Dataset Description and Methods for Historical and Projected Climate Data for Ag State Summaries

Datasets

The historical meteorological dataset utilized in the reports is the gridMET dataset (Abatzoglou 2013) [available at: http://www.climatologylab.org/gridmet.html]. GridMET is a hybrid spatially interpolated dataset that incorporates approaches and data from two widely used climatic datasets: the National Land Data Assimilation System Phase 2 (NLDAS-2, Mitchell et al. 2004) and Parameter-elevation Regressions on Independent Slopes Model (PRISM, (Daly et al. 2008). These two datasets are used to combine the desirable attributes of both original datasets, the high temporal resolution of NLDAS-2 at daily and sub-daily time scales and the fine spatial resolution of PRISM, into one cohesive dataset that is spatially and temporally complete. The final gridMET data are available at a spatial resolution of 4 km at a daily timestep from 1979 through 2021. Extensive validation of the resulting dataset was conducted in Abatzoglou (2013) against multiple networks of automated and manned observing stations.

The Multivariate Adaptive Constructed Analogs (MACA) (available at: https://climate.northwestknowledge.net/MACA/) includes 20 statistically downscaled global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 5 with two representative concentration pathways (RCP's): 4.5 and 8.5 (van Vuuren et al., 2011). The two RCPs depict two possible futures regarding global greenhouse gas emissions: 4.5 depicts an increase in global greenhouse gas emissions through the mid-21st century and reductions after that point, while 8.5 depicts growing emissions throughout the 21st century. Resulting greenhouse gas concentrations in the year 2100 for each scenario are ~ 500 ppm CO_2 under RCP 4.5 and ~950 ppm CO_2 under RCP 8.5 (Clarke et al. 2009). The MACA technique works through identifying a series of large-scale meteorological patterns from gridded observations (gridMET in the case of these reports), which are then coarsened to a representative GCM resolution. GCM output is then compared to the historical pattern types within a 15-day moving window and are matched to a specific pattern from the observations, allowing fine scale detail from the observations to be retained. Additionally, GCMs are bias corrected prior to and after pattern typing, annual and seasonal trends are removed before pattern typing and reintroduced following to ensure trends remain consistent with the GCM data. Additionally, bias correction of temperatures and precipitation are performed jointly. Each model also includes a historical model period from 1979-2005 that is bias corrected to the 1979-2005 period from gridMET. Two projected future time periods were avaialble from MACA: 2040-2059 (mid-century) and 2080-2099 (late-century) for RCPs 4.5 and 8.5. 17 of the original 20 models contained all the variables required for this report (Table 1).

Table 1. Statistically downscaled CMIP-5 GCMs from MACA included in reports.

Model Name	Model Country	Model Agency	Atmosphere Resolution (Lon x Lat)	Ensemble Used
bcc-csm1-1-m	China	Beijing Climate Center, China Meteorological Administration	1.12 deg x 1.12 deg	r1i1p1

BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University, China	2.8 deg x 2.8 deg	r1i1p1
CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis	2.8 deg x 2.8 deg	r1i1p1
CNRM-CM5	France	National Centre of Meteorological Research, France	1.4 deg x 1.4 deg	r1i1p1
CSIRO-Mk3-6-0	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia	1.8 deg x 1.8 deg	r1i1p1
GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg	r1i1p1
GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory, USA	2.5 deg x 2.0 deg	r1i1p1
HadGEM2-ES	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg	r1i1p1
HadGEM2-CC	United Kingdom	Met Office Hadley Center, UK	1.88 deg x 1.25 deg	r1i1p1
inmcm4	Russia	Institute for Numerical Mathematics, Russia	2.0 deg x 1.5 deg	r1i1p1
IPSL-CM5A-LR	France	Institut Pierre Simon Laplace, France	3.75 deg x 1.8 deg	r1i1p1
IPSL-CM5A-MR	France	Institut Pierre Simon Laplace, France	2.5 deg x 1.25 deg	r1i1p1
IPSL-CM5B-LR	France	Institut Pierre Simon Laplace, France	2.75 deg x 1.8 deg	r1i1p1
MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies,and Japan Agency for Marine-Earth Science and Technology	1.4 deg x 1.4 deg	r1i1p1
MIROC-ESM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg	r1i1p1
MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	2.8 deg x 2.8 deg	r1i1p1
MRI-CGCM3	Japan	Meteorological Research Institute, Japan	1.1 deg x 1.1 deg	r1i1p1

