the spring, resulting in up to 14 fewer days of ice cover each year compared to previous decades (Johnson & Stefan, 2006; Walsh et al., 2025). While evidence supports a long-term trend of shorter ice seasons, substantial interannual variability in ice cover has increased over time and is expected to continue (Walsh et al., 2025). Warming is also reducing ice thickness and increasing the frequency of freeze-thaw cycles, reducing ice quality and strength. Clear ice, which is the strongest and safest type of lake ice, is particularly sensitive to warming and can weaken quickly (Vikström et al., 2025). This may result in even fewer days when lake ice is thick enough for safe recreation and transportation (Woolway et al., 2022). Additionally,

longer periods of ice- and snow-free conditions can further amplify local winter warming by reducing albedo, allowing lakes to absorb more solar radiation (Liess et al., 2022).

Assessments of historical ice cover in Minnesota have exhibited strong sensitivity to the selected time period of analysis, with trend reversals, accelerations, and decelerations evident over time (Johnson & Stefan, 2006; Walsh et al., 2025). These patterns reflect the dynamic nature of lake ice and emphasize the importance of being cautious when using historical records alone to indicate possible future conditions.

Ice in and ice out: Selected studies and key findings

Johnson, S. L., & Stefan, H. G. (2006). Indicators of climate warming in Minnesota: Lake ice covers and snowmelt runoff. *Climatic Change*, 75(4), 421–453. <https://doi.org/10.1007/s10584-006-0356-0>

- **Keywords:** ice duration, ice trend variability
- Relevant quotes:
 - “MN lakes now have 14 fewer days of ice cover compared to the 1950s. Ice is forming on MN lakes about 1.5 days later per year and melting earlier in the spring.”
 - “Although hidden among strong variability from year to year, ice-out dates on 73 lakes have been shifting to an earlier date at a rate of –0.13 days/year from 1965 to 2002, while ice-in dates on 34 lakes have been delayed by 0.75 days/year from 1979 to 2002. From 1990 to 2002 the rates of change increased to –0.25 days/year for ice-out and 1.44 days/year for ice-in. “
 - “The recent rates of change calculated from the records are very noteworthy, but must not be used to project future parameter values, since trends cannot continue indefinitely, and trend reversals can be seen in some of the long-term records.”

Liess, S., Twine, T. E., Snyder, P. K., Hutchison, W. D., Konar-Steenberg, G., Keeler, B. L., & Brauman, K. A. (2022). High-resolution climate projections over Minnesota for the 21st century. *Earth and Space Science*, 9(3), Article e2021EA001893.

<https://doi.org/10.1029/2021EA001893>

- **Keywords:** ice duration, snow cover, albedo, climate projections
- Relevant quotes:
 - “Lakes will be ice-free [and snow free] for longer periods and the resulting decrease in albedo will contribute to local winter warming.”

Vikström, K., Weyhenmeyer, G., Jakobsson, E., & Peternell, M. (2025). Rapid lake ice structure changes across Swedish lakes puts public ice safety at risk. *Ambio*, 54, 122–134.

<https://doi.org/10.1007/s13280-024-02067-8>

- **Keywords:** ice duration, ice structure, safety, Sweden

- Relevant quotes:
 - “Warming is reducing ice thickness and increasing freeze–thaw cycles. In turn, this weakens ice and reduces overall ice quality. Clear ice, which is the strongest and safest type of ice, is particularly sensitive to warming and can weaken quickly.”
 - “The number of days when daily mean air temperatures stayed above the freezing point during the ice cover period was significantly related to both the thickness of the clear ice layer and the thickness of the white ice layer ($p < 0.05$). An increasing number of days with $T > 0^{\circ}\text{C}$ during the ice cover period caused a particularly rapid decline in the thickness of the clear ice layer which in turn resulted in a rapid decrease in the estimated allowable load on ice ($p < 0.05$).”
 - “Clear ice commonly exhibits lower amounts of impurities such as air bubbles and consists of large crystals with a clear direction of growth giving clear ice a strong bearing capacity.”
 - “White ice typically consists of smaller, granular crystals showing randomised directions of growth with a higher amount of impurities, homogeneously distributed or concentrated in layer or lenses. The bearing strength of white ice is lower than that of clear ice and varies alongside ice temperature.”

Walsh, J. R., Rounds, C. I., Vitense, K., Masui, H. K., Blumenfeld, K. A., Boulay, P. J., Thomas, S. M., Honsey, A. E., Blinick, N. S., Rude, C. L., Bacon, J. A., LaRoque, A. A., Leão, T. C. C., & Hansen, G. J. A. (2025). Variable phenology but consistent loss of ice cover on 1213 Minnesota lakes. *Limnology and Oceanography Letters*, 10(4), 506–515.

<https://doi.org/10.1002/lol2.70015>

- **Keywords:** ice duration, ice trend variability
- Relevant quotes:
 - “We analyzed variation and trends in ice cover phenology from 1213 lakes over 74 yr (1949–2022) in Minnesota (USA), during which ice cover duration declined at a rate of 2 d per decade (14 d total) and became more variable. Despite variation in phenology, just 10–20% of lakes differed from statewide phenological trends”
 - “The day of ice formation shifted slightly later by 0.8 d per decade, though the CI included zero....The day of ice breakup shifted earlier at a relatively constant rate of 1.2 d per decade”
 - “We found considerable variation in the estimated ice cover trend and per-decade change estimates over time frames of analysis that were 40 yr or shorter; these estimates were often uncertain.”
 - “Indeed, trend reversals, accelerations, and decelerations over shorter time series durations were common here, even using our approach that accounts for random annual variation. Apparent decelerations in recent decades have important implications for interpreting long-term change in datasets that begin

in the 2000s or later, which would constitute most remotely sensed ice cover data. Our results suggest ice cover dynamics will continue to be variable from year to year or even decade to decade (and possibly more over time with increasing variation in ice cover) and estimates of accelerating lake ice loss in recent decades may not be persistent.”

Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

- **Keywords:** ice cover, cultural activities, drownings
- Relevant quotes:
 - “Ice cover, an important feature of northern lake systems, is declining in response to rising winter air temperatures, 150 with the most abrupt changes beginning in the 1990s. Loss of ice cover is projected to continue through the end of the century, with greater losses under high scenarios, 150 threatening some cultural activities and services (Figure 24.6). 151 Winter drownings have also increased along with temperatures, which have decreased ice cover.” (24-14)

Woolway, R. I., Huang, L., Sharma, S., Lee, S., Rodgers, K. B., & Timmermann, A. (2022). Lake ice will be less safe for recreation and transportation under future warming. *Earth's Future*, 10(10), Article e2022EF002907. <https://doi.org/10.1029/2022EF002907>

- **Keywords:** ice duration, ice thickness, safety
- Relevant quotes:
 - “Our Large Ensemble simulations suggest that the duration of safe lake ice will shorten considerably in response to the projected future increase in global average air temperature. With a 1.5°C increase (i.e., 2024–2038) of global air temperature since the start of the 20th century (1900–1929), the duration of safe lake ice will shorten, on average, by 13 days”
 - “In warm and wet/snowy winters, there is more white ice relative to black ice, which is half as strong. The presence of white ice reduces lower load bearing capacity and requires even thicker ice to sustain the same amount of human weight. As extreme warm, wet/snowy winters and freeze-thaw events become more common, ice will need to be even greater than 10 cm thick to be safer for people to use.”

References

- Abatzoglou, J. T., & Brown, T. J. (2012). A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, 32(5), 772–780. <https://doi.org/10.1002/joc.2312>
- Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, 33(1), 121–131. <https://doi.org/10.1002/joc.3413>
- Alder, J. R., & Hostetler, S. W. (2013). *USGS National Climate Change Viewer* [Web tool]. U.S. Geological Survey. <https://doi.org/10.5066/F7W9575T>
- Alder, J. R. (2025). *CMIP6-LOCA2 spatial summaries of counties (TIGER 2023) from 1950–2100 for the Contiguous United States* [Dataset]. U.S. Geological Survey. <https://doi.org/10.5066/P1N9IRWC>
- Allen, J. T., & Tippet, M. K. (2015). The characteristics of United States hail reports: 1955–2014. *Electronic Journal of Severe Storms Meteorology*, 10(3), 1–31. <https://doi.org/10.55599/ejssm.v10i3.60>
- Ashley, W. S., Haberlie, A. M., & Gensini, V. A. (2020). Reduced frequency and size of late-twenty-first-century snowstorms over North America. *Nature Climate Change*, 10(6), 539–544. <https://doi.org/10.1038/s41558-020-0774-4>
- Boulay, P. (n.d.). *Overview of Extensive Ice Storms in Minnesota*. Minnesota State Climatology Office, Minnesota Department of Natural Resources. https://files.dnr.state.mn.us/natural_resources/climate/summaries_and_publications/ice_storms_in_minnesota.pdf
- Briley, L., Dougherty, R., Wells, K., Hercula, T., Notaro, M., Rood, R., Andresen, J., Marsik, F., Prosperi, A., Jorns, J., Channell, K., Hutchinson, S., Kemp, C., & Gates, O. (Eds.). (2021a). *A practitioner's guide to climate model scenarios*. Great Lakes Integrated Sciences and Assessments (GLISA). https://glisa.umich.edu/wp-content/uploads/2021/03/A_Practitioners_Guide_to_Climate_Model_Scenarios.pdf
- Briley, L. J., Rood, R. B., & Notaro, M. (2021b). Large lakes in climate models: A Great Lakes case study on the usability of CMIP5. *Journal of Great Lakes Research*, 47(2), 405–418. <https://doi.org/10.1016/j.jglr.2021.01.010>
- Brooks, H. E. (2013). Severe thunderstorms and climate change. *Atmospheric Research*, 123, 129–138. <https://doi.org/10.1016/j.atmosres.2012.04.002>
- Chen, H., Sun, J., & Lin, W. (2020). Anthropogenic influence would increase intense snowfall events over parts of the Northern Hemisphere in the future. *Environmental Research Letters*, 15(11), Article 114022. <https://doi.org/10.1088/1748-9326/abb93>
- Copernicus Climate Change Service. (2021). *CMIP6 climate projections* [Dataset]. Copernicus Climate Data Store (CDS). <https://doi.org/10.24381/cds.c866074c>
- Daly, C., Doggett, M. K., Smith, J. I., Olson, K. V., Halbleib, M. D., Dimcovic, Z., Keon, D., Loiselle, R. A., Steinberg, B., Ryan, A. D., Pancake, C. M., & Kaspar, E. M. (2021). Challenges in observation-based mapping of daily precipitation across the conterminous United

- States. *Journal of Atmospheric and Oceanic Technology*, 38, 1979–1992.
<https://doi.org/10.1175/JTECH-D-21-0054.1>
- Danco, J. F., & Martin, E. R. (2018). Understanding the influence of ENSO on the Great Plains low-level jet in CMIP5 models. *Climate Dynamics*, 51, 1537–1558.
<https://doi.org/10.1007/s00382-017-3970-9>
- Durre, I., Menne, M. J., Gleason, B. E., Houston, T. G., & Vose, R. S. (2010). Comprehensive automated quality assurance of daily surface observations. *Journal of Applied Meteorology and Climatology*, 49(8), 1615–1633.
<https://doi.org/10.1175/2010JAMC2375.1>
- Ekström, M., Grose, M. R., & Whetton, P. H. (2015). An appraisal of downscaling methods used in climate change research. *WIREs Climate Change*, 6(3), 301–319.
<https://doi.org/10.1002/wcc.339>
- England, J. F., Jr., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas, W. O., Veilleux, A. G., Kiang, J. E., & Mason, R. R., Jr. (2019). *Guidelines for determining flood flow frequency—Bulletin 17C (Techniques and Methods, Book 4, Chap. B5)*. U.S. Geological Survey.
<https://doi.org/10.3133/tm4B5>
- Gao, P., Terando, A. J., Kupfer, J. A., Varner, J. M., Stambaugh, M. C., Lei, T. L., & Hiers, J. K. (2021). Robust projections of future fire probability for the conterminous United States. *Science of The Total Environment*, 789(1), Article 147872.
<https://doi.org/10.1016/j.scitotenv.2021.147872>
- Groisman, P. Y., & Legates, D. R. (1994). The accuracy of United States precipitation data. *Bulletin of the American Meteorological Society*, 75(2), 215–228. [https://doi.org/10.1175/1520-0477\(1994\)075<0215:TAOUSP>2.0.CO;2](https://doi.org/10.1175/1520-0477(1994)075<0215:TAOUSP>2.0.CO;2)
- Hegewisch, K. C. & Abatzoglou, J. T. (2026). *Climate Toolbox* [Web tool].
<https://climatetoolbox.org/>
- Hoell, A., Hoerling, M., Eischeid, J., & Barsugli, J. (2021). Preconditions for extreme wet winters over the contiguous United States. *Weather and Climate Extremes*, 33, Article 100333.
<https://doi.org/10.1016/j.wace.2021.100333>
- Hondula, D. M., Meltzer, S., Balling, R. C., & Iñiguez, P. (2022). Spatial analysis of United States National Weather Service excessive heat warnings and heat advisories. *Bulletin of the American Meteorological Society*, 103, E2017–E2031. <https://doi.org/10.1175/BAMS-D-21-0069.1>
- Intergovernmental Panel on Climate Change (IPCC). (2023). *Climate change 2023: Synthesis report*. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (H. Lee & J. Romero, Eds.).
<https://doi.org/10.59327/IPCC/AR6-9789291691647>
- Intergovernmental Panel on Climate Change (IPCC). (2021). *Climate change 2021: The physical science basis*. Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou, Eds.). Cambridge University Press. <https://doi.org/10.1017/9781009157896>

- Johnson, S. L., & Stefan, H. G. (2006). Indicators of climate warming in Minnesota: Lake ice covers and snowmelt runoff. *Climatic Change*, 75(4), 421–453. <https://doi.org/10.1007/s10584-006-0356-0>
- Jones, M. W., Smith, A., Betts, R., Canadell, J. G., Prentice, I. C., & Le Quéré, C. (2020). *Climate change increases the risk of wildfires*. Tyndall Centre for Climate Change Research. <http://www.jstor.org/stable/resrep51248>
- Katzenberger, A., Pérez-Carrasquilla, J. S., Gemmell, K., Galytska, E., Leclerc, C., Punya, P., Roy, I., Varuolo-Clarke, A., Tošić, M., & Črnivec, N. (2026). Developing guidelines for working with multi-model ensembles in CMIP. *Earth System Dynamics*, 17(3), 495–532. <https://doi.org/10.5194/esd-17-495-2026>
- Klink, K. (2002). Trends and interannual variability of wind speed distributions in Minnesota. *Journal of Climate*, 15(22), 3311–3317. [https://doi.org/10.1175/1520-0442\(2002\)015<3311:TAIVOW>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<3311:TAIVOW>2.0.CO;2)
- Kunkel, K. E., Palecki, M. A., Hubbard, K. G., Robinson, D. A., Redmond, K. T., & Easterling, D. R. (2007). Trend identification in twentieth-century U.S. snowfall: The challenges. *Journal of Atmospheric and Oceanic Technology*, 24(1), 64–73. <https://doi.org/10.1175/JTECH2017.1>
- Leeper, R. D., Bilotta, R., Petersen, B., Stiles, C. J., Heim, R., Fuchs, B., Prat, O. P., Palecki, M., & Ansari, S. (2022). Characterizing U.S. drought over the past 20 years using the U.S. drought monitor. *International Journal of Climatology*, 42(12), 6616–6630. <https://doi.org/10.1002/joc.7653>
- Lehner, F., Deser, C., Maher, N., Marotzke, J., Fischer, E. M., Brunner, L., Knutti, R., & Hawkins, E. (2020). Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. *Earth System Dynamics*, 11(2), 491–508. <https://doi.org/10.5194/esd-11-491-2020>
- Liess, S., Twine, T. E., Snyder, P. K., Hutchison, W. D., Konar-Steenberg, G., Keeler, B. L., & Brauman, K. A. (2022). High-resolution climate projections over Minnesota for the 21st century. *Earth and Space Science*, 9(3), Article e2021EA001893. <https://doi.org/10.1029/2021EA001893>
- Liess, S., Roop, H. A., Twine, T. E., Clark, S., Coffman, D., Dolma, D., Farris, A., Fernandez, A., Gorman, J., & Meyer, N. (2026). County-scale climate projections over Minnesota and the effects of lakes. *Water Resources Research*, 62(2), Article e2025WR040415. <https://doi.org/10.1029/2025WR040415>
- Lukas, J., & Vano, J. (2024). *CMIP6 frequently asked questions: A resource for water managers*. Aspen Global Change Institute. <https://doi.org/10.69925/QIXT9885>
- Marvel, K., Su, W., Delgado, R., Aarons, S., Chatterjee, A., Garcia, M. E., Hausfather, Z., Hayhoe, K., Hence, D. A., Jewett, E. B., Robel, A., Singh, D., Tripathi, A., & Vose, R. S. (2023). *Chapter 2: Climate trends*. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH2>

- Meehl, G. A., Boer, G. J., Covey, C., Latif, M., & Stouffer, R. J. (1997). Intercomparison makes for a better climate model. *Eos Transactions American Geophysical Union*, 78(41), 445–451. <https://doi.org/10.1029/97EO00276>
- Meinshausen, M., Nicholls, Z. R. J., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J. G., Daniel, J. S., John, A., Krummel, P. B., Luderer, G., Meinshausen, N., Montzka, S. A., Rayner, P. J., Reimann, S., Smith, S. J., van den Berg, M., Velders, G. J. M., Vollmer, M. K., & Wang, R. H. J. (2020). The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. *Geoscientific Model Development*, 13(8), 3571–3605. <https://doi.org/10.5194/gmd-13-3571-2020>
- Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology*, 29(7), 897–910. <https://doi.org/10.1175/JTECH-D-11-00103.1>
- Midwest Regional Climate Center (MRCC). (2026a). *cli-MATE: MRCC Application Tools Environment* [Web tool]. National Oceanic and Atmospheric Administration. <https://mrcc.purdue.edu/newclimate/home>
- Midwest Regional Climate Center (MRCC). (2026b). *Snowfall Climatology Toolbox* [Web tool]. National Oceanic and Atmospheric Administration. <https://mrcc.purdue.edu/resources/climateTools/snowfallclimatology>
- Minnesota Climate Adaptation Partnership. (n.d.). *Minnesota Climate Mapping and Analysis Tool* [Web tool]. University of Minnesota. <https://app.climate.umn.edu/>
- Minnesota Department of Health. (2025). *Minnesota extreme heat toolbox* (Version 2.0). <https://www.health.state.mn.us/communities/environment/climate/docs/mnextremeheattoolkit.pdf>
- Minnesota Department of Natural Resources. (2026). *2026 Lake ice out dates* [Dataset]. https://www.dnr.state.mn.us/ice_out/index.html
- Minnesota Department of Natural Resources. (n.d.-a). *Historic mega-rain events in Minnesota*. https://www.dnr.state.mn.us/climate/summaries_and_publications/mega_rain_event_s.html
- Minnesota Department of Natural Resources. (n.d.-b). *Minnesota Climate Explorer* [Web tool]. <https://climate-explorer.dnr.state.mn.us/>
- Minnesota Department of Natural Resources. (n.d.-c). *Minnesota Flash Floods*. https://www.dnr.state.mn.us/climate/summaries_and_publications/flash_floods.html
- Minnesota State Climatology Office. (n.d.). *Climate Journal*. Minnesota Department of Natural Resources. <https://www.dnr.state.mn.us/climate/journal/index.html>
- Mora, C., Dousset, B., Caldwell, I. R., Powell, F. E., Geronimo, R. C., Bielecki, C. R., Counsell, C. W. W., Dietrich, B. S., Johnston, E. T., Louis, L. V., Lucas, M. P., McKenzie, M. M., Shea, A. G., Tseng, H., Giambelluca, T. W., Leon, L. R., Hawkins, E., & Trauernicht, C. (2017). Global risk of deadly heat. *Nature Climate Change*, 7, 501–506. <https://doi.org/10.1038/nclimate3322>

-
- National Centers for Environmental Information (NCEI). (2019). *NOAA offers climate data for counties*. National Oceanic and Atmospheric Administration. <https://www.ncei.noaa.gov/news/noaa-offers-climate-data-counties>
- National Centers for Environmental Information (NCEI). (2026a). *Storm events database* [Dataset]. National Oceanic and Atmospheric Administration. <https://www.ncei.noaa.gov/stormevents/>
- National Centers for Environmental Information (NCEI). (2026b). *Climate at a glance* [Web tool]. National Oceanic and Atmospheric Administration. <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/>
- National Drought Mitigation Center. (2026a). *Drought classification*. University of Nebraska–Lincoln. <https://droughtmonitor.unl.edu/About/AbouttheData/DroughtClassification.aspx>
- National Drought Mitigation Center. (2026b). *What is the USDM?*. University of Nebraska–Lincoln. <https://droughtmonitor.unl.edu/About/WhatistheUSDM.aspx>
- National Oceanic and Atmospheric Administration. (n.d.). *July 4, 1977 derecho: The Independence Day derecho of 1977*. <https://www.spc.noaa.gov/misc/AbtDerechos/casepages/jul41977page.htm>
- National Weather Service. (n.d.-a). *Heat Forecast Tools*. National Oceanic and Atmospheric Administration. <https://www.weather.gov/safety/heat-tools>
- National Weather Service. (n.d.-b). *National Weather Service guidance for extreme cold warnings and cold weather advisories*. National Oceanic and Atmospheric Administration. <https://www.arcgis.com/apps/instant/basic/index.html?appid=59e3b7653a734e47aca16c5aa5b301c0>
- National Weather Service. (n.d.-c). *National Weather Service winter storm warning for heavy snow criteria* [Web tool]. National Oceanic and Atmospheric Administration. <https://www.arcgis.com/apps/instant/basic/index.html?appid=e4d92ef4da394c5c89979605689d9949>
- National Weather Service. (n.d.-d). *WFO MPX watch, warning, advisory criteria*. National Oceanic and Atmospheric Administration. https://www.weather.gov/mpx/www_criteria
- National Weather Service. (2021). *National Weather Service instruction 10-1605: Storm data preparation*. National Oceanic and Atmospheric Administration. https://www.weather.gov/media/directives/010_pdfs/pd01016005curr.pdf
- National Weather Service. (2022). *The heat index equation*. National Oceanic and Atmospheric Administration. https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml?os=win&ref=app
- Notaro, M., Bennington, V., & Vavrus, S. (2015). Dynamically downscaled projections of lake-effect snow in the Great Lakes Basin. *Journal of Climate*, 28(4), 1661–1684. <https://doi.org/10.1175/JCLI-D-14-00467.1>
- Pierce, D. W., Su, L., Cayan, D. R., Risser, M. D., Livneh, B., & Lettenmaier, D. P. (2021). An extreme-preserving long-term gridded daily precipitation dataset for the

