Regionally Downscaled Climate Model Data:
Implications for electric power transmission network in the Pacific Northwest

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Regionally Downscaled Climate (RDC) Model Data

Work part of two separate, but highly-related projects:

“Co-optimization and anticipative planning methods for bulk transmission and resource planning under long-run uncertainties” (Bonneville Power Administration)

“Integrated Electric/Water Systems Modeling for the Pacific Northwest” (Ames National Laboratory/DOE)”

Impact of climate change on electric power grid expansion

- Projected likely increase in average near-surface temperature over the U.S. by more than 1.5 °C by end of century (Collins et al. 2013)
- Projected decrease in average precipitation over mid-latitudes (Collins et al. 2013)
- Projected 8-10% decrease in average wind speed over N. America by mid-century (Karnauskas et al. 2017)

Would result in:

- Increase in demand for cooling, increased load
- Decrease in hydro power potential
- Decrease in wind power potential

These are continental projections, what are the projections specifically for the Pacific Northwest?

Global Climate Models are used to forecast the state of the environment decades into the future

- The Coupled Model Intercomparison Project 5 (CMIP5) of the World Climate Research Programme (WCRP) has generated 100+ climate forecast projections out to 2100
- Based on different climate models from centers around the world
- With different parameterization schemes (convective weather, microphysics, turbulence, etc.) and/or different model initialization approaches
- Climate projections available for research purposes at various data portals including:
  - http://cmip-pcmdi.llnl.gov/cmip5/docs/CMIP5_modeling_groups.pdf
  - https://climate.northwestknowledge.net
  - https://esgf-data.dkrz.de

Partial list of CMIP5 GCM models and contributors

Model	Institution	Country
CNRM-CM5	Centre National de Recherches Meteorologiques	France
CESM	National Center for Atmospheric Research	USA
ACCESS	Commonwealth Scientific and Ind. Research Org.	Australia
MPI-ESM	Max Planck Institut für Meteorologie	Germany
BCC-CSM	Beijing Climate Center (国家气候中心)	China (PRC)
CCCMA	Canadian Centre for Climate Modelling and Analysis	Canada

- Total 29 contributing entities world-wide
- Full list given at https://cmip.llnl.gov/cmip5/docs/CMIP5_modeling_groups.pdf

Regional down-scaling of GCM data

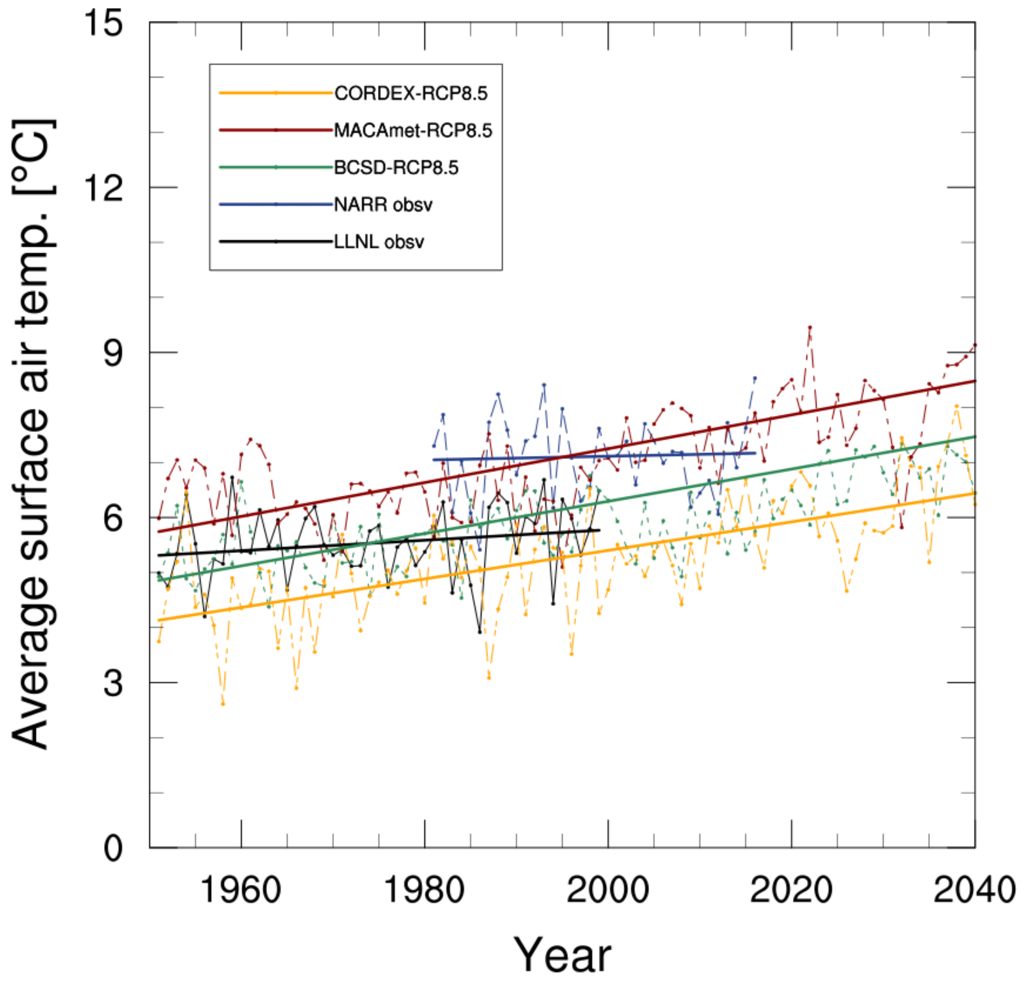
- GCM data are global, ~1-2° spatial resolution
- To study regional effects of climate, GCM data on a finer spatial scale is needed
- Several collaborative efforts have produced regionally down-scaled climate (RDC) data at 1/8 ° (~12 km) resolution
    - Using statistical, bias-correction techniques
    - Using a regional climate model