Methods

Historical Data Analysis

Data for the Midwestern United States were extracted for the states of: MN, IA, MO, WI, IL, MI, IN, OH, and KY for the report period of record (1979-2021) from gridMET. Annual and seasonal values were calculated for each year in the historical period from 1979-2021 for each grid cell in the study domain. Averages were used for temperature and vapor pressure deficit, totals for precipitation, and number of days for extreme precipitation (days with 2 inches or greater precipitation). Additionally growing season length was calculated for each year in the historical period. Growing season length for these reports is defined as the number of days between the latest occurrence of a minimum daily temperature less than 32 degrees Fahrenheit in the spring and the first occurrence of a minimum daily temperature less than 32 degrees Fahrenheit in the fall. Mean values and linear trend estimates for the historical period were calculated for all variables. Linear trend estimates were multiplied by the number of years in the historical record (43) for an estimate of the total change over the period. Data included in mean/total state-level values include the average of all grid cells that are contained within each state's geographical boundaries.

Projected Future Climate Analysis

Projected climate for the study region was determined in a multi-step process of comparing climate model output from MACA for each model, emissions scenario, and future time period (2040-2059 and 2080-2099) to the historical period (1979-2005) for the variables shown in Table 2. Vapor pressure deficit output is not available in MACA. Instead, maximum and minimum daily relative humidity were included as an indicator of atmospheric moisture. This was done for each of the 17 included climate models for each grid cell in the study region. Change factors, quantifying the change between each future time period/emissions scenario and the historical base period, were calculated for each calendar month (e.g. January, February, etc.) for the variables listed in Table 2.

Table 2. Principal climate variables used in determining the magnitude of projected climate change.

Variable	Description
Temperature	Average Daily Air Temperature
Precipitation	Daily Accumulated Precipitation
RH Max	Daily Maximum Relative Humidity
RH Min	Daily Minimum Relative Humidity

Following Maraun and Widmann (2018), a delta-method approach was applied to the gridMET time series on a monthly basis. This consisted of applying the monthly change factors from MACA, to the daily gridMET/observational data from each month over the historical period (1979-2005) to generate time series of projected climate grounded in the day-to-day variability inherent in the observed data, rather than the historical climate model output. This method was preferred over implementing climate model output directly from MACA. The reason being that even downscaled and bias-corrected climate models do not always replicate the day-to-day variability of observed data, as the corrections involved in downscaling operate on longer time scales (15-days in the case of MACA) and are more appropriate for assessing changes on monthly time scales or longer. The result is 17 time series of daily projected climate for each future time period and emissions scenario, which were then used to characterize how the climate is projected to change for the study region on an annual and seasonal basis for the principal variables (Table 2) and key daily temperature thresholds (Table 3). State-level averages were determined by averaging all grid cells that are contained within each state's geographical boundaries. The author team teams were provided with ensemble mean values, well as the minimum ensemble member value, median ensemble member value, and the maximum ensemble member values for all projected variables and emissions scenarios.

Table 3. Key daily temperature thresholds analyzed

Temperature Threshold	Description
Minimum Temperatures < 0°F	Change in the number of days minimum daily temperature falls below 0°F
Minimum Temperatures < 32°F	Change in the number of days minimum daily temperature falls below 32°F
Minimum Temperatures > 80°F	Change in the number of days minimum daily temperature stays above 80°F
Maximum Temperatures > 86°F	Change in the number of days maximum daily temperature rises above 86°F
Maximum Temperatures > 95°F	Change in the number of days maximum daily temperature rises above 95°F
Growing Season Length	Change in the length of the growing season, as defined as the number of days between the last spring freeze (minimum temperature < 32°F) and first fall freeze in a given year.

References

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