-
- conterminous United States. *Journal of Hydrometeorology*, 22(7), 1883–1895. <https://doi.org/10.1175/JHM-D-20-0212.1>
- Pierce, D. W., Cayan, D. R., Feldman, D. R., & Risser, M. D. (2023). Future increases in North American extreme precipitation in CMIP6 downscaled with LOCA. *Journal of Hydrometeorology*, 24(5), 951–975. <https://doi.org/10.1175/JHM-D-22-0194.1>
- Potvin, C. K., Broyles, C., Skinner, P. S., Brooks, H. E., & Rasmussen, E. (2019). A Bayesian hierarchical modeling framework for correcting reporting bias in the U.S. tornado database. *Weather and Forecasting*, 34(1), 15–30. <https://doi.org/10.1175/WAF-D-18-0137.1>
- Prein, A. F. (2023). Thunderstorm straight line winds intensify with climate change. *Nature Climate Change*, 13(12), 1353–1359. <https://doi.org/10.1038/s41558-023-01852-9>
- Raupach, T. H., Martius, O., Allen, J. T., Kunz, M., Lasher-Trapp, S., Mohr, S., Rasmussen, K. L., Trapp, R. J., & Zhang, Q. (2021). The effects of climate change on hailstorms. *Nature Reviews Earth & Environment*, 2(3), 213–226. <https://doi.org/10.1038/s43017-020-00133-9>
- Regional Climate Centers (RCC). (2026). *Applied Climate Information System* [Web Tool]. National Oceanic and Atmospheric Administration. <https://www.rcc-acis.org/>
- Ribeiro, S., Caineta, J., & Costa, A. C. (2016). Review and discussion of homogenisation methods for climate data. *Physics and Chemistry of the Earth, Parts A/B/C*, 94, 167–179. <https://doi.org/10.1016/j.pce.2015.08.007>
- Roufa, C. M., Ashley, W. S., Haberlie, A. M., Corner, J. M., Hawthorne, K. T., Moeller, L. K., Gensini, V. A., & Michaelis, A. C. (2026). Projected mid- and late-century changes in severe convective storms across the United States from dynamically downscaled climate simulations. *International Journal of Climatology*, Article e70475. <https://doi.org/10.1002/joc.70475>
- Sharma, A., Wasko, C., & Lettenmaier, D. P. (2018). If precipitation extremes are increasing, why aren't floods? *Water Resources Research*, 54(11), 8545–8551. <https://doi.org/10.1029/2018WR023749>
- Svoboda, M., LeCompte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., Rippey, B., Tinker, R., Palecki, M., Stooksbury, D., Miskus, D., & Stephens, S. (2002). The Drought Monitor. *Bulletin of the American Meteorological Society*, 83(8), 1181–1190. <https://doi.org/10.1175/1520-0477-83.8.1181>
- Svoma, B. M., & Cervený, R. (2012). Analyzing bias in prominent climatic data sets. *Progress in Physical Geography: Earth and Environment*, 36(3), 333–347. <https://doi.org/10.1177/0309133312438084>
- Terando, A. J., Tucker, A., Runyon, A., Miller, J., Perkins, J., Kimbrel, S., Cross, A., & Boyles, R. (2024). *Best practices for incorporating climate change science into Department of the Interior analyses, consultations, and decision making: The U.S. Department of the Interior technical and applications guide*. Climate Science Applications Coordination Team, U.S. Department of the Interior. <https://doi.org/10.21429/hjgj-j073>

-
- Trapp, R. J., & Hoogewind, K. A. (2016). The realization of extreme tornadic storm events under future anthropogenic climate change. *Journal of Climate*, 29(14), 5251–5265. <https://doi.org/10.1175/JCLI-D-15-0623.1>
- Trzaska, S., & Schnarr, E. (2014). *A review of downscaling methods for climate change projections*. Tetra Tech ARD. https://ciesin.columbia.edu/sites/ciesin.columbia.edu/files/content/Downscaling_CLEARED_000.cleaned.pdf
- UC Merced. (n.d.-a). *GridMET* [Dataset]. Climatology Lab, Sierra Nevada Research Institute. <https://www.climatologylab.org/gridmet.html>
- UC Merced. (n.d.-b). *Multivariate Adaptive Constructed Analogs (MACA) Datasets* [Dataset]. Northwest Knowledge Network. <https://climate.northwestknowledge.net/MACA/index.php>
- Ullrich, P. (2023). *Validation of LOCA2 and STAR-ESDM statistically downscaled products* (LLNL-TR-856094). Lawrence Livermore National Laboratory. <https://doi.org/10.2172/2202926>
- U.S. Census Bureau. (2023). *tl_2023_us_county*, TIGER/Line Shapefiles [Dataset]. <https://www2.census.gov/geo/tiger/TIGER2023/COUNTY/>
- U.S. Environmental Protection Agency (EPA). (n.d.). *Air Quality Index (AQI) basics*. AirNow. <https://www.airnow.gov/aqi/aqi-basics/>
- U.S. Environmental Protection Agency (EPA). (2026a). *Interactive map of air quality monitors [Dataset and data visualization]*. <https://www.epa.gov/outdoor-air-quality-data/interactive-map-air-quality-monitors>
- U.S. Environmental Protection Agency (EPA). (2026b). *Pre-generated data files* [Dataset]. AirData. https://aqs.epa.gov/aqsweb/airdata/download_files.html
- U.S. Environmental Protection Agency (EPA). (2026c). *Technical assistance document for the reporting of daily air quality – the Air Quality Index (AQI) (EPA-403/B-26-003)*. <https://document.airnow.gov/technical-assistance-document-for-the-reporting-of-daily-air-quailty.pdf>
- U.S. Federal Government. (2024). *Climate Resilience Information System* [Web tool] <https://cris.climate.gov>
- van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., & Rose, S. K. (2011). The representative concentration pathways: An overview. *Climatic Change*, 109(5), 1–33. <https://doi.org/10.1007/s10584-011-0148-z>
- Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate*, 23(7), 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>
- Vikström, K., Weyhenmeyer, G., Jakobsson, E., & Peterzell, M. (2025). Rapid lake ice structure changes across Swedish lakes puts public ice safety at risk. *Ambio*, 54, 122–134. <https://doi.org/10.1007/s13280-024-02067-8>
- Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams, C. N., Jr., Fenimore, C., Gleason, K., & Arndt, D. (2014a). Improved historical temperature and precipitation

- time series for U.S. climate divisions. *Journal of Applied Meteorology and Climatology*, 53(5), 1232–1251. <https://doi.org/10.1175/JAMC-D-13-0248.1>
- Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams C. N., Jr., Fenimore, C., Gleason, K., & Arndt, D. (2014b). *NOAA Monthly U.S. Climate Divisional Database (NClimDiv)* [Dataset]. NOAA National Climatic Data Center. <https://doi.org/10.7289/V5M32STR>
- Vose, R. S., Applequist, S., Squires, M., Durre, I., Menne, M. J., Williams Jr., C. N., Fenimore, C., Gleason, K., & Arndt, D. (2014c). *NOAA Monthly U.S. Climate Gridded Dataset (nClimGrid), Version 1* [Dataset]. NOAA National Centers for Environmental Information. <https://doi.org/10.7289/V5SX6B56>
- Walker, M. D. (2026, January 25–29). *Population bias in NOAA Storm Events Database reports of severe wind and hail: Implications for risk and impacts assessment in rural areas*. 106th Annual Meeting of the American Meteorological Society, Houston, TX, United States. https://blueskiesmeteorology.com/wp-content/uploads/AMS-Extended-Abstract_Population-Bias-in-NOAA-SED.pdf
- Walsh, J. R., Rounds, C. I., Vitense, K., Masui, H. K., Blumenfeld, K. A., Boulay, P. J., Thomas, S. M., Honsey, A. E., Blinick, N. S., Rude, C. L., Bacon, J. A., LaRoque, A. A., Leão, T. C. C., & Hansen, G. J. A. (2025). Variable phenology but consistent loss of ice cover on 1213 Minnesota lakes. *Limnology and Oceanography Letters*, 10(4), 506–515. <https://doi.org/10.1002/lol2.70015>
- Wang, G., Kirchhoff, C. J., Seth, A., Abatzoglou, J. T., Livneh, B., Pierce, D. W., Fomenko, L., & Ding, T. (2020). Projected changes of precipitation characteristics depend on downscaling method and training data: MACA versus LOCA using the S.S. Northeast as an example. *Journal of Hydrometeorology*, 21(12), 2739–2758. <https://doi.org/10.1175/JHM-D-19-0275.1>
- Wang, J., Xue, P., Pringle, W., Yang, Z., & Qian, Y. (2022). Impacts of lake surface temperature on the summer climate over the Great Lakes Region. *Journal of Geophysical Research: Atmospheres*, 127(11). Article e2021JD036231. <https://doi.org/10.1029/2021JD036231>
- West, J. J., Nolte, C. G., Bell, M. L., Fiore, A. M., Georgopoulos, P. G., Hess, J. J., Mickley, L. J., O'Neill, S. M., Pierce, J. R., Pinder, R. W., Pusede, S., Shindell, D. T., & Wilson, S. M. (2023). Chapter 14: Air quality. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH14>
- Williams-Sether, T., & Sanocki, C. (2025). *Peak streamflow trends in Minnesota and their relation to changes in climate, water years 1921–2020* (Scientific Investigations Report Nos. 2023–5064–E). U.S. Geological Survey. <https://doi.org/10.3133/sir20235064E>
- Wilson, A. B., Baker, J. M., Ainsworth, E. A., Andresen, J., Austin, J. A., Dukes, J. S., Gibbons, E., Hoppe, B. O., LeDee, O. E., Noel, J., Roop, H. A., Smith, S. A., Todey, D. P., Wolf, R., & Wood, J. D. (2023). Chapter 24: Midwest. In A. R. Crimmins, C. W. Avery, D. R. Easterling, K. E. Kunkel, B. C. Stewart, & T. K. Maycock (Eds.), *Fifth National Climate Assessment*. U.S. Global Change Research Program. <https://doi.org/10.7930/NCA5.2023.CH24>

-
- Woods, M. J., Trapp, R. J., & Mallinson, H. M. (2023). The impact of human-induced climate change on future tornado intensity as revealed through multi-scale modeling. *Geophysical Research Letters*, 50(15), Article e2023GL104796. <https://doi.org/10.1029/2023GL104796>
- Woolway, R. I., Huang, L., Sharma, S., Lee, S., Rodgers, K. B., & Timmermann, A. (2022). Lake ice will be less safe for recreation and transportation under future warming. *Earth's Future*, 10(10), Article e2022EF002907. <https://doi.org/10.1029/2022EF002907>
- Wooten, A., Terando, A., Reich, B. J., Boyles, R. P., & Semazzi, F. (2017). Characterizing sources of uncertainty from global climate models and downscaling techniques. *Journal of Applied Meteorology and Climatology*, 56(12), 3245–3262. <https://doi.org/10.1175/JAMC-D-17-0087.1>
- World Meteorological Organization (WMO). (2017). *WMO Guidelines on the Calculation of Climate Normals* (WMO-No. 1203). <https://library.wmo.int/idurl/4/55797>

Appendices

Appendix A: additional plots

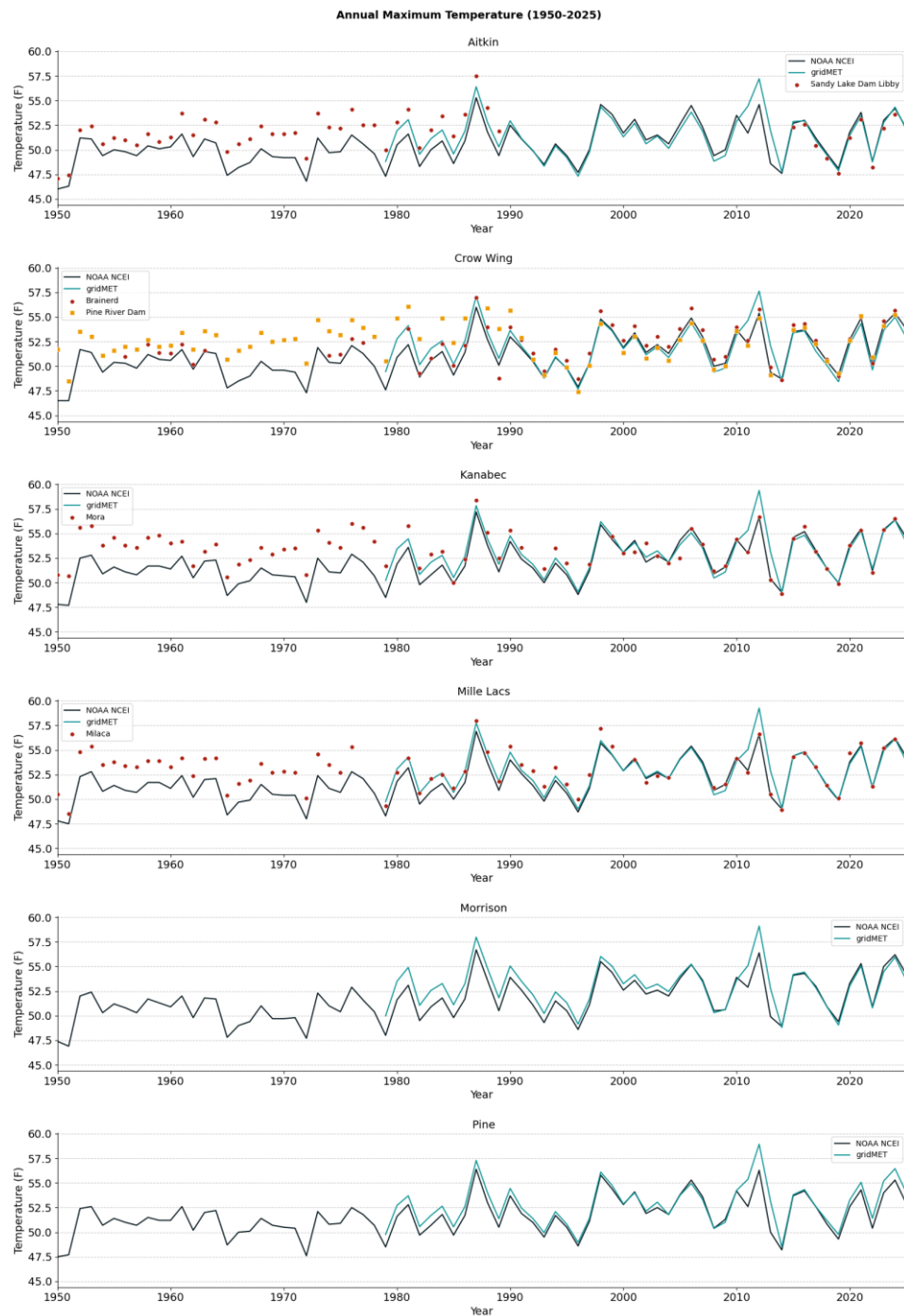


Figure A1. Annual average maximum temperature across the six-county region in different observational datasets. Gridded and aggregated datasets (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from weather stations are shown as points when available (see Appendix B: Analysis methodology).

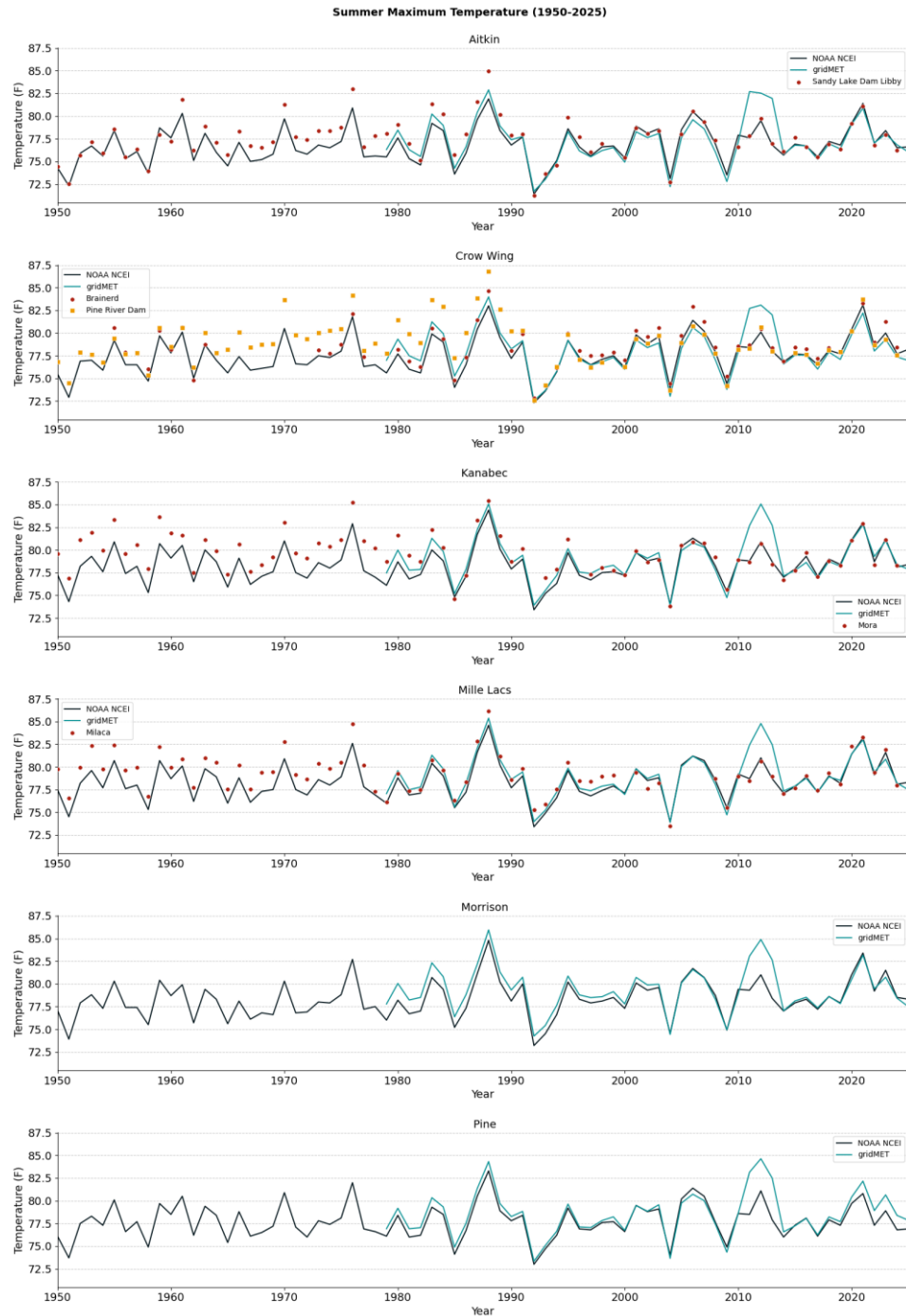


Figure A2. Summer (June–August) average maximum temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).



Figure A3. Winter (December–February) average maximum temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

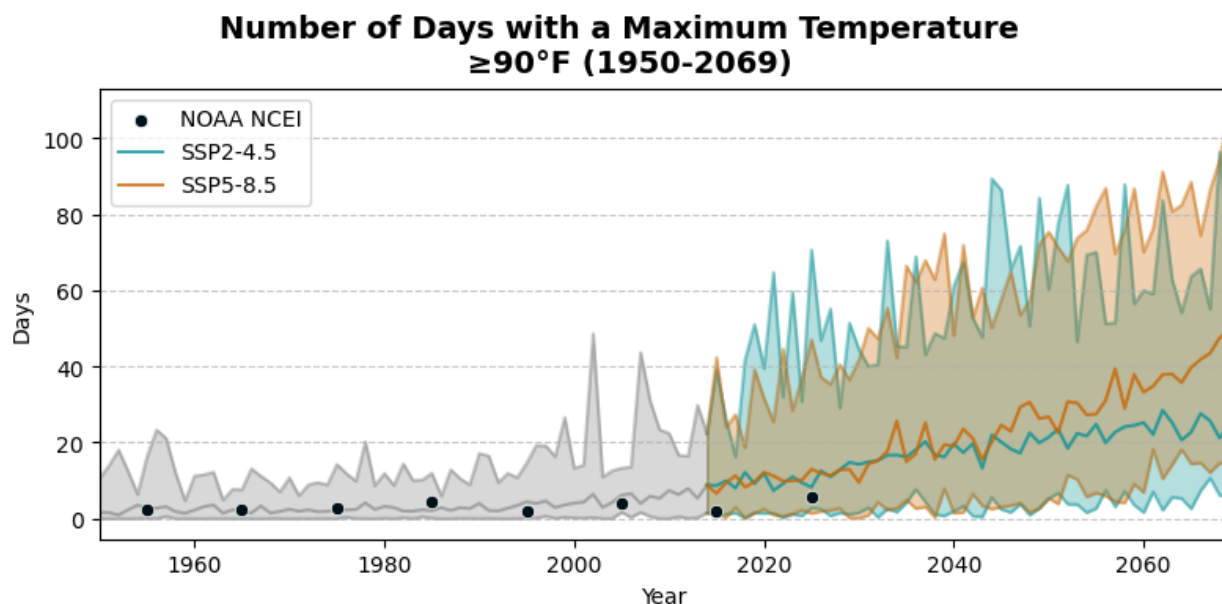


Figure A4. Annual total days with a maximum temperature greater than or equal to 90°F from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

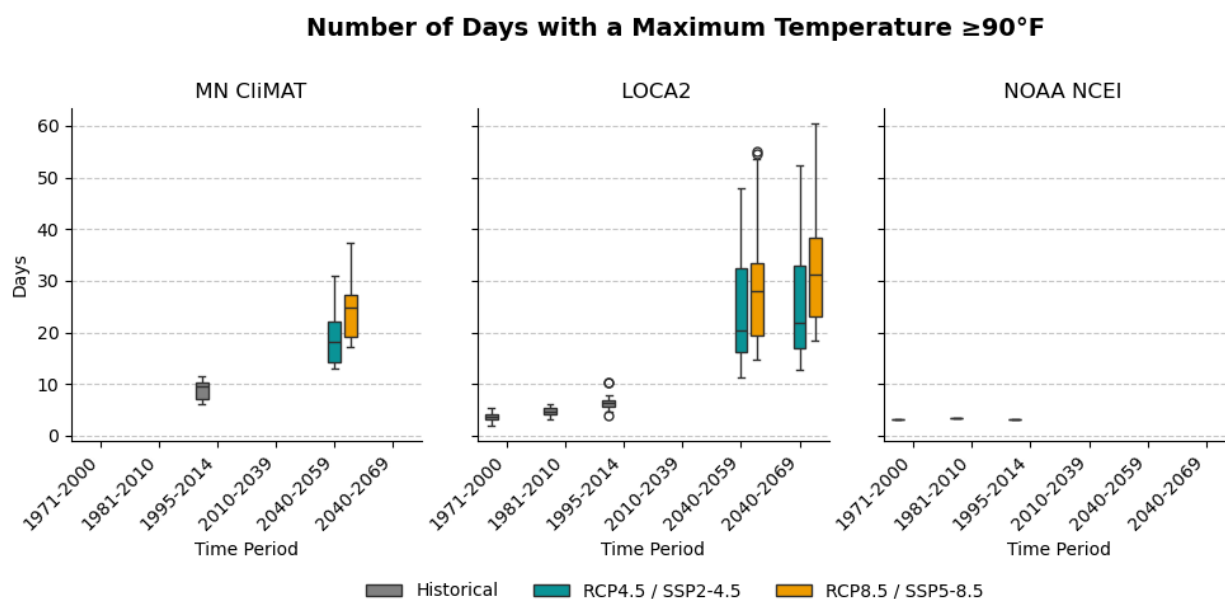


Figure A5. Comparison of period averages of annual total days with a maximum temperature greater than or equal to 90°F across datasets. Note that MN CliMAT data are values greater than 90°F. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$ and LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP and LOCA2 = SSP.

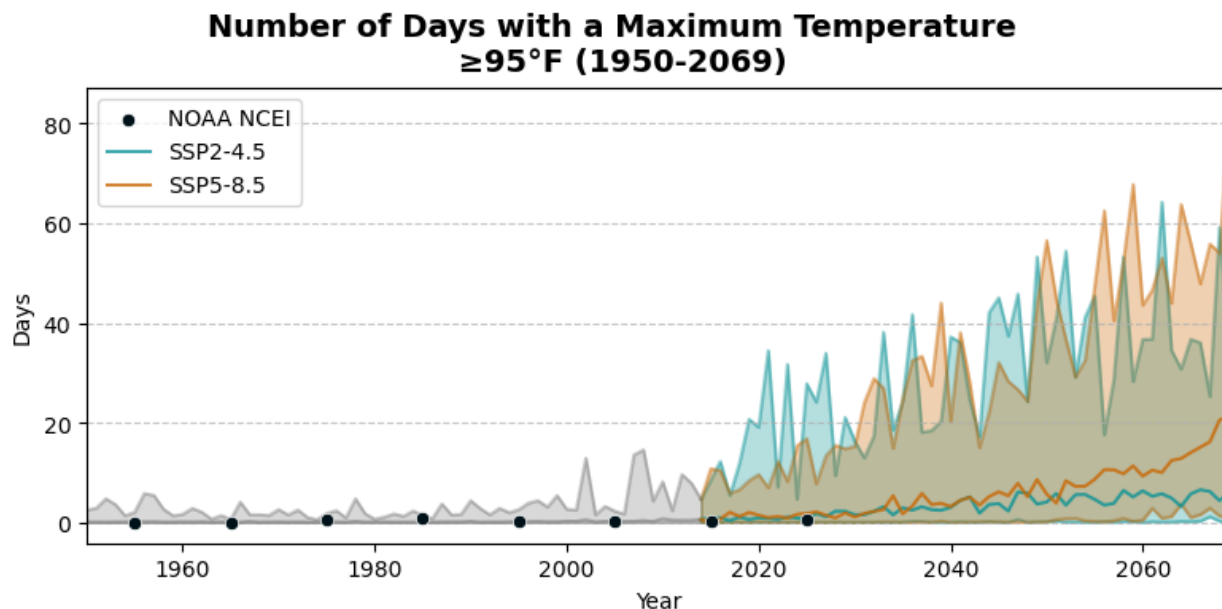


Figure A6. Annual total days with a maximum temperature greater than or equal to 95°F from 1950–2069 from LOCA2 climate model simulations ($n=23$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

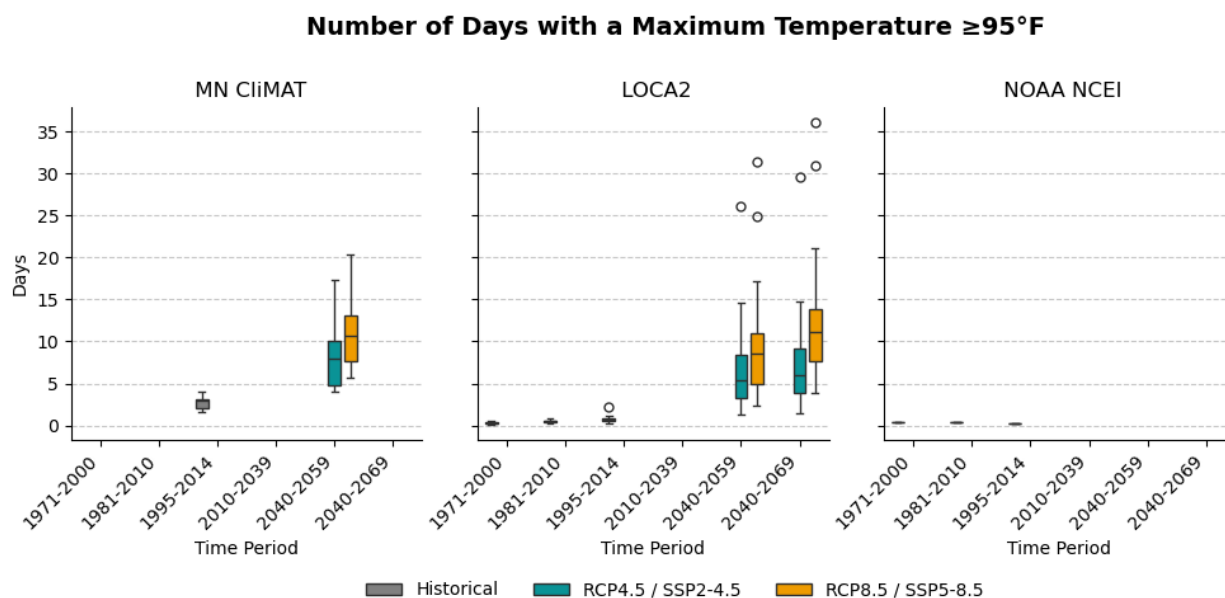


Figure A7. Comparison of period averages of annual total days with a maximum temperature greater than or equal to 95°F across datasets. Note that MN CliMAT data are values greater than 95°F . Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; LOCA2 $n=23$) and observational datasets ($n=1$). NOAA NCEI period averages are calculated using decadal average values. Emissions scenarios associated with each dataset include MN CliMAT = SSP; and LOCA2 = SSP.

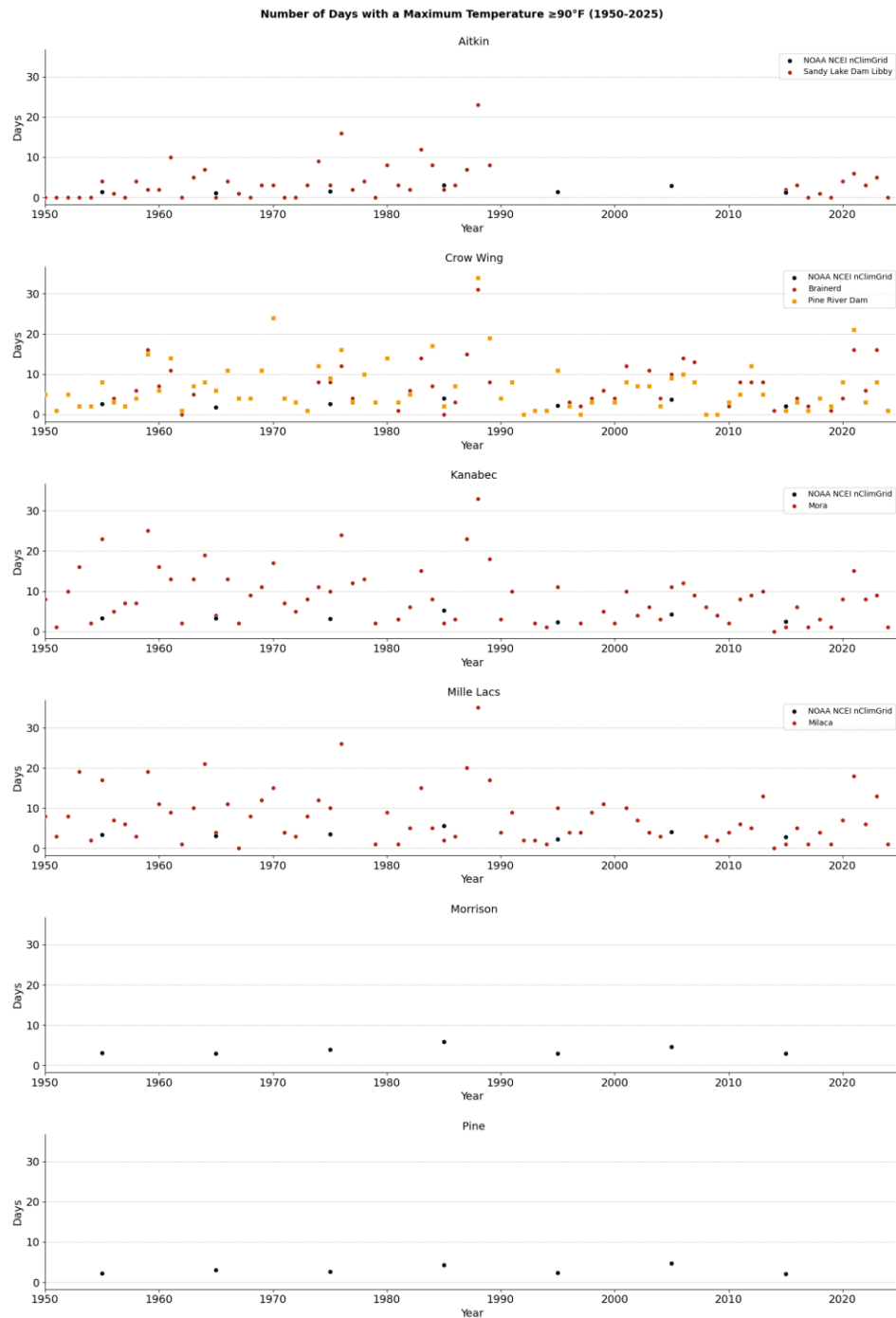


Figure A8. Annual total days with a maximum temperature greater than or equal to 90°F across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available (see Appendix B: Analysis methodology).

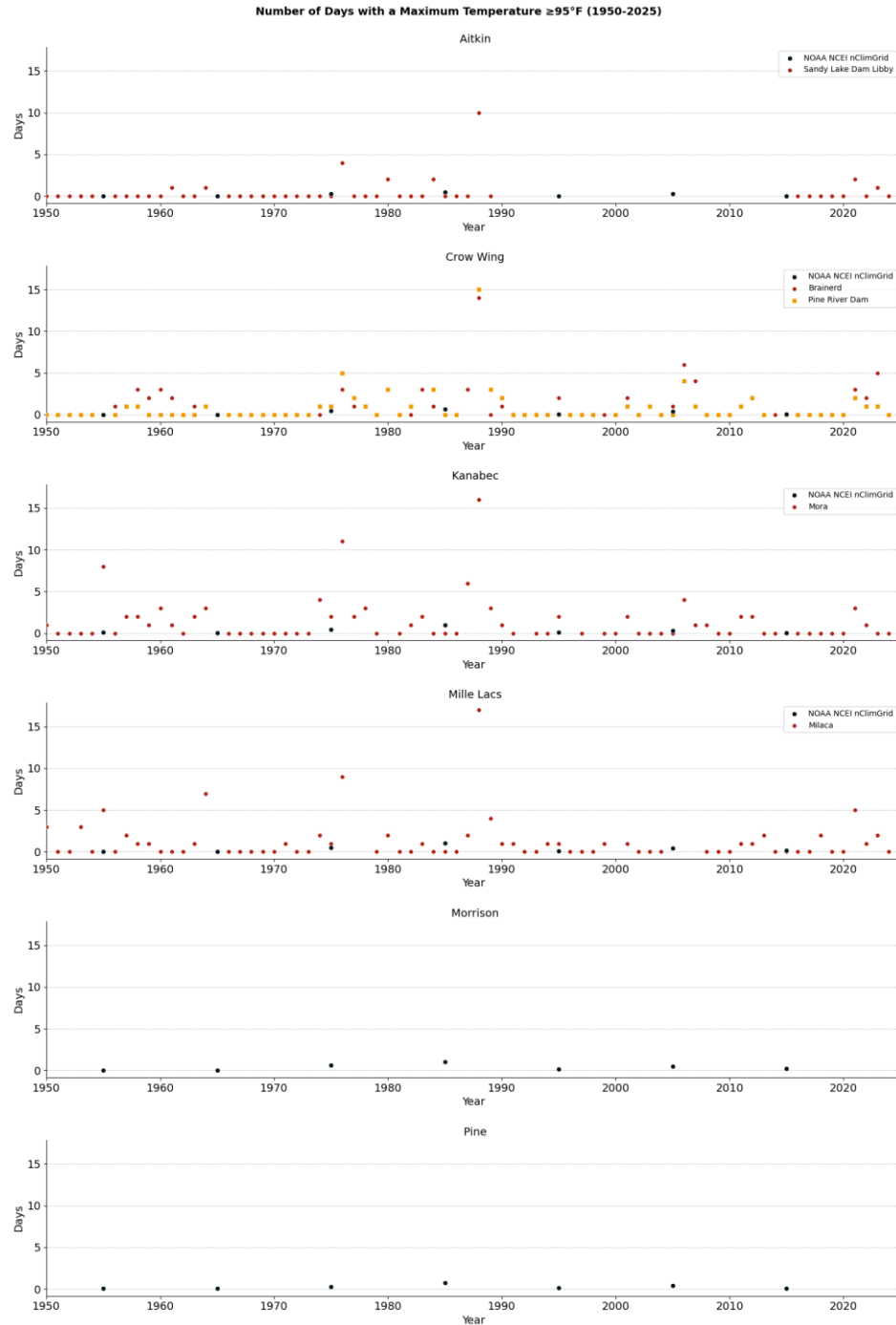


Figure A9. Annual total days with a maximum temperature greater than or equal to 95°F across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available (see Appendix B: Analysis methodology).

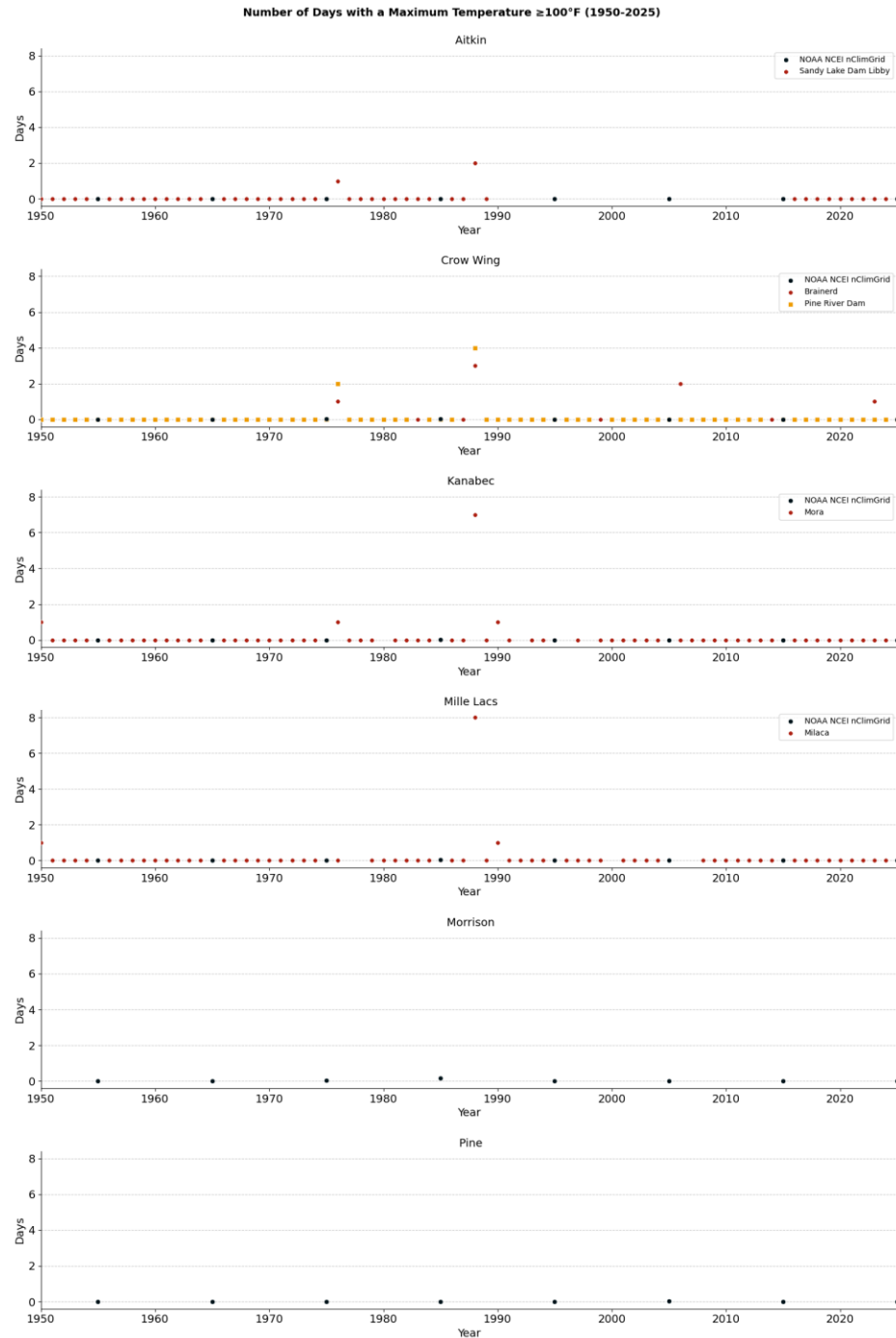


Figure A10. Annual total days with a maximum temperature greater than or equal to 100°F across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available (see Appendix B: Analysis methodology).

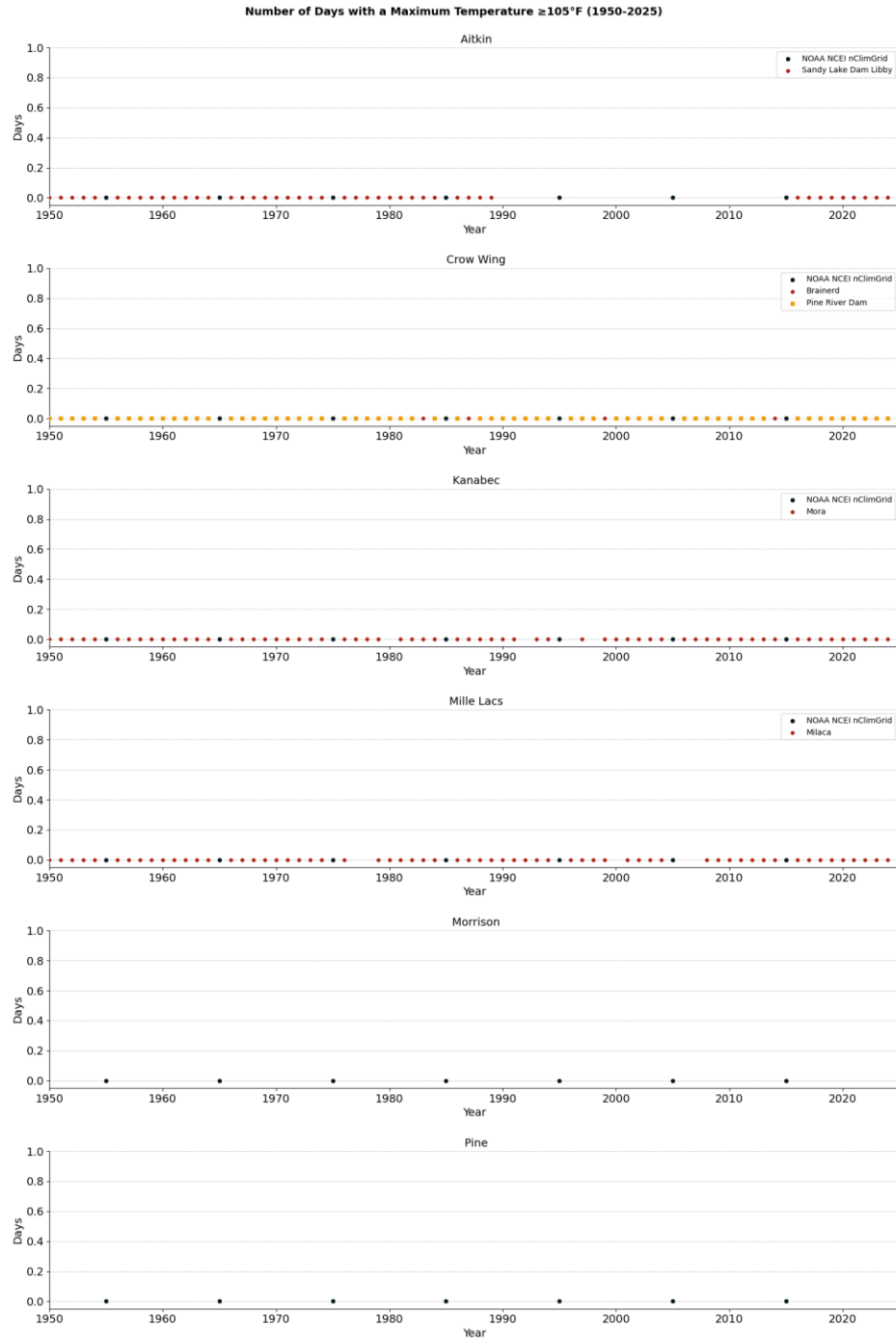


Figure A11. Annual total days with a maximum temperature greater than or equal to 105°F across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available (see Appendix B: Analysis methodology).

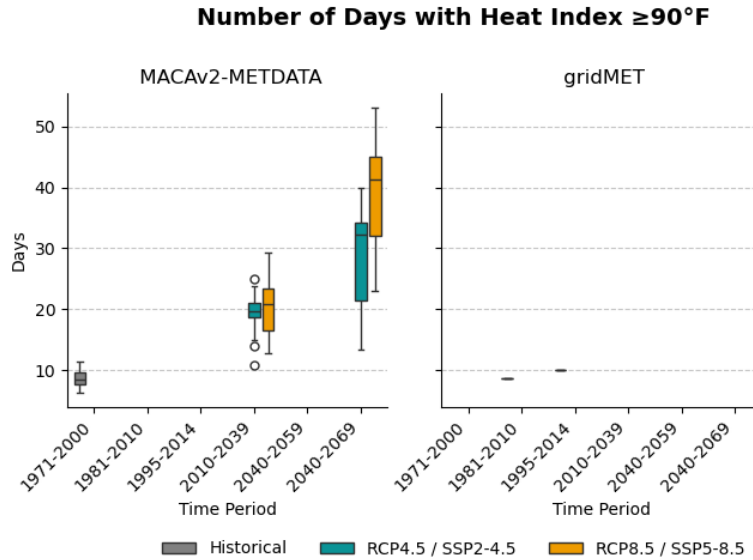


Figure A12. Comparison of period averages of annual total days from April–October with heat index greater than or equal to 90°F across datasets. Boxplots summarize the variation among climate simulations (MACAv2-METDATA $n=20$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MACAv2-METDATA = RCP.

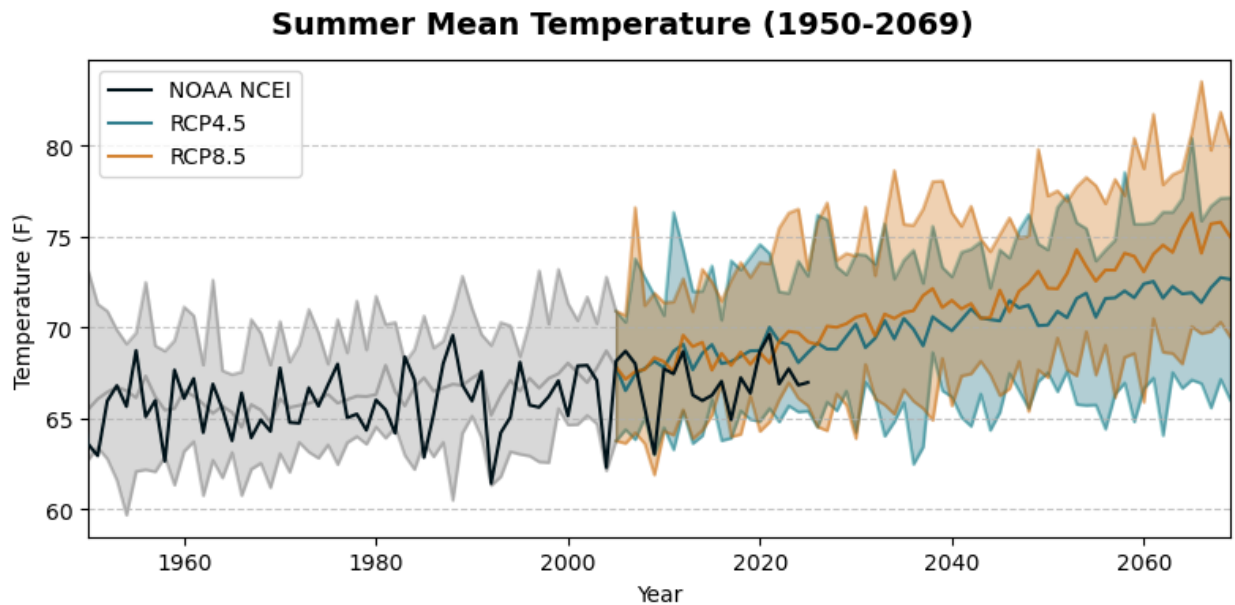


Figure A13. Summer (June–August) average mean temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

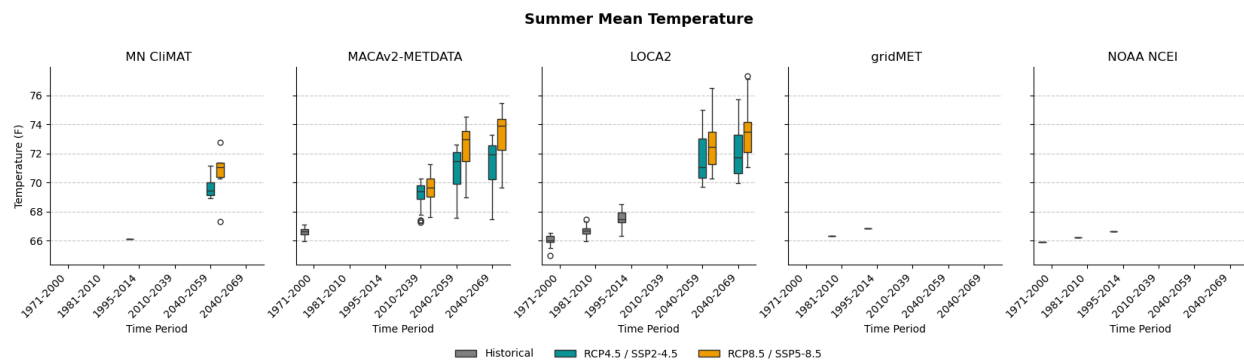


Figure A14. Comparison of period averages of summer (June–August) average mean temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

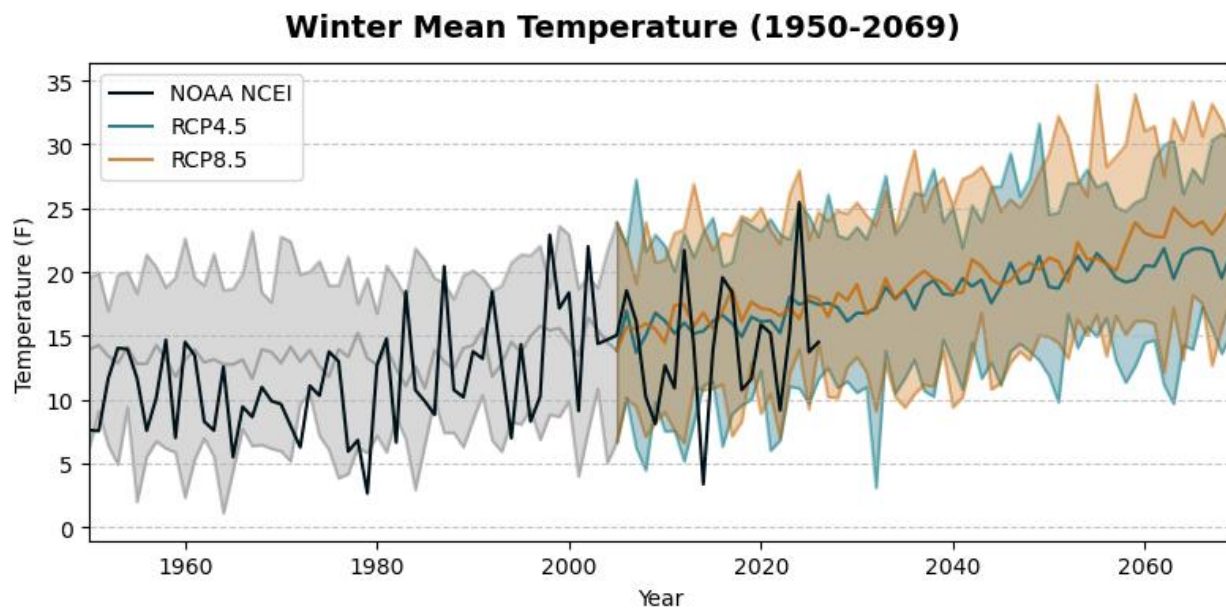


Figure A15. Winter (December–February) average mean temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

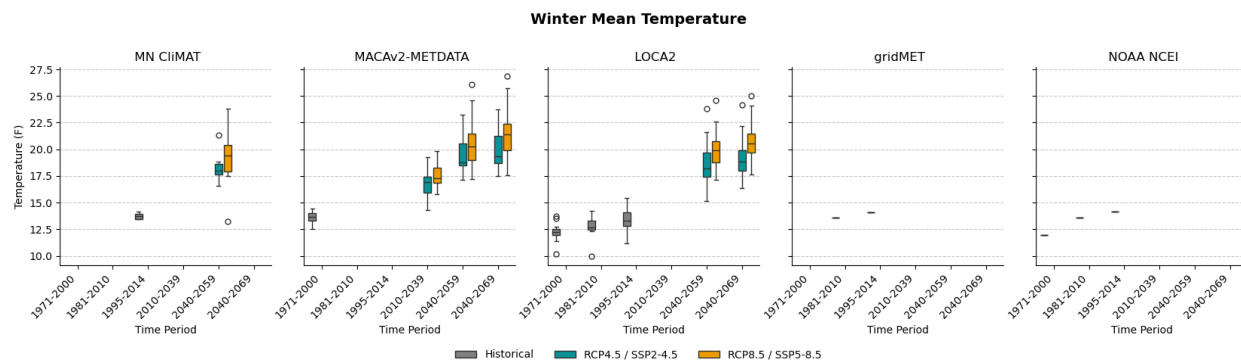


Figure A16. Comparison of period averages of winter (December–February) average mean temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

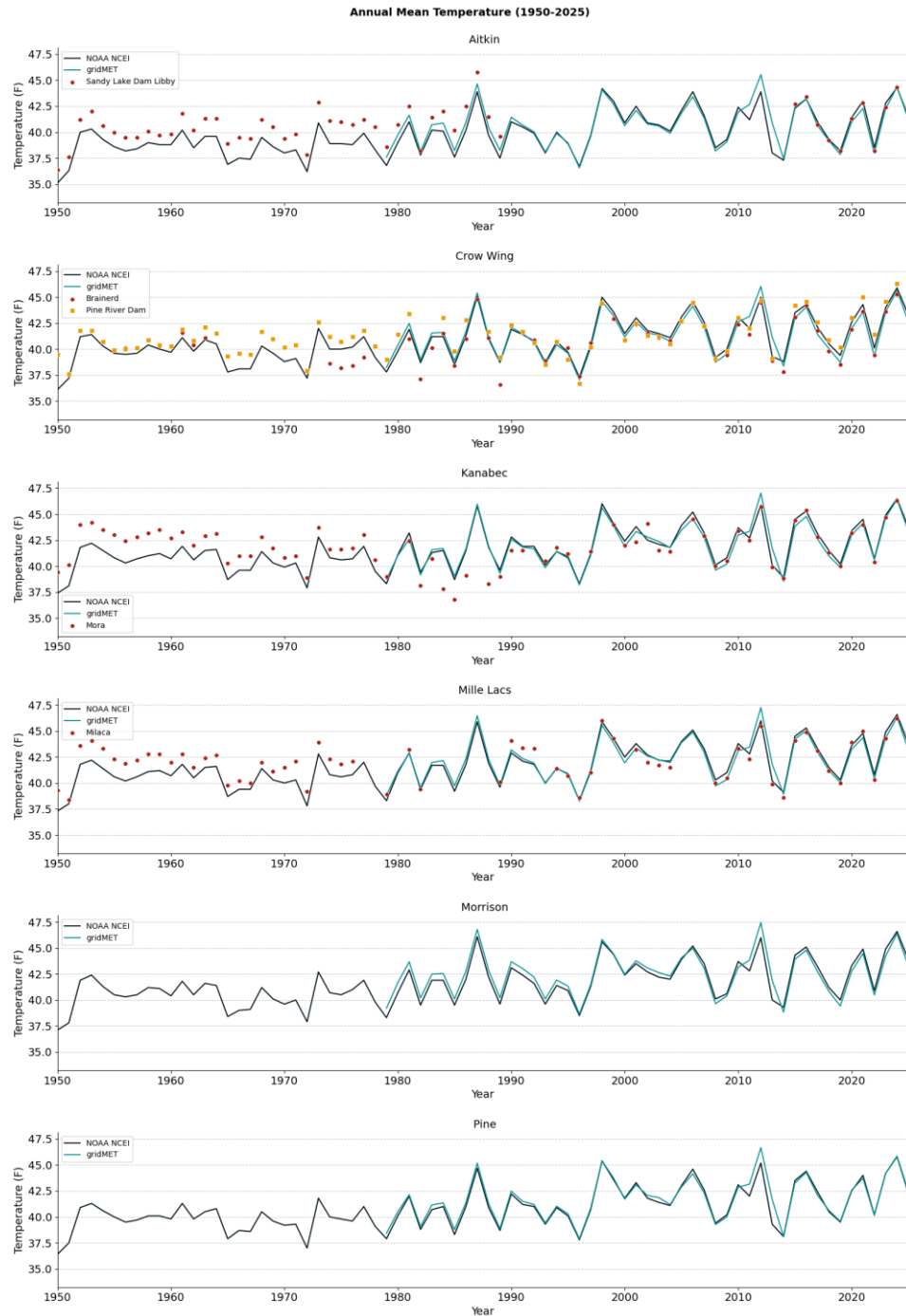


Figure A17. Annual average mean temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

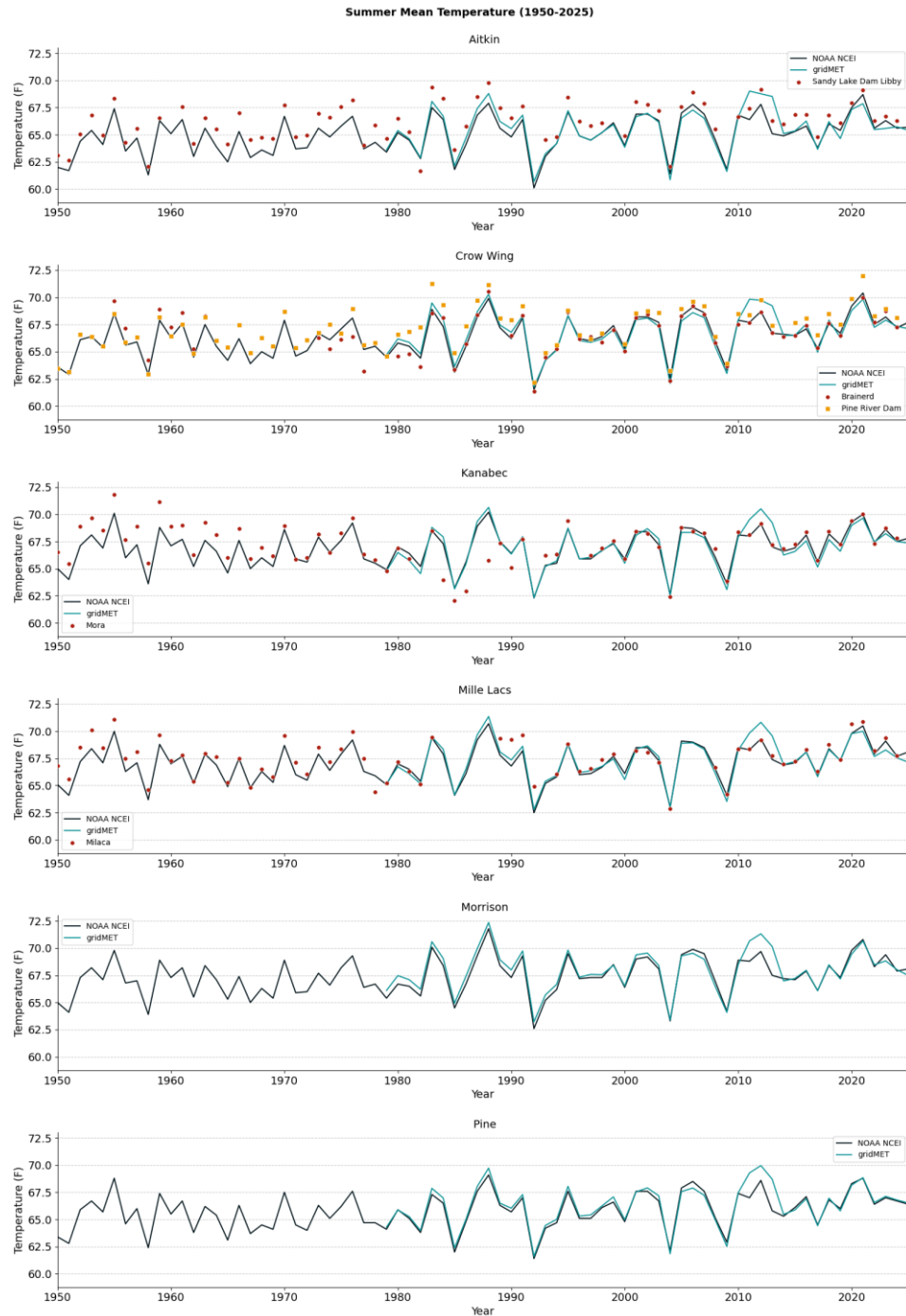


Figure A18. Summer (June–August) average mean temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

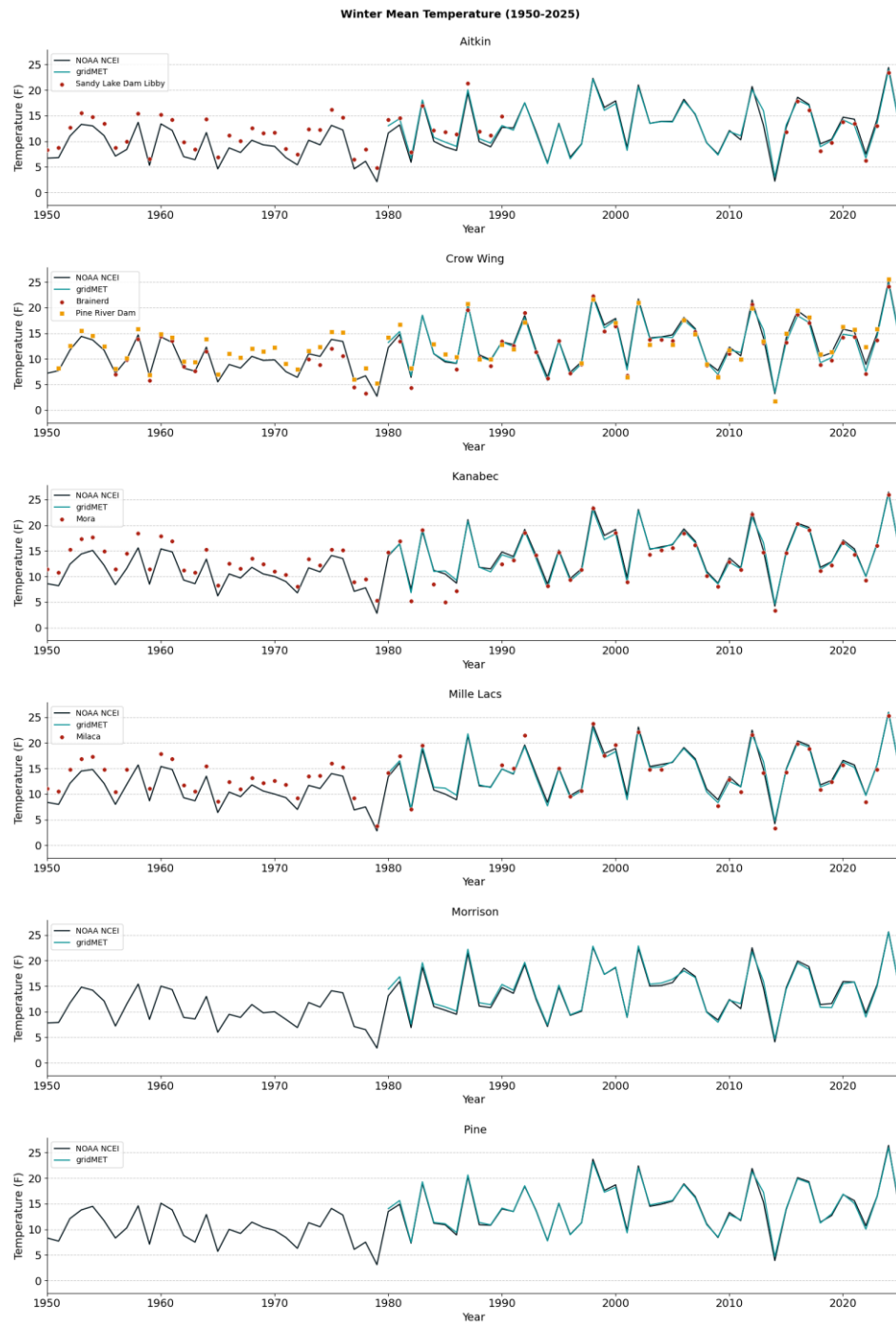


Figure A19. Winter (December–February) average mean temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

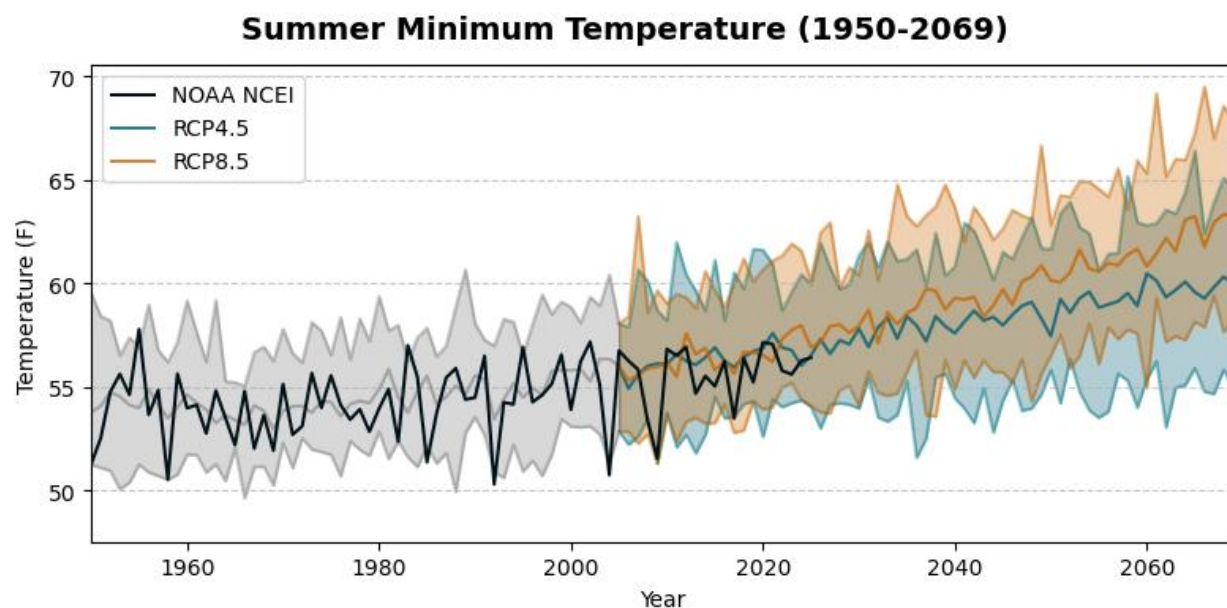


Figure A20. Summer (June–August) average minimum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

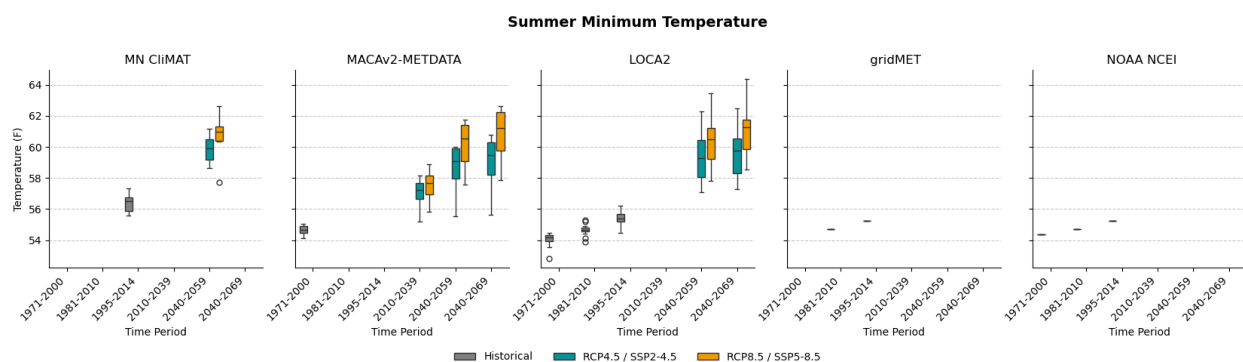


Figure A21. Comparison of period averages of summer (June–August) average minimum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

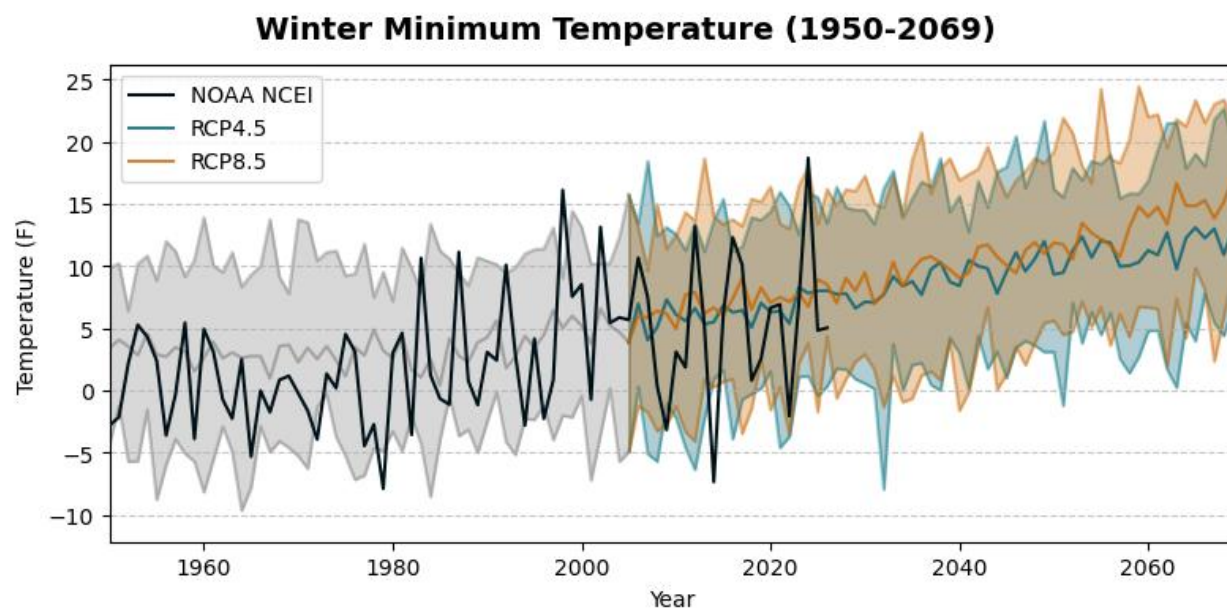


Figure A22. Winter (December–February) average minimum temperature from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

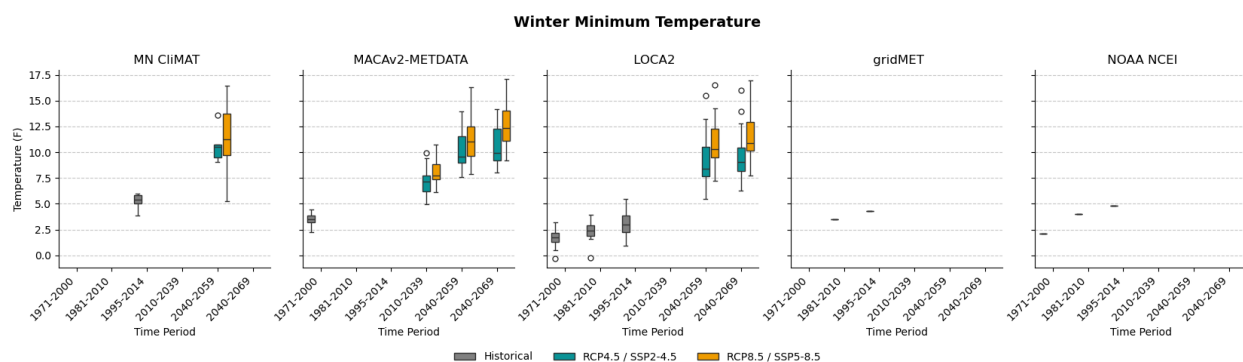


Figure A23. Comparison of period averages of winter (December–February) average minimum temperature across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

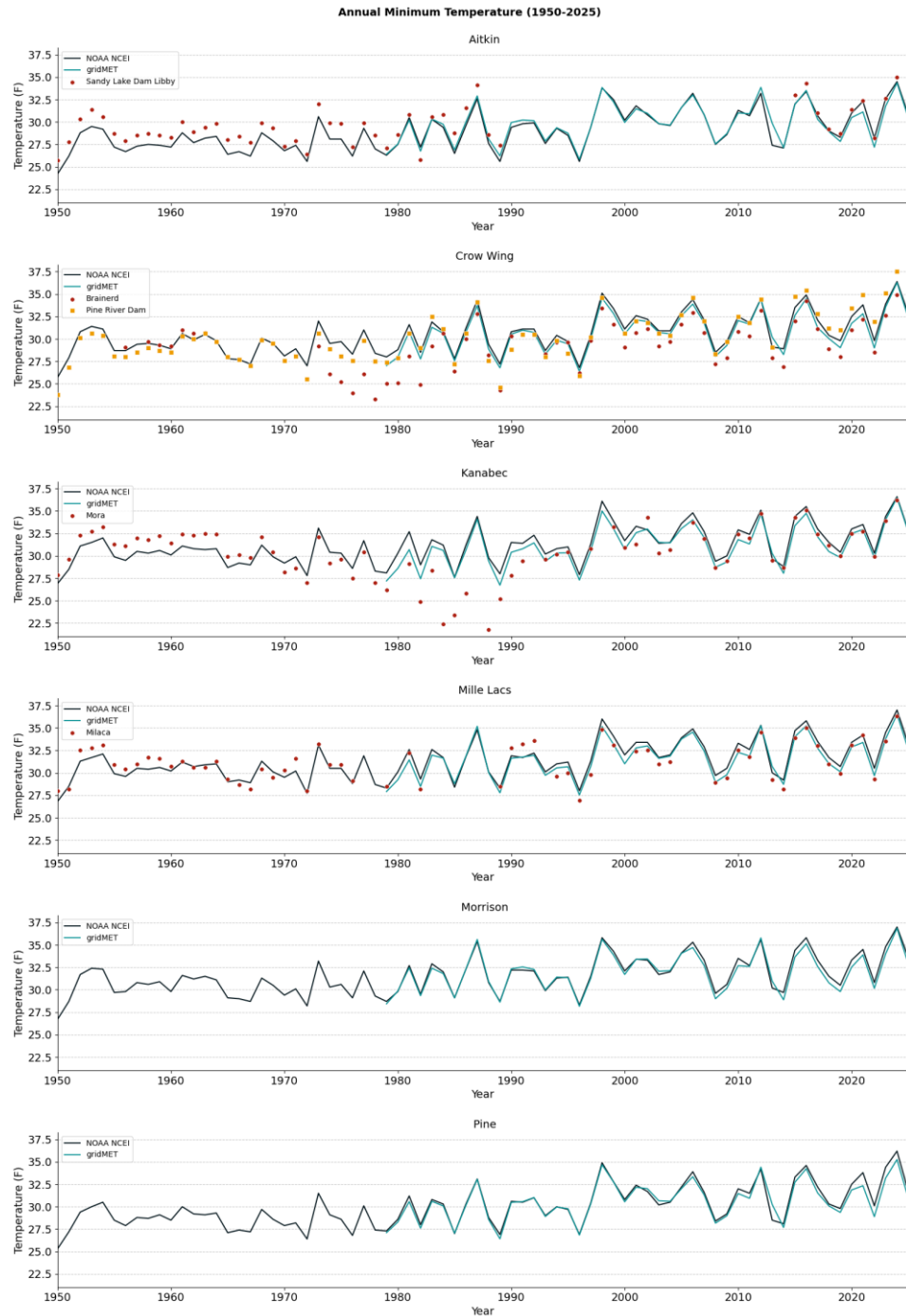


Figure A24. Annual average minimum temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

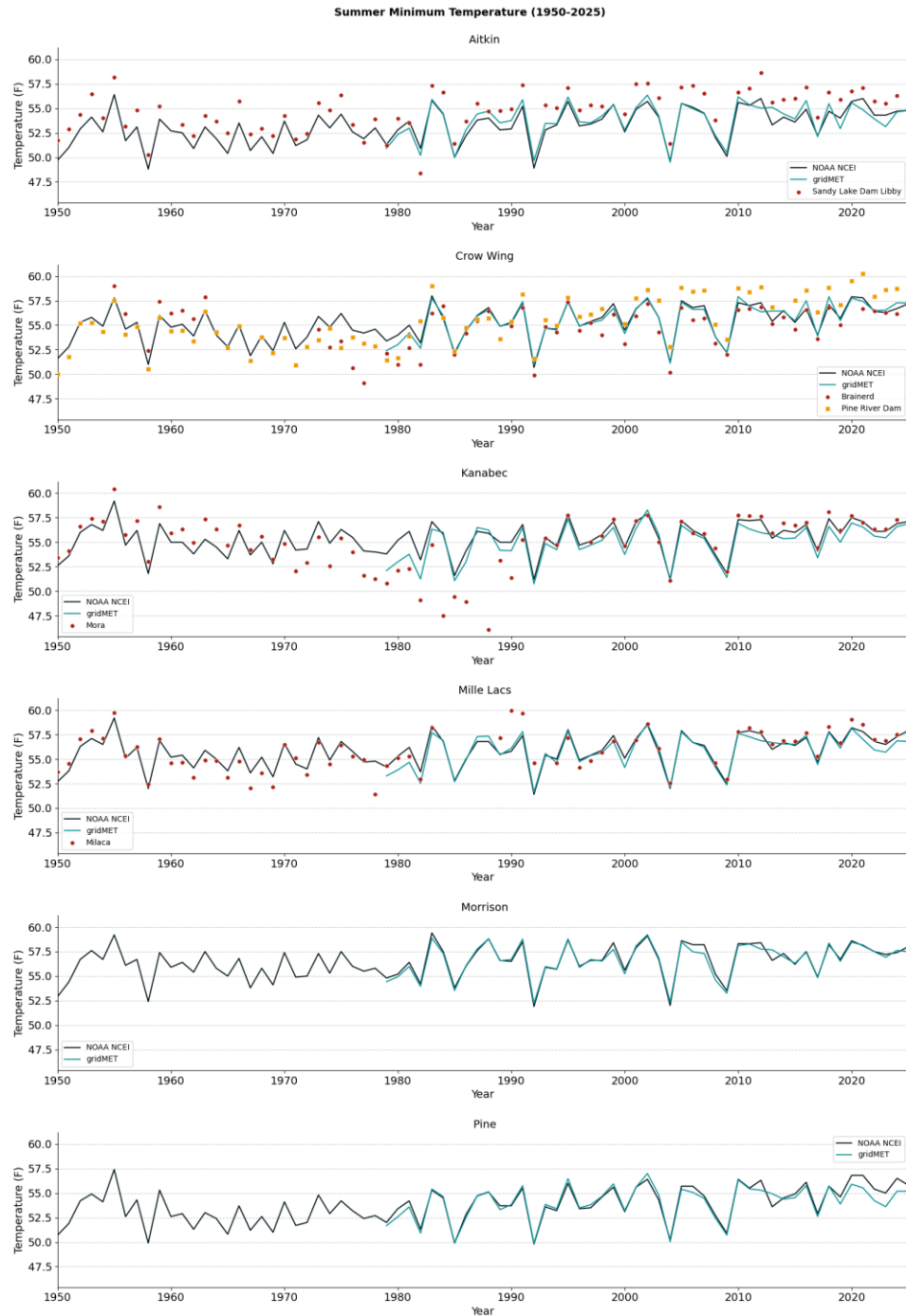


Figure A25. Summer (June–August) average minimum temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

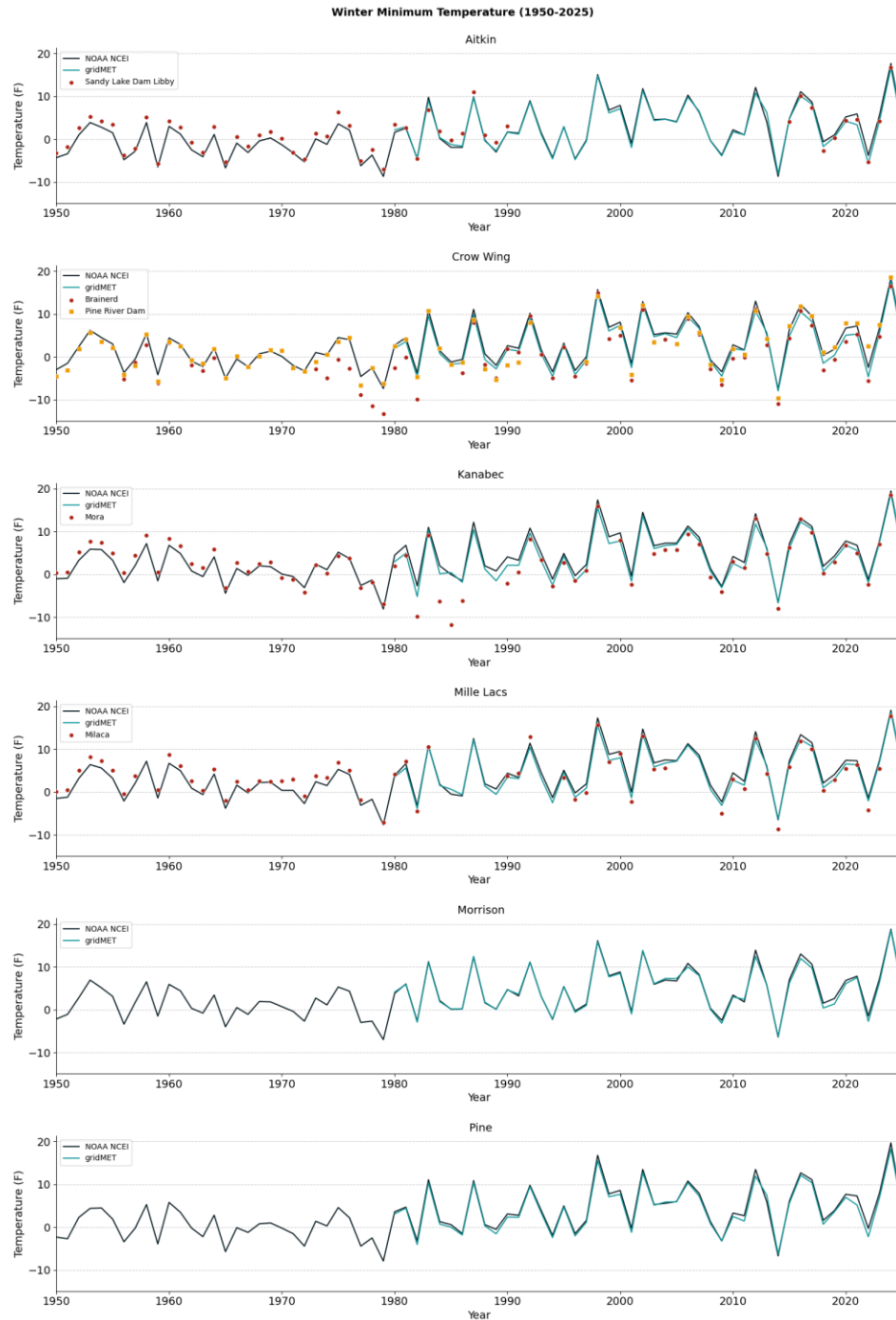


Figure A26. Winter (December–February) average minimum temperature across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

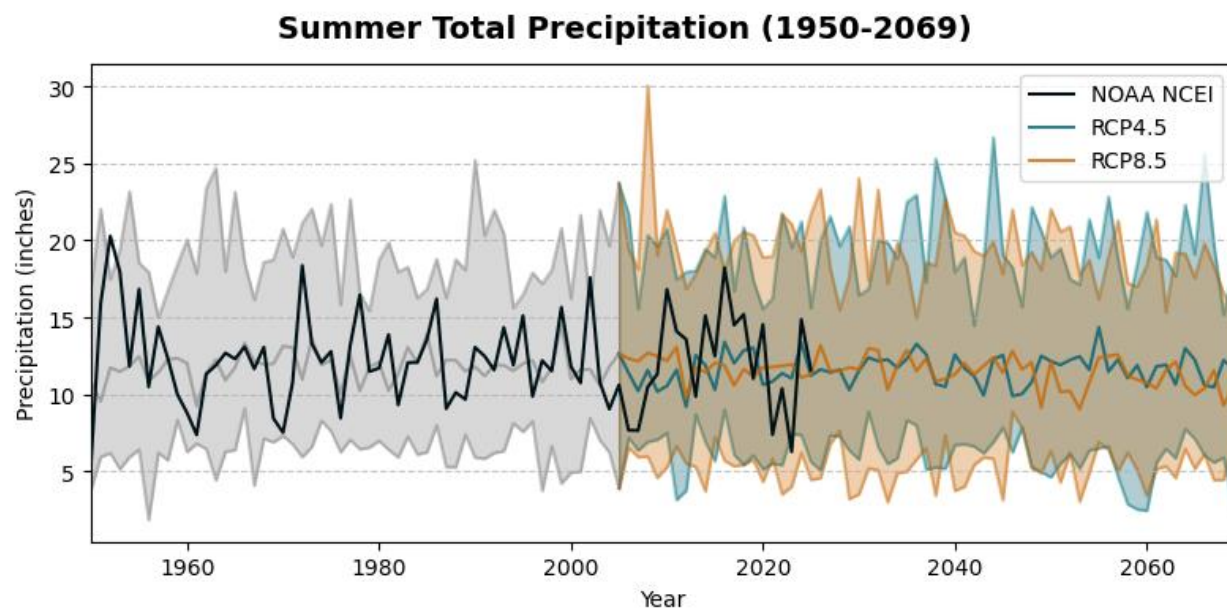


Figure A27. Summer (June–August) total precipitation from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

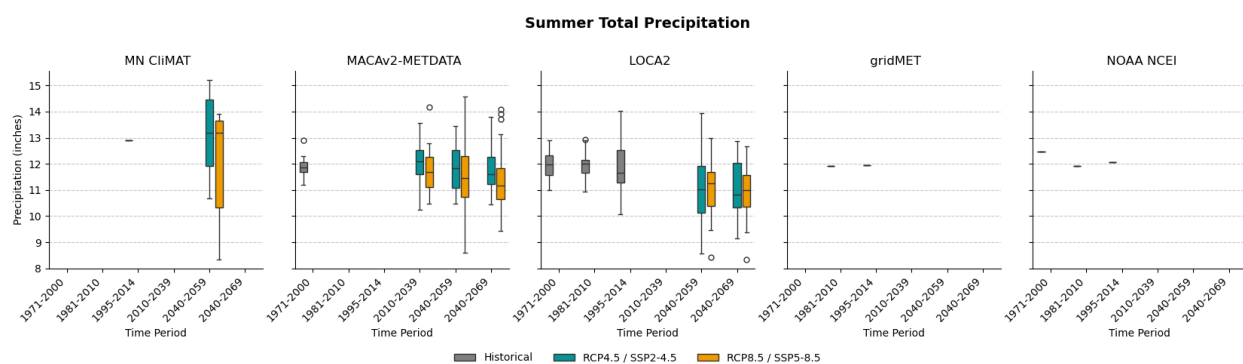


Figure A28. Comparison of period averages of summer (June–August) total precipitation across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

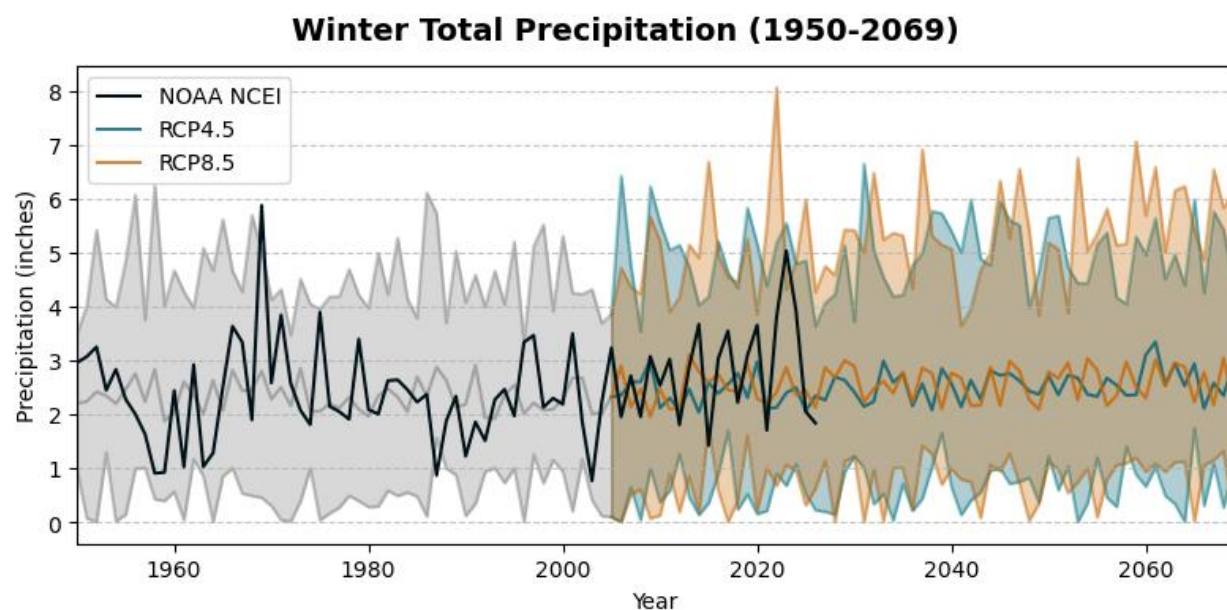


Figure A29. Winter (December–February) total precipitation from 1950–2069 from MACAv2-METDATA climate model simulations ($n=20$) and the NOAA NCEI nClimGrid-monthly historical dataset ($n=1$).

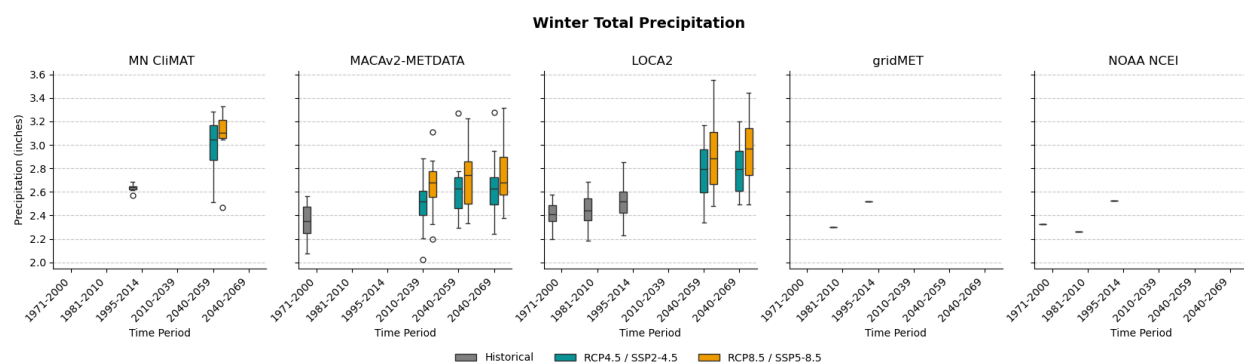


Figure A30. Comparison of period averages of winter (December–February) total precipitation across datasets. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$; MACAv2-METDATA $n=20$; LOCA2 $n=23$) and observational datasets ($n=1$). Emissions scenarios associated with each dataset include MN CliMAT = SSP; MACAv2-METDATA = RCP; and LOCA2 = SSP.

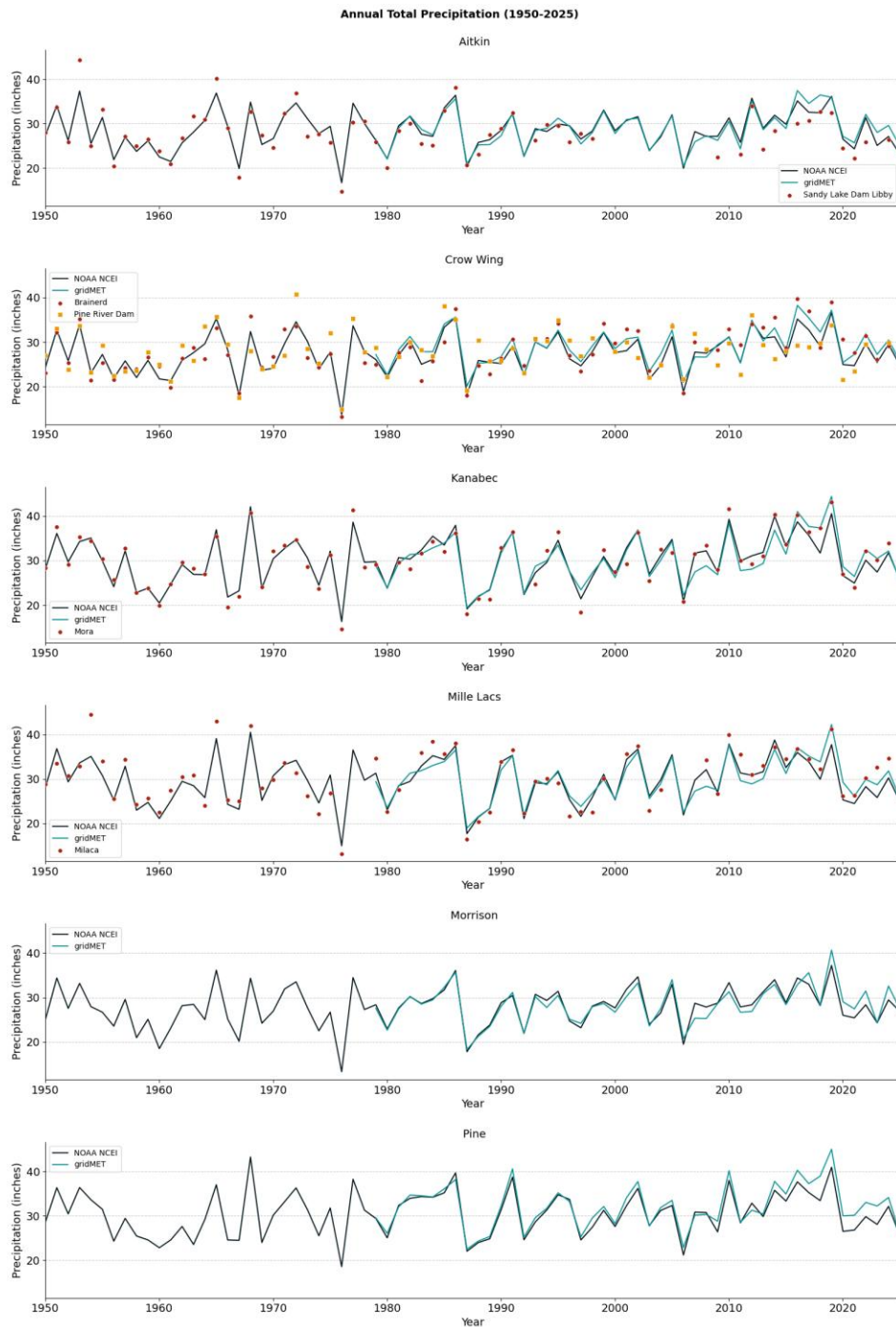


Figure A31. Annual total precipitation across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

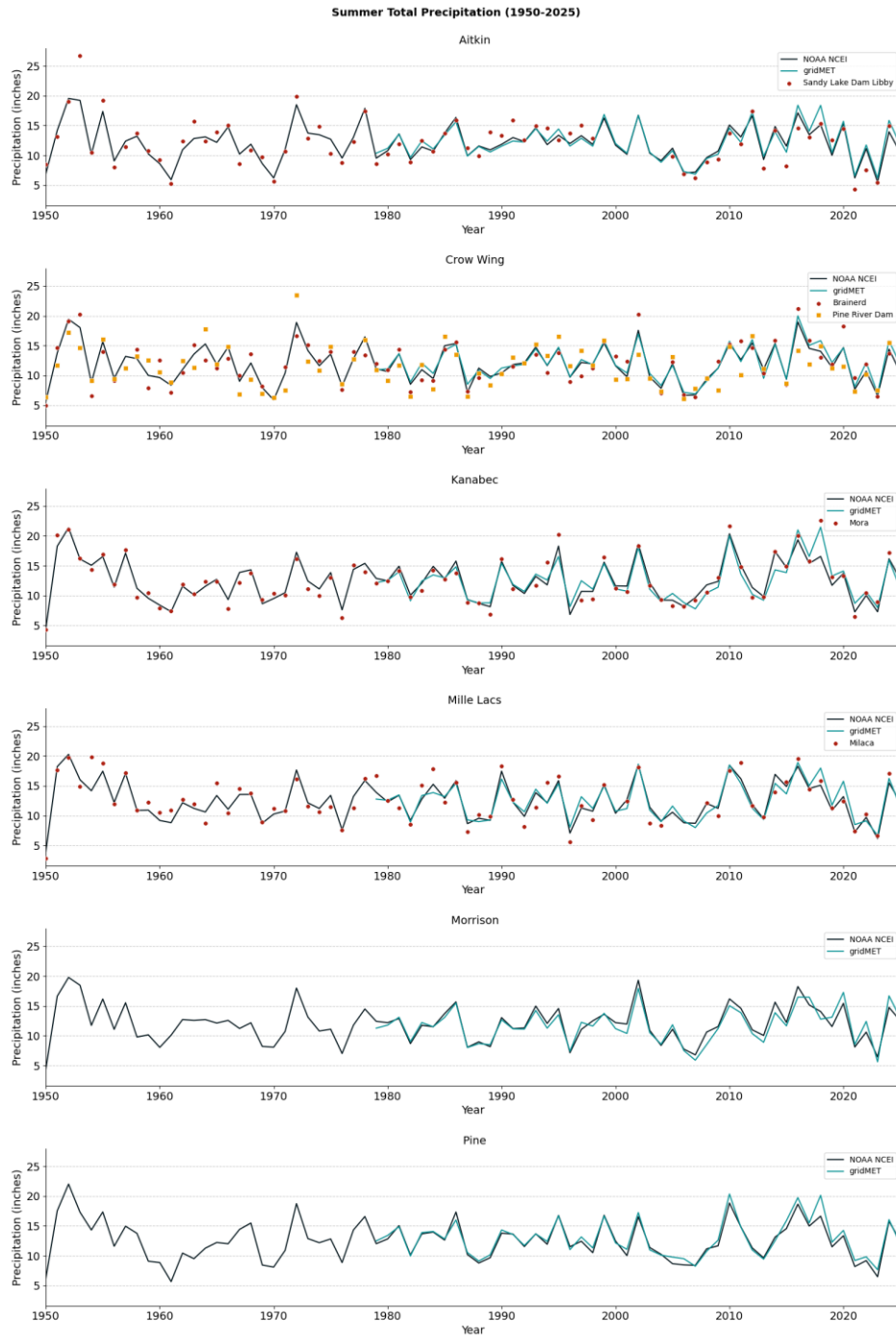


Figure A32. Summer (June–August) total precipitation across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

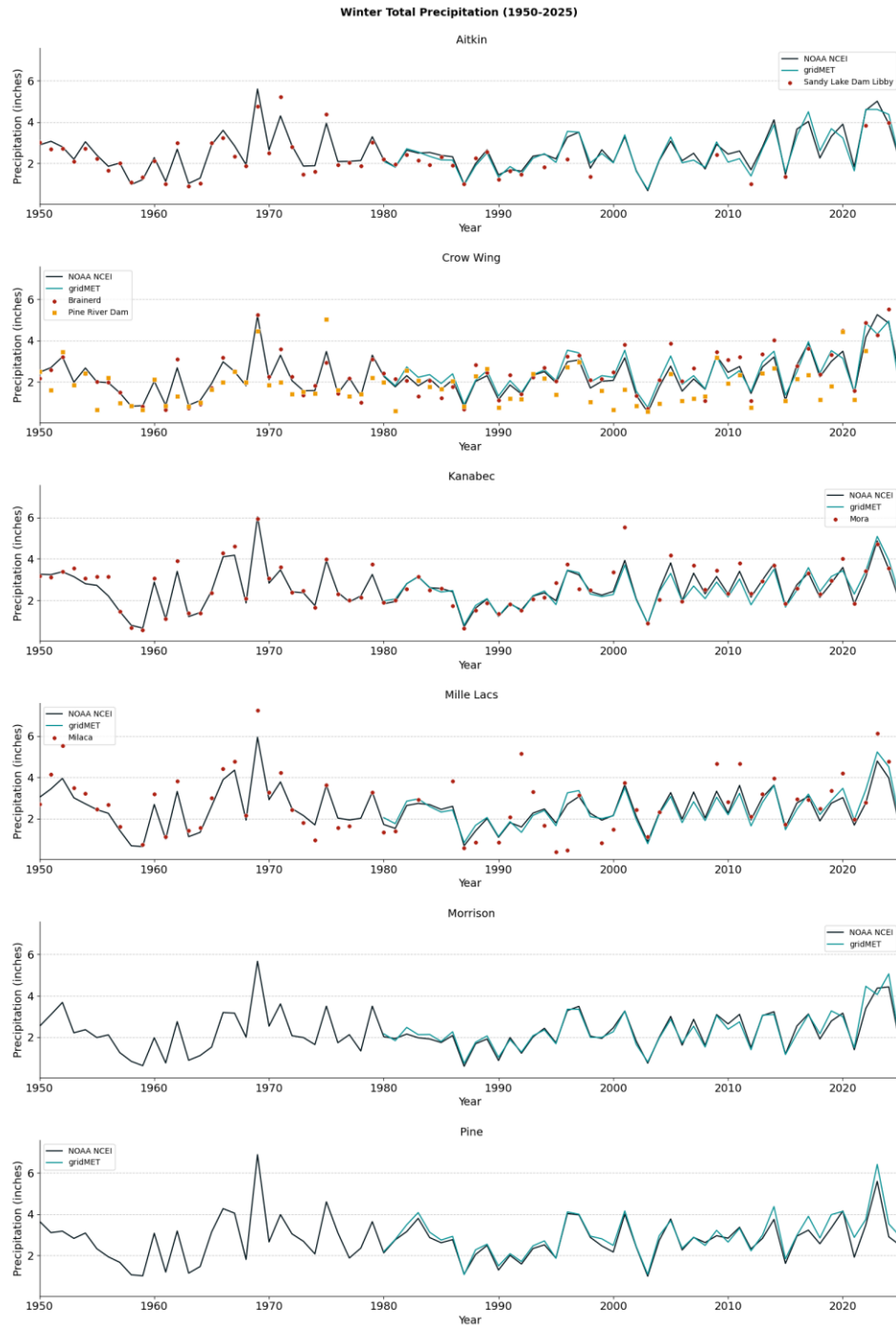


Figure A33. Winter (December–February) total precipitation across the six-county region in different observational datasets. Gridded and aggregated (NOAA NCEI nClimGrid-monthly and gridMET) are shown as lines. Data from stations are shown as points when available (see Appendix B: Analysis methodology).

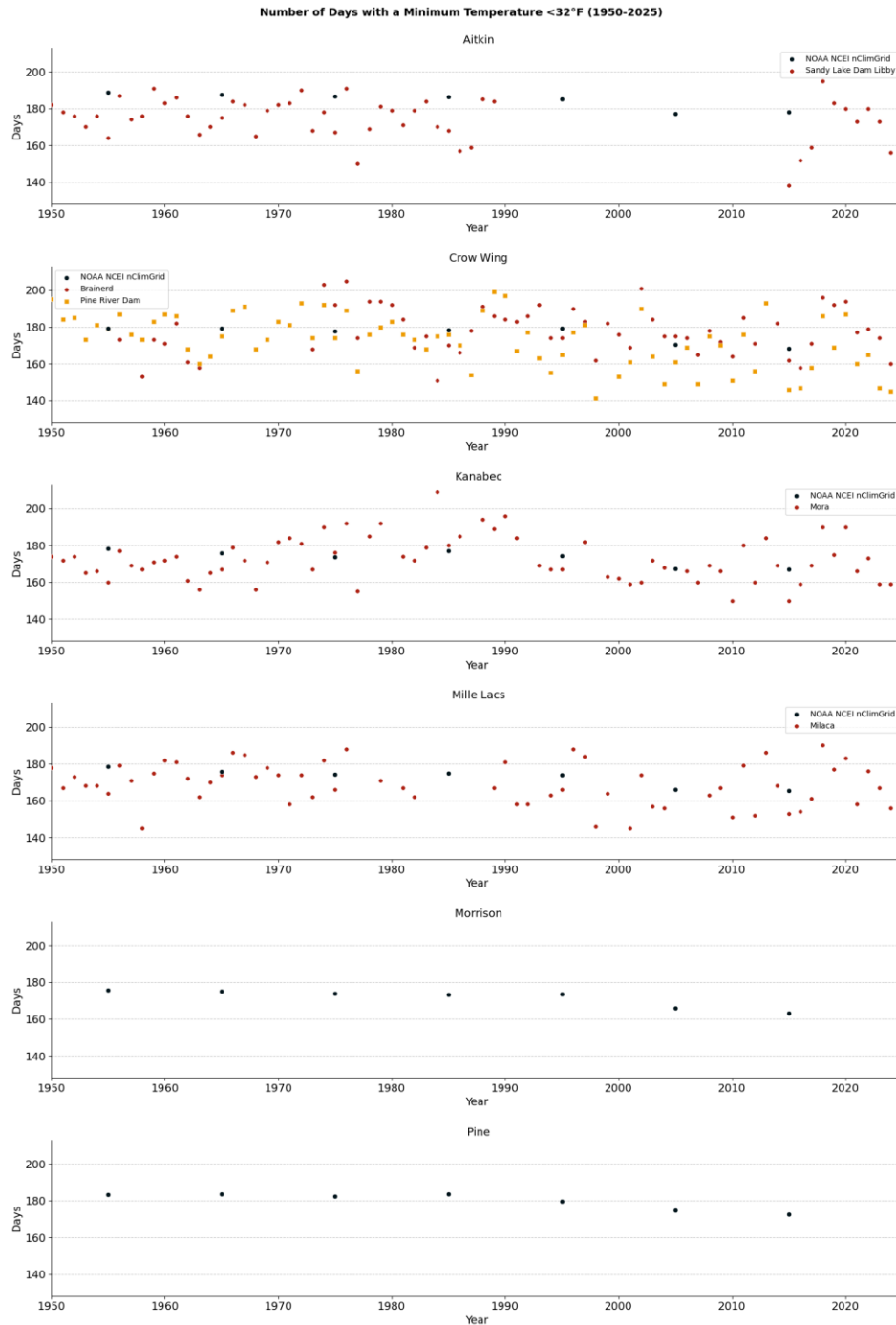


Figure A34. Annual total days with a minimum temperature less than or equal to 32°F across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). NOAA NCEI nClimGrid-monthly values are days with a minimum temperature less than or equal to 32°F. Data from stations are shown as points when available and show days with a minimum temperature less than 32°F (see Appendix B: Analysis methodology).

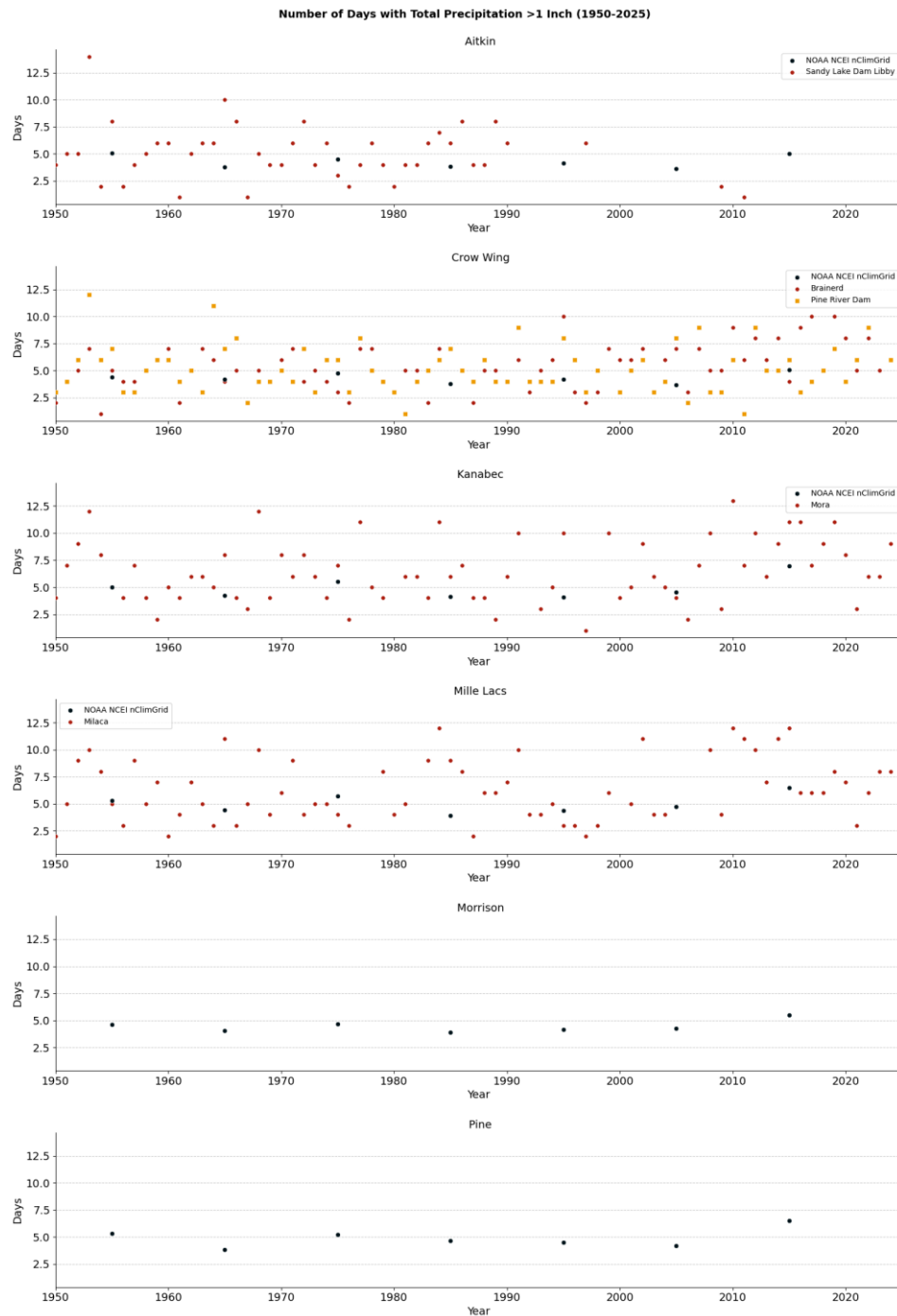


Figure A35. Annual total days with precipitation greater than or equal to 1 inch across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available and show days with precipitation greater than 1 inch (see Appendix B: Analysis methodology).

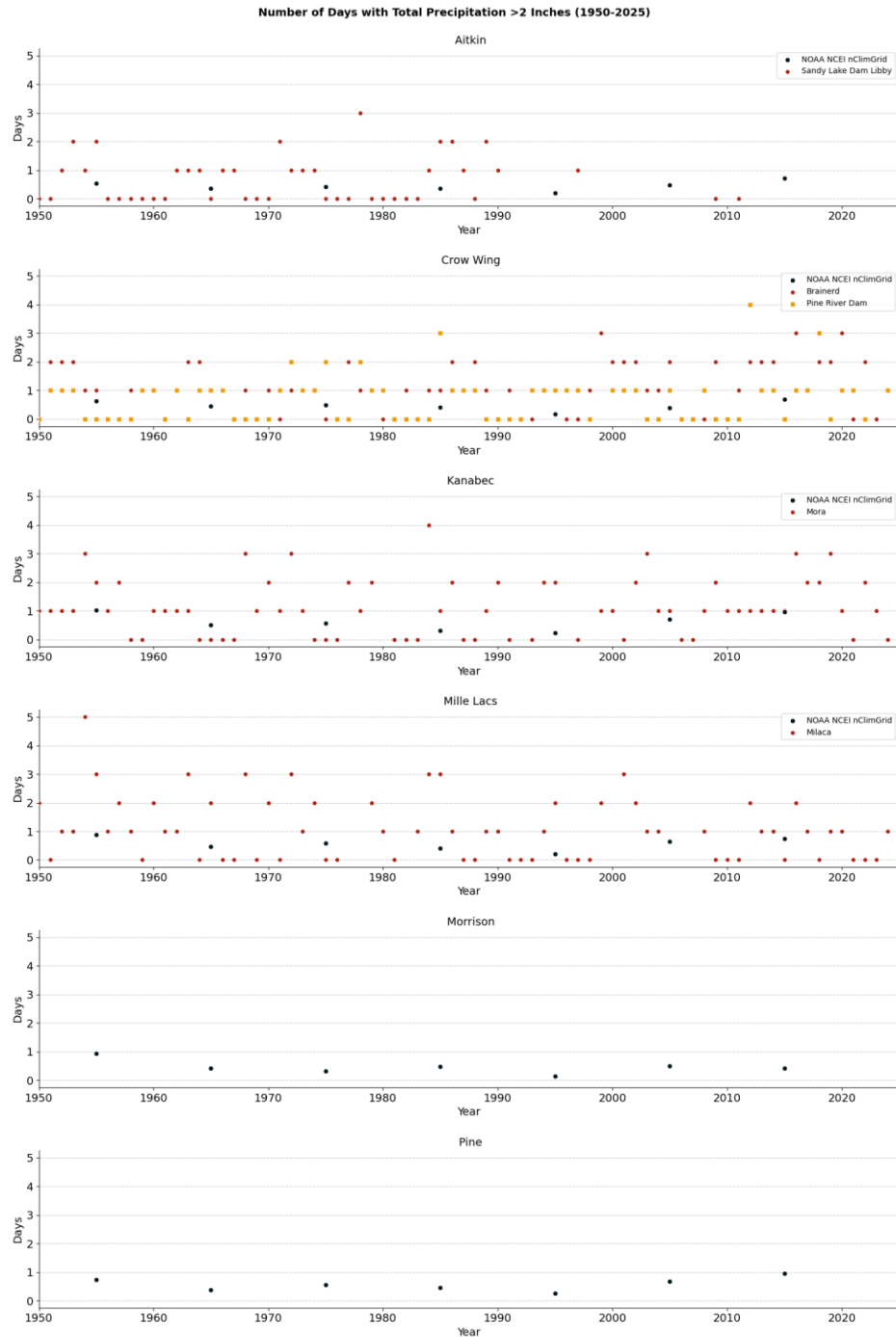


Figure A36. Annual total days with precipitation greater than or equal to 2 inches across the six-county region in different observational datasets. Gridded and aggregated data from NOAA NCEI nClimGrid-monthly are shown as decadal average points (black). Data from stations are shown as points when available and show days with precipitation greater than 2 inches (see Appendix B: Analysis methodology).

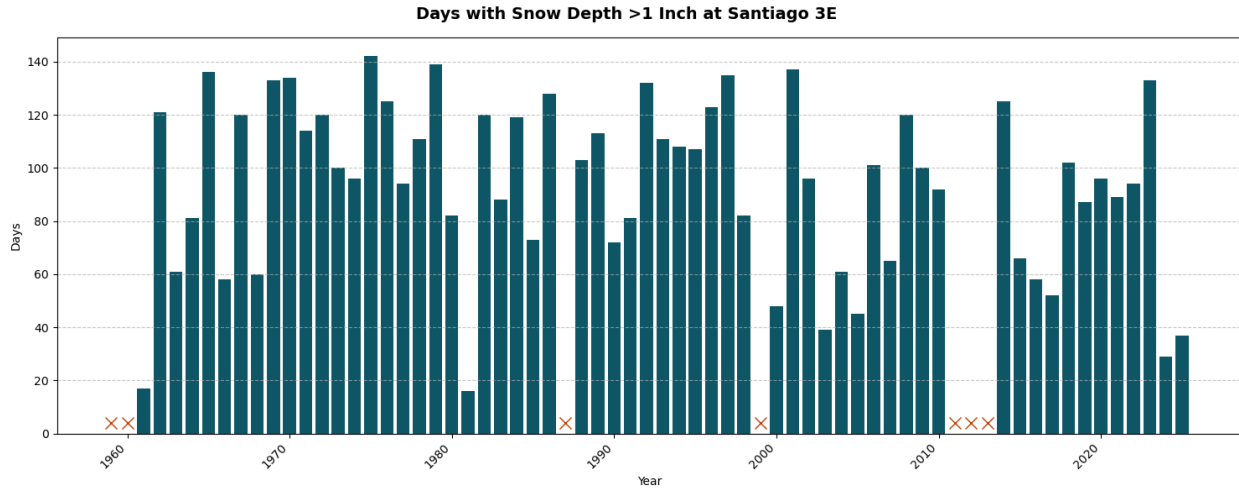


Figure A37. Snow year (July–June) days with snow depth greater than 1 inch at Santiago 3E station in Sherburne County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

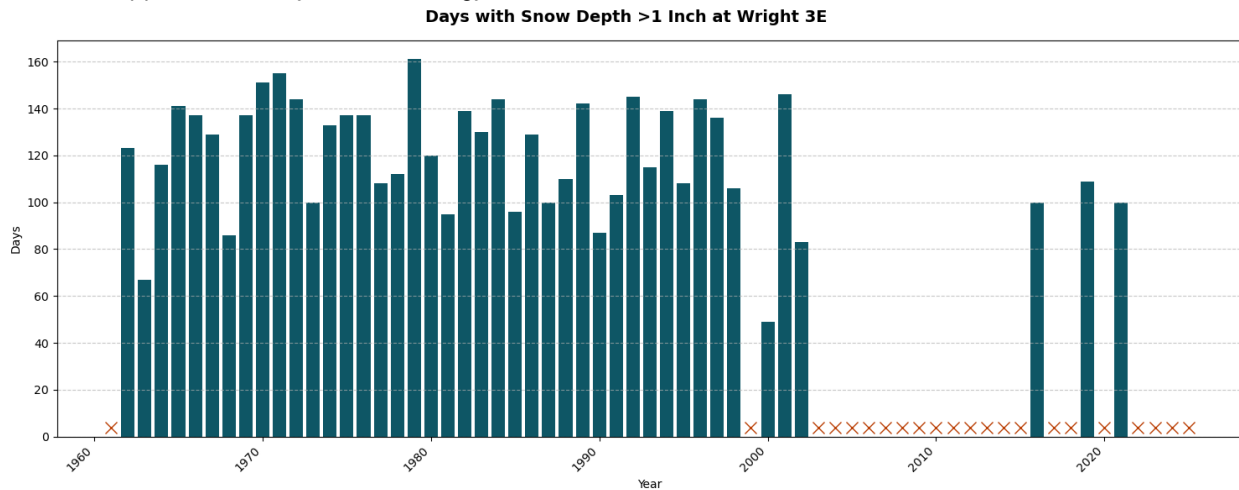


Figure A38. Snow year (July–June) days with snow depth greater than 1 inch at Wright 3E station in Carlton County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

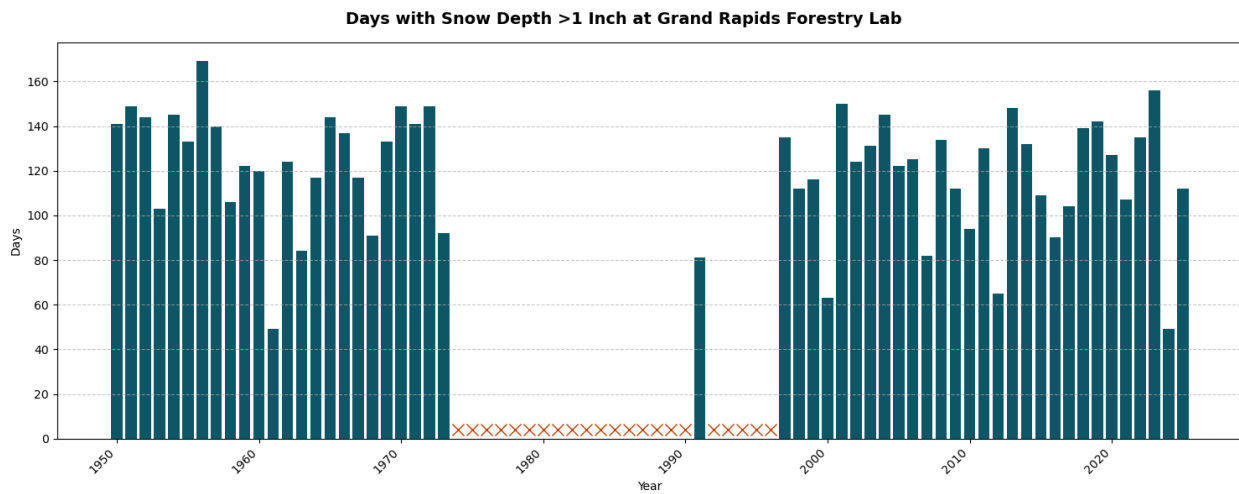


Figure A39. Snow year (July–June) days with snow depth greater than 1 inch at Grand Rapids Forestry Lab station in Itasca County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

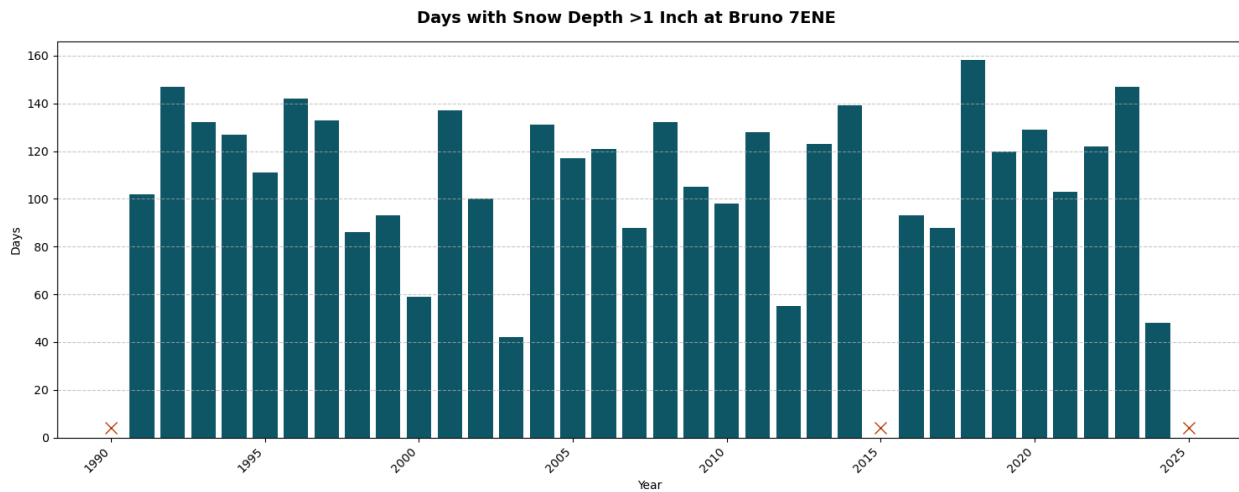


Figure A40. Snow year (July–June) days with snow depth greater than 1 inch at Bruno 7ENE station in Pine County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

Days with Snow Depth >1 Inch

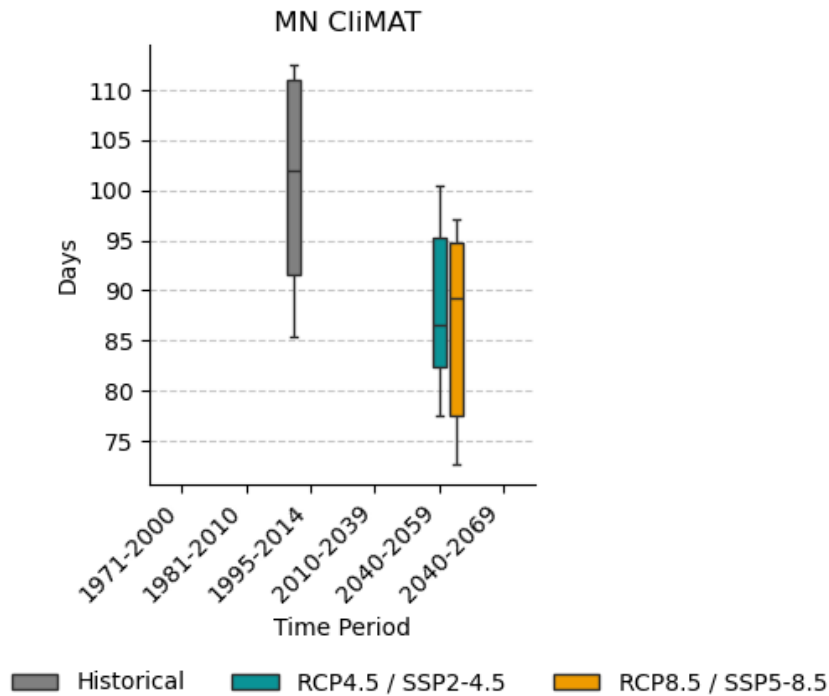


Figure A41. Comparison of period averages of calendar year (January–December) days with snow depth greater than 1 inch in MN CliMAT. Boxplots summarize the variation among climate simulations (MN CliMAT $n=6$). Emissions scenarios associated with each dataset include MN CliMAT = SSP.

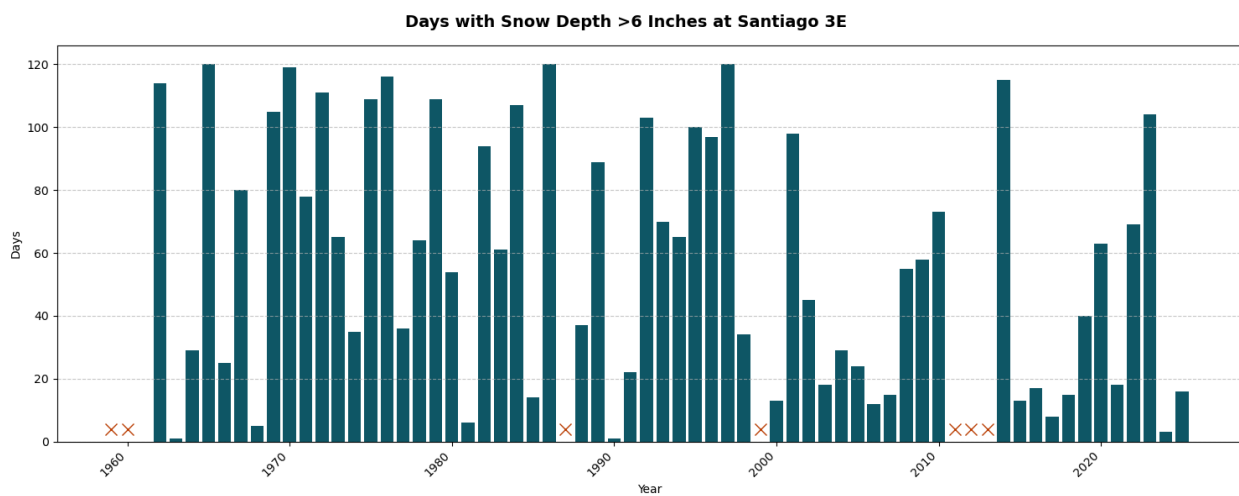


Figure A42. Snow year (July–June) days with snow depth greater than 6 inches at Santiago 3E station in Sherburne County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

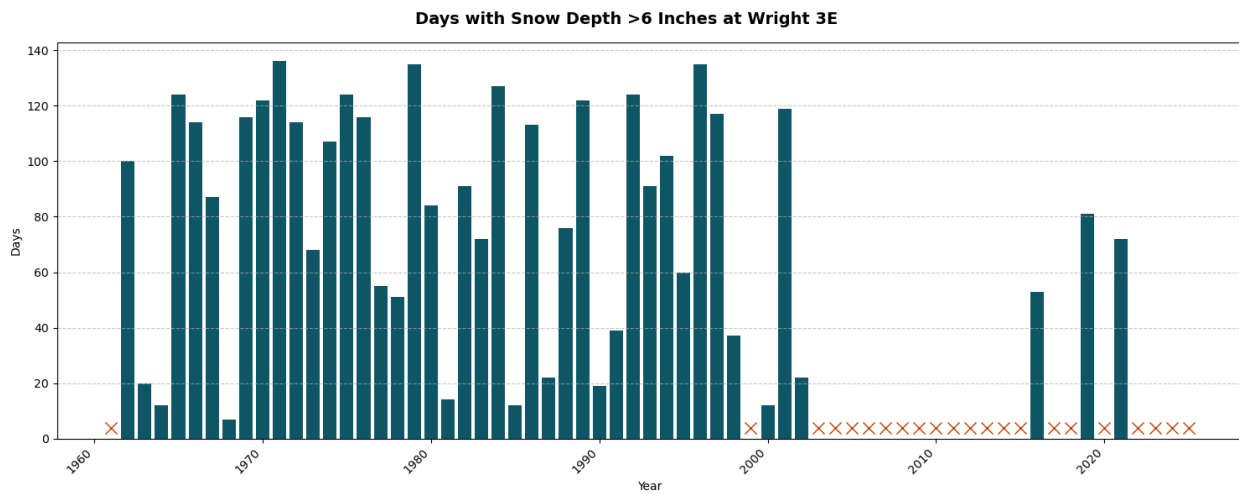


Figure A43. Snow year (July–June) days with snow depth greater than 6 inches at Wright 3E station in Carlton County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

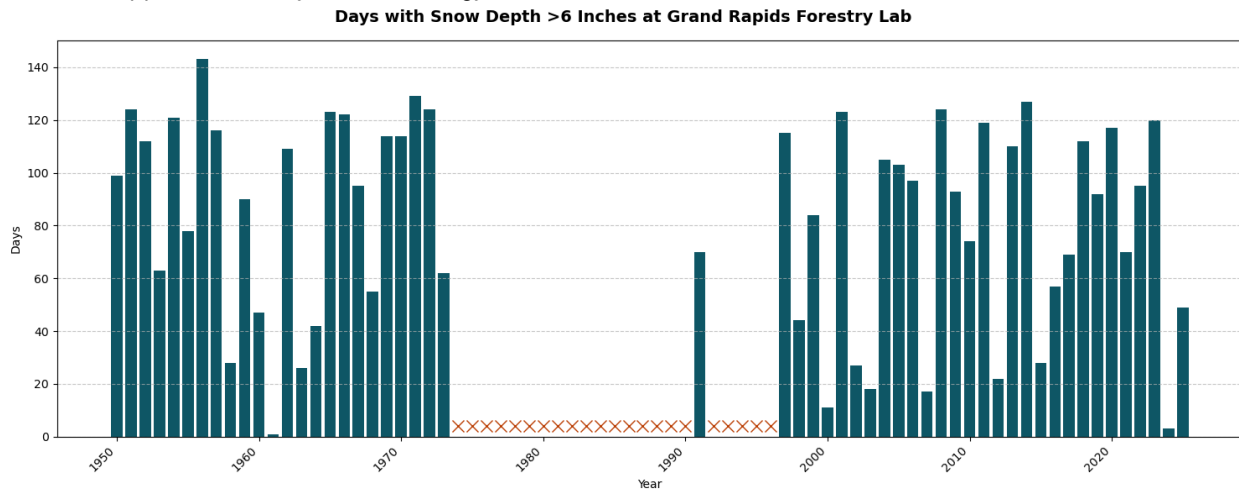


Figure A44. Snow year (July–June) days with snow depth greater than 6 inches at Grand Rapids Forestry Lab station in Itasca County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

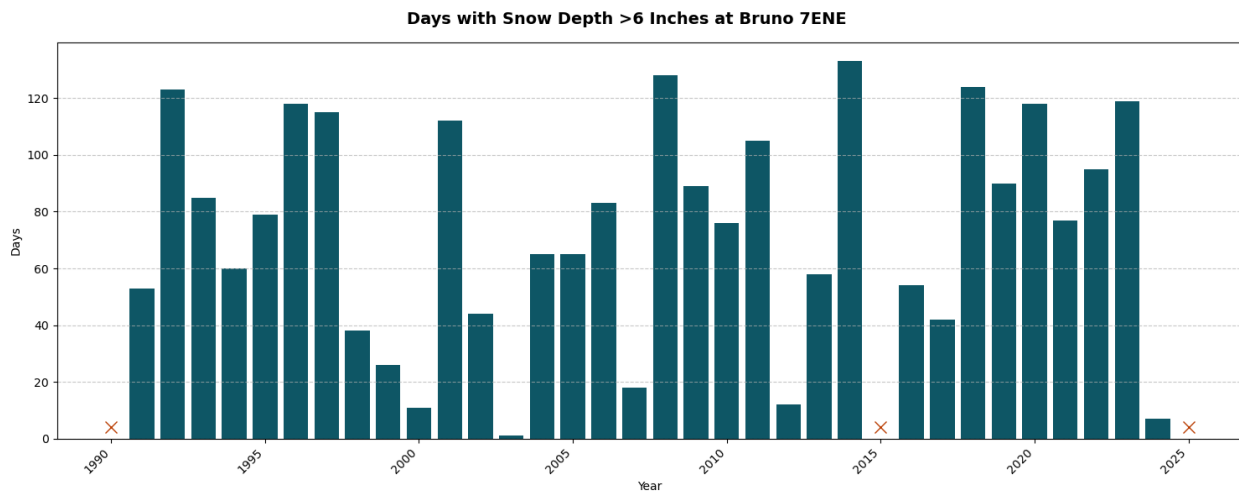


Figure A45. Snow year (July–June) days with snow depth greater than 6 inches at Bruno 7ENE station in Pine County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

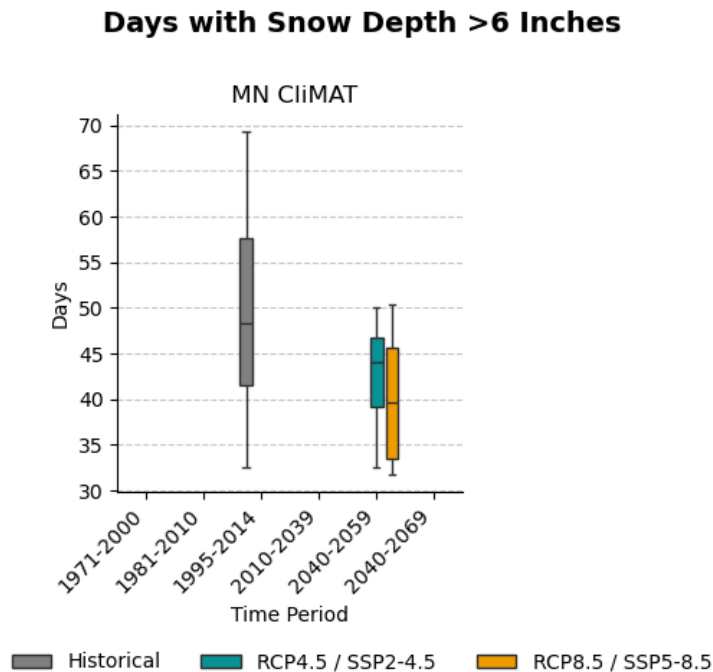


Figure A46. Comparison of period averages of calendar year (January–December) days with snow depth greater than 6 inches in MN CliMAT. Boxplots summarize the variation among climate simulations (MN CliMAT n=6). Emissions scenarios associated with each dataset include MN CliMAT = SSP.

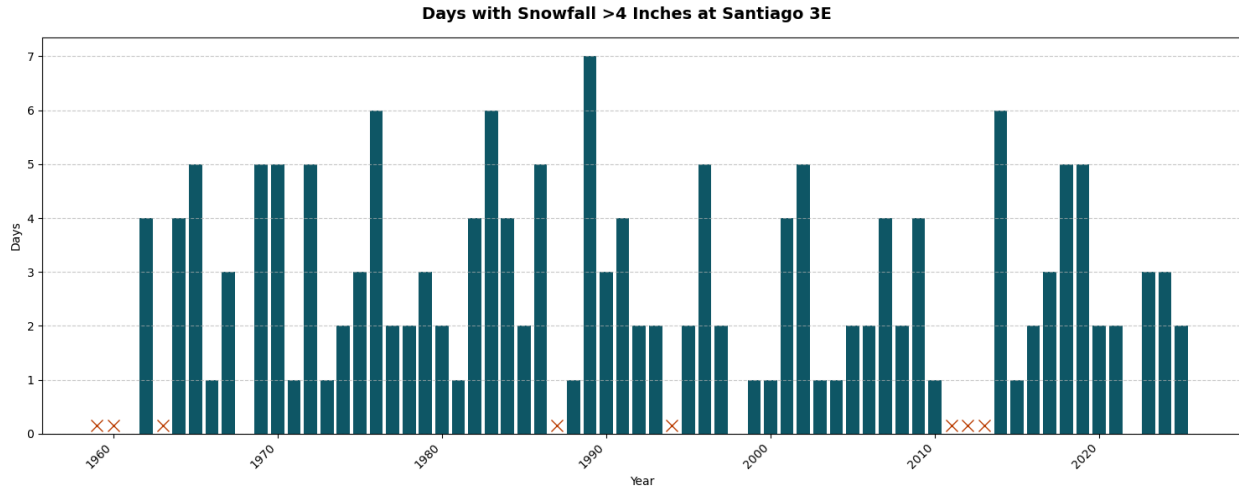


Figure A47. Snow year (July–June) days with snowfall greater than 4 inches at Santiago 3E station in Sherburne County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

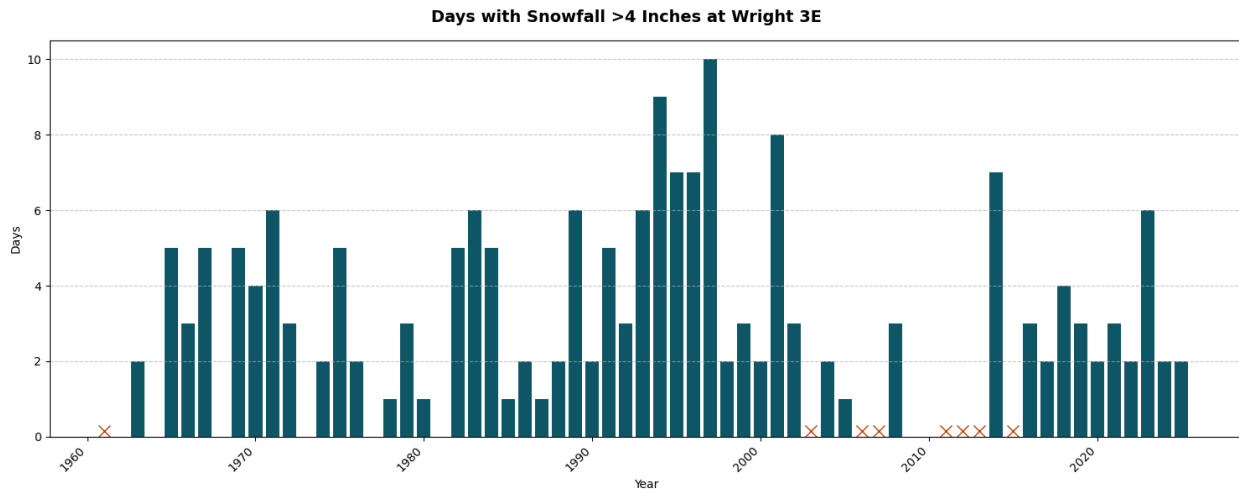


Figure A48. Snow year (July–June) days with snowfall greater than 4 inches at Wright 3E station in Carlton County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

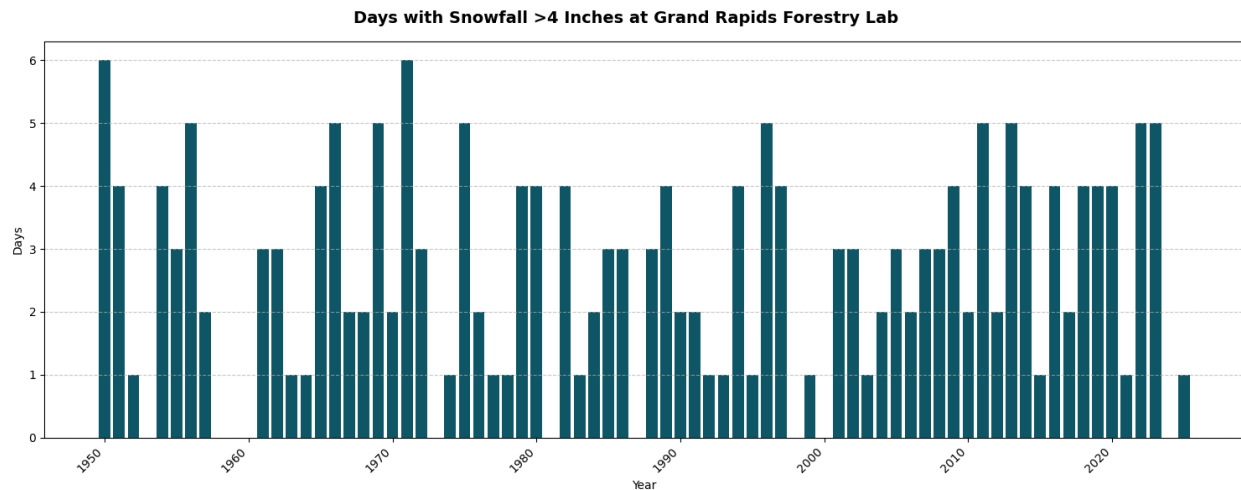


Figure A49. Snow year (July–June) days with snowfall greater than 4 inches at Grand Rapids Forestry Lab station in Itasca County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

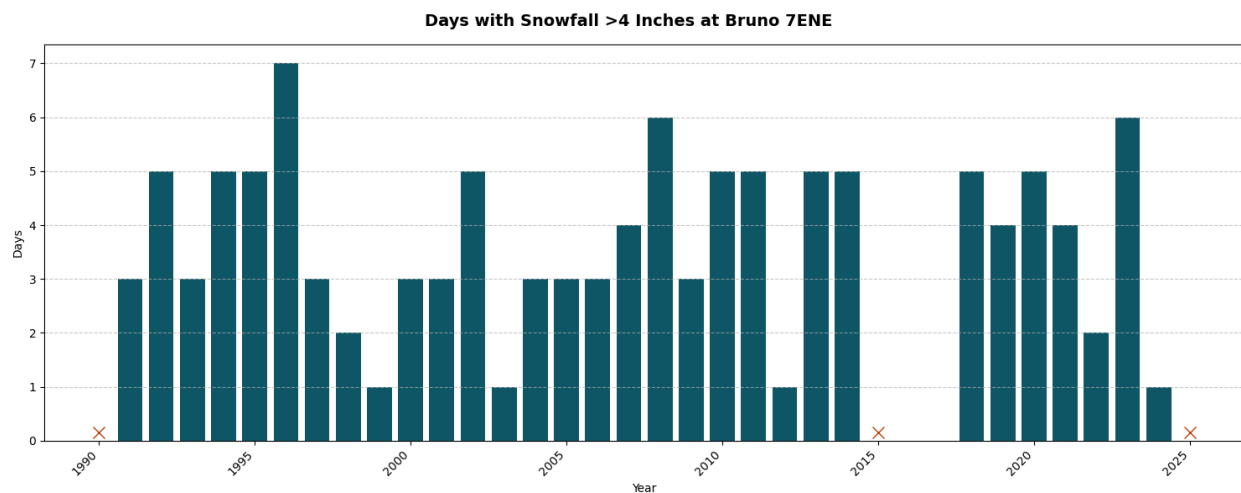


Figure A50. Snow year (July–June) days with snowfall greater than 4 inches at Bruno 7ENE station in Pine County (refer to Figure 1) for the period of record from ACIS. Years with missing data are marked with a red x at the x-axis (see Appendix B: Analysis methodology).

Appendix B: Analysis methodology

Hazards data retrieval

Hazard events

Key reported hazard events were obtained from the NOAA Storm Events Database (NCEI, 2026a; Table B1). The NOAA Storm Events Database was selected because it included event-level records for all hazards of interest which enabled consistent methods of analysis across hazards. Other products were evaluated (e.g., FEMA Resilience Analysis and Planning Tool [RAPT] and the Climate Hazard and Mitigation Planning [CHaMP] tool) but were not used because they were often based on the same underlying data, did not include all hazards of interest, and were primarily designed as hazard visualization and decision-support tools rather than primary data sources.

Table B1. Hazard events within this report and their corresponding name and available data range within the NOAA Storm Events Database.

Report Name	NOAA Storm Events Database Name	Available Data Range
Heat advisories	Heat	Jan. 1996–Feb. 2026
Extreme heat warnings	Excessive heat	Jan. 1996–Feb. 2026
Extreme cold warnings	Extreme cold/wind chill	Jan. 1996–Feb. 2026
Flash floods	Flash flood	Jan. 1996–Feb. 2026
Blizzards	Blizzard	Jan. 1996–Feb. 2026
Heavy snow	Heavy snow	Jan. 1996–Feb. 2026
Winter storms	Winter storm	Jan. 1996–Feb. 2026
Ice storms	Ice storm	Jan. 1996–Feb. 2026
Tornadoes	Tornado	Jan. 1950–Feb. 2026
Thunderstorm winds	Thunderstorm Wind	Jan. 1955–Feb. 2026
Hail	Hail	Jan. 1955–Feb. 2026
Annual wildfires	Wildfire	Jan. 1996–Feb. 2026

At the time of the report, data were retrieved using the following methods:

- <https://www.ncei.noaa.gov/stormevents/>
- Start Search → Select States/Areas → Select Counties → Select Event Types [NOAA Storm Events Database Name] → Begin Date [01/01/1950] → End Date [12/31/2025] → Download Table CSV

After retrieval, we identified all dates during which a hazard event was reported. These dates were totaled by hazard, five-year time periods, and county. A study area total was also calculated by identifying dates during which a hazard event was reported within any of the six counties, which ensured the same hazard event would not be counted multiple times. Lastly, we identified the seasonality of reported hazards by calculating the total number of reported events for a particular hazard and identifying the proportion occurring during each month.

Air quality

Annual summary data for ambient air quality were obtained at the county level, when available, from the EPA's Air Quality System (AQS) repository (Environmental Protection Agency 2026).

At the time of the report, data were retrieved using the following methods:

- https://aq5.epa.gov/aq5web/airdata/download_files.html
- Table of Annual Summary Data → AQI by County [*annual_aqi_by_county_year.zip*] → *download all desired years*

After retrieval, we processed the data to gain insight into AQI categories and primary pollutants. First, we divided the number of days on which measurements from any monitoring site in the county were reported to the AQS database by the total number of days within the time period to indicate the proportion of days data were collected. Next, we calculated the percent of measured days within each AQI category. Lastly, we calculated the percent of measured days during which a given pollutant had the highest AQI value of all measured pollutants.

Ice in and ice out

Ice in and ice out data were obtained for two key lakes from the Minnesota Department of Natural Resources, with data also reported by the department and Minnesota Pollution Control Agency (Minnesota Department of Natural Resources 2026).

At the time of the report, data were retrieved using the following methods:

- https://www.dnr.state.mn.us/ice_out/index.html
- Click pin on lake of interest → select 'all ice out data for this lake' → Download data under Ice Out Summary or Ice In Summary

After retrieval, ice in and ice out dates were plotted for each lake of interest.

Climate data retrieval

All data from the tools below were obtained for all six individual counties or individual weather stations. For county-based data, an all-county weighted average was generated using county areas from the 2023 United States Census Bureau TIGER/Line Shapefiles (U.S. Census Bureau, 2023).

Climate Toolbox

At the time of the report, data were retrieved using the following methods:

Historical and future annual time series of the 20 member MACAv2-METDATA ensemble from 1950–2100 for RCP4.5 and RCP8.5 for counties:

- <https://climatetoolbox.org/tool/future-time-series>
- Variables downloaded were maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter)
- Choose Location (Set County Area) → Choose Data Variable → Choose Data Calendar Time Period (Start Month: End Month) → Choose Data Future Scenario (BOTH Lower Emissions RCP 4.5; Higher Emissions RCP 8.5) → Make Request

Historical and future period averages of the 20 member MACAv2-METDATA ensemble from 1950–2100 for RCP4.5 and RCP8.5 for counties:

- <https://climatetoolbox.org/tool/future-boxplots>
- Variables downloaded are annual days with a maximum temperature greater than or equal to 90°F, 100°F, and 105°F; Annual days with a minimum temperature greater than or equal to 32°F; annual maximum consecutive dry days (days with less than 0.2 mm of precipitation)
- Choose Location (Set County Area) → Choose Data Calendar Time Period (Start Month, End Month) → Choose Data Variable

Historical annual time series of gridMET from 1979–2025 for counties:

- <https://climatetoolbox.org/tool/historical-climate-tracker>
- Variables downloaded are maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter); Annual days with a maximum temperature greater than or equal to 90°F, 95°F, 100°F, and 105°F
- Choose Location (Set County Area) → Choose Data Future Climate Experiments (CMIP5 RCPs) → Choose Data Future Scenario (Lower Emissions RCP 4.5; Higher Emissions RCP 8.5) → Choose Data Calendar Time Period (Jan–Dec) → Choose Data Variable

Historical monthly climatology of gridMET for 1981–2010 for counties:

- <https://climatetoolbox.org/tool/Historical-Climograph>
- Variables downloaded are maximum temperature, minimum temperature, and total precipitation
- Choose Location (Set County Area) → select Dataset (Contiguous USA gridMET) → Temperature & Precipitation → Climatology Years
- After retrieval, limited processing was done on the data, including converting days greater than or equal to 32°F to days less than 32°F.

Minnesota Climate Mapping and Analysis Tool (MN CliMAT)

At the time of the report, data were retrieved using the following methods:

Historical and future period averages of the six-member MN CliMAT ensemble from 1995–2014 and 2040–2059 for SSP2-4.5 and SSP5-8.5 for counties:

- <https://app.climate.umn.edu/> → Create Spreadsheet
- Variables downloaded were maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter); Annual days with a maximum temperature greater than 90°F, 95°F, and 100°F; Annual days with a minimum temperature less than 32°F; Average snow depth (January–December); days with snow depth greater than 1 inch and 6 inches (January–December); annual days with total precipitation greater than 1 inch and 2 inches; annual maximum 1-day and 5-day precipitation
- County selection → Modeled Values + Difference → Historical and mid-century for SSP2-4.5 and SSP5-8.5 → All individual models and ensemble mean → variables → Year, DJF (winter), JJA (summer)

CMIP6-LOCA2

At the time of the report, data were retrieved using the following methods:

Historical and future annual time series of the 23 member LOCA2 ensemble from 1950–2100 for SSP2-4.5 and SSP5-8.5 for counties:

- netCDF files (CMIP6-LOCA2_1950-2100_County2023_monthly.nc and CMIP6-LOCA2_Thresholds_1950-2100_County2023_annual.nc) were obtained from the USGS Data Release CMIP6-LOCA2 spatial summaries of counties (TIGER 2023) from 1950–2100 for the Contiguous United States (Alder, 2025).
- Variables used are maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter); Annual days with a maximum temperature greater than or equal to 90°F, 95°F, 100°F, and 105°F; Annual days with a minimum temperature less than 32°F (Frost Days); annual days with total precipitation greater than 1 inch and 2 inches; annual maximum 1-day and 5-day precipitation; annual maximum consecutive dry days

After retrieval temperature variables were converted from Celsius to Fahrenheit and precipitation was converted from mm/day to inches/day. For aggregation of daily to monthly totals and monthly to annual means weighted averages and sums accounted for the number of days in a month.

Applied Climate Information System (ACIS)

At the time of the report, data were retrieved using the following methods:

Historical monthly and annual time series for the period of record for select stations:

- <https://scacis.rcc-acis.org/>
- Variables downloaded were maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter); annual days with a maximum temperature greater than or equal to 90°F, 95°F, 100°F, and 105°F; annual days with a minimum temperature less than 32°F; annual days with total precipitation greater than 1 inch and 2 inches; average total annual snowfall (snow year July–June); Average snow depth (snow year July–June); days with snow depth greater than 1 inch and 6 inches (snow year July–June); Days with snowfall greater than 4 inches (snow year July–June)
- Measured Values: Single Station Products → Monthly Summarized Data → Variable → Summary Mean or Sum → por–2026; Seasonal calculation method = average of months (recommended); Month Range = 1–12 for annual and summer, 12–2 for December–February mean; check boxes for “include missing days count”
- Threshold Values: Single Station Products → Monthly Summarized Data → Variable → Summary Number of Days → Set threshold → por–2026; Seasonal calculation method = average of months (recommended); Month Range = 1–12 for annual and summer, 12–2 for December–February mean; check boxes for “include missing days count”

All measurements were downloaded with the number of missing days. For most variables, an annual value was marked as missing if more than 10% of days in a given time frame were missing (36 days for annual; 9 for seasonal). For snow metrics, missing values from October–May were summed with 25 days as the threshold. ACIS calculates the mean temperature as the average of the minimum and maximum daily temperature. NOAA National Centers for Environmental Information (NCEI) nClimGrid Products.

At the time of the report, data were retrieved using the following methods:

Historical time series for 1895–2025 for counties:

- <https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/time-series>
- Raw monthly values of maximum minimum and average temperature as well as total precipitation were downloaded
- Additional variables downloaded are maximum, mean, and minimum temperature for January–December (annual), June–August (summer), and December–February (winter) and total precipitation for January–December (annual), June–August (summer), and December–February (winter)
- County → Time Series → Select State → County → Parameter → Time Scale and Month (e.g., for annual Total Precipitation select 12-month, December);

Historical decadal average for 1950–2025 for counties:

- <https://cris.climate.gov/search> → Filter tags to “NCA5” and “nClimGrid”
- Data were downloaded for:

-
- nClimGrid Historical Observations [Cold Days](#): Annual days with a minimum temperature less than or equal to 32°F.
 - nClimGrid Historical Observations [Hot Days](#): Annual days with a maximum temperature greater than or equal to 90°F, 95°F, 100°F, and 105°F
 - nClimGrid Historical Observations [Days with Heavy Precipitation](#): Annual days with total precipitation greater than or equal to 1 inch and 2 inches
 - nClimGrid Historical Observations [Precipitation Totals](#): Annual maximum 1-day and 5-day precipitation
 - Scroll down to Layers → County → filter by County → Download CSV (counties are defined based on 2022 Tiger boundaries)

For more information concerning the research in this report, contact
the Center Director, USGS National Climate Adaptation Science Center

12201 Sunrise Valley Drive MS 516
Reston, VA 20192

Or visit the Climate Adaptation Science Centers Climate Adaptation
Technical Services Team website at usgs.gov/CASC/CATS