CMIP5-related RDC efforts

- Lawrence Livermore National Laboratory (LLNL) and Bureau of Reclamation
  - Collaborators: Climate Analytics Group, Climate Central, Santa Clara U., Scripps Instit. of Oceanography, U.S. Army Corps of Engineers, U.S. Geological Survey
- Multivariate Adaptive Constructed Analogs (MACA) datasets
  - Collaborators: U. of Idaho, Regional Approaches to Climate Change, Climate Impacts Research Consortium, NOAA's Regional Integrated Sciences and Assessments, Northwest Climate Science Center, Dept. of the Interior Southeast Climate Science Center
- Coordinated Regional Climate Downscaling Experiment (CORDEX)
  - Associated with the World Climate Research Programme (WCRP)
  - Collaborators from N. America: Nat. Ctr. for Atm. Research, Iowa State U., Cornell U., OURANOS (Quebec)

Domain of interest in the Pacific Northwest

CMIP5 RDC Data



Annual average near-surface forecast and observational analysis temperatures for the Pacific Northwest

Bold lines show temporal trend of ensemble averages

Ensembles

- LLNL: 42 RDC datasets
- MACA: 20 RDC datasets
- CORDEX: 1-3 RDC datasets

Observational datasets

- Objectively analyzed observations with model for (dynamically balanced) background state
- Provides 3D gridded depiction of the current environment (including points for which explicit observations are not available)

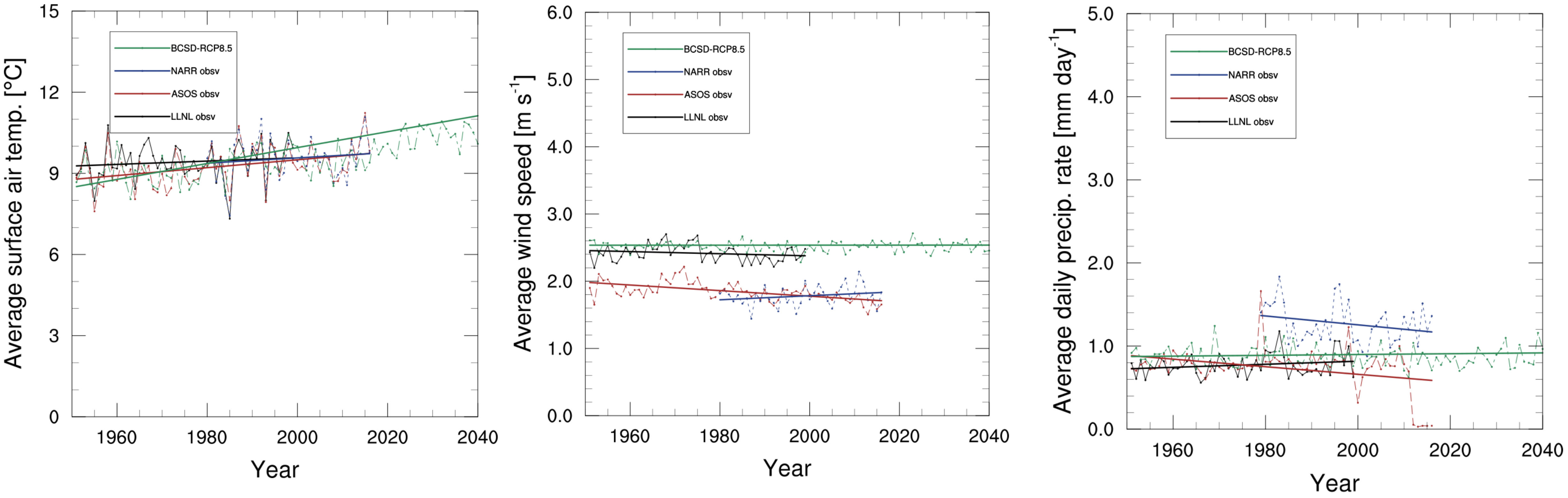
Various datasets:

- LLNL data
  - Training dataset (Maurer, 2002)
- MACA data
  - Training dataset (Abatzoglou, 2013)
- North American Regional Reanalysis (NARR)
  - Produced by NOAA's Nat. Center for Environmental Prediction (NCEP)
  - Data available 1979-present
- PRISM
  - Produced by Oregon State U.
  - Data 1981-present; average daily/monthly re-analysis
  - Precip, mean max/min temps., mean dewpt. temp. (no wind data)

Evaluation of observational datasets using ASOS data

- Automated Surface Observing System (ASOS)
- Hourly recording of temperature, pressure, dewpoint temperature, wind speed, wind direction, cloud cover
- 900 sites mainly located at airports

Evaluation of observational datasets using ASOS data

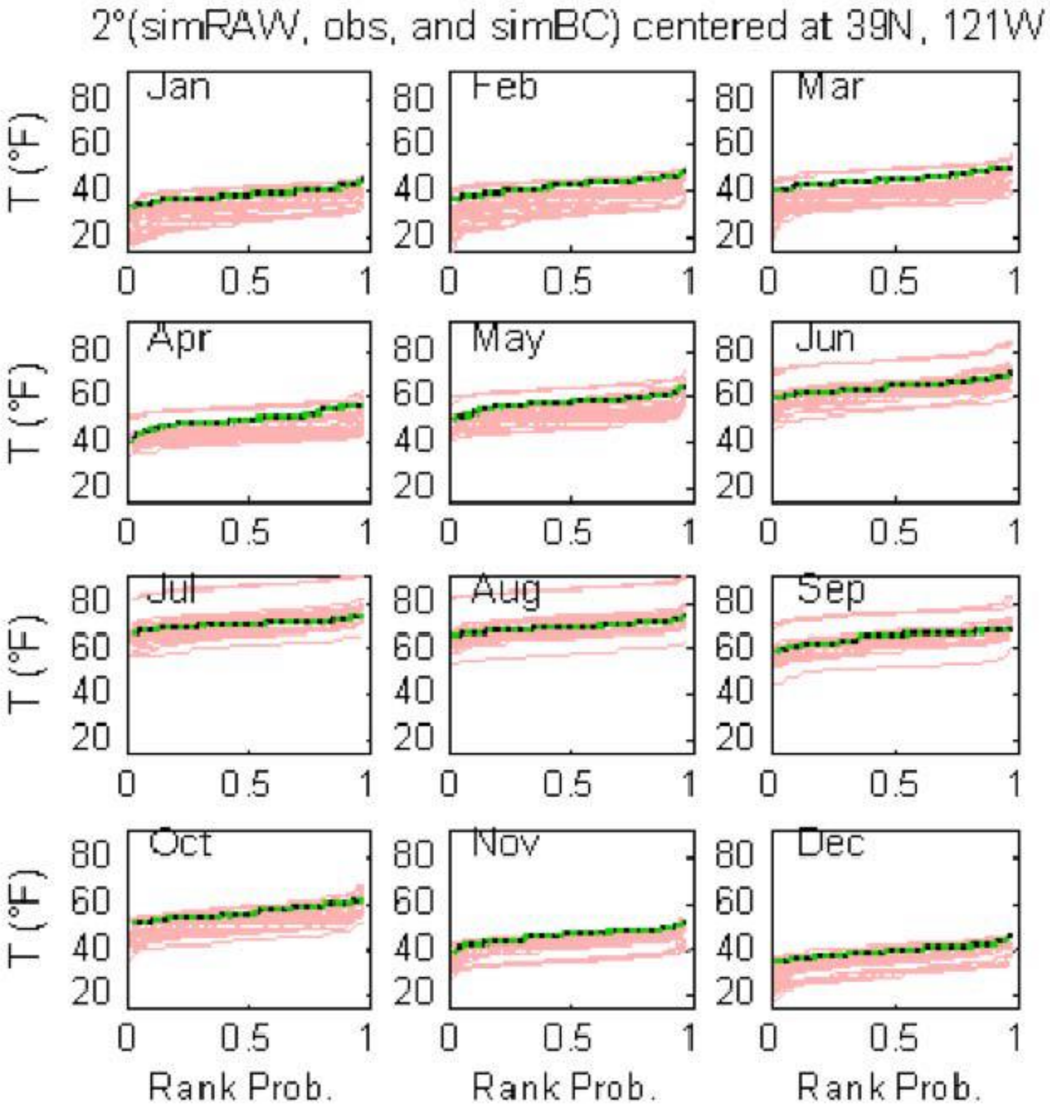


Data averaged across 9 ASOS sites.

Bias-correction methods

- Bias-correction spatial disaggregation (BCSD) (Wood et al. 2002 & 2004)
  - Quantile mapping to map one probability distribution to another, removes systematic errors
  - Spatial-disaggregation
- Bias-correction constructed analogues (BCCA) (Hidalgo et al. 2008, Maurer et al. 2010)
- Multivariate Adaptive Constructed Analogs (MACA) (Abatzoglou and Brown, 2011)
  - Uses a training dataset of observed cases to match spatial patterns in climate models

Bias-correction: Quantile mapping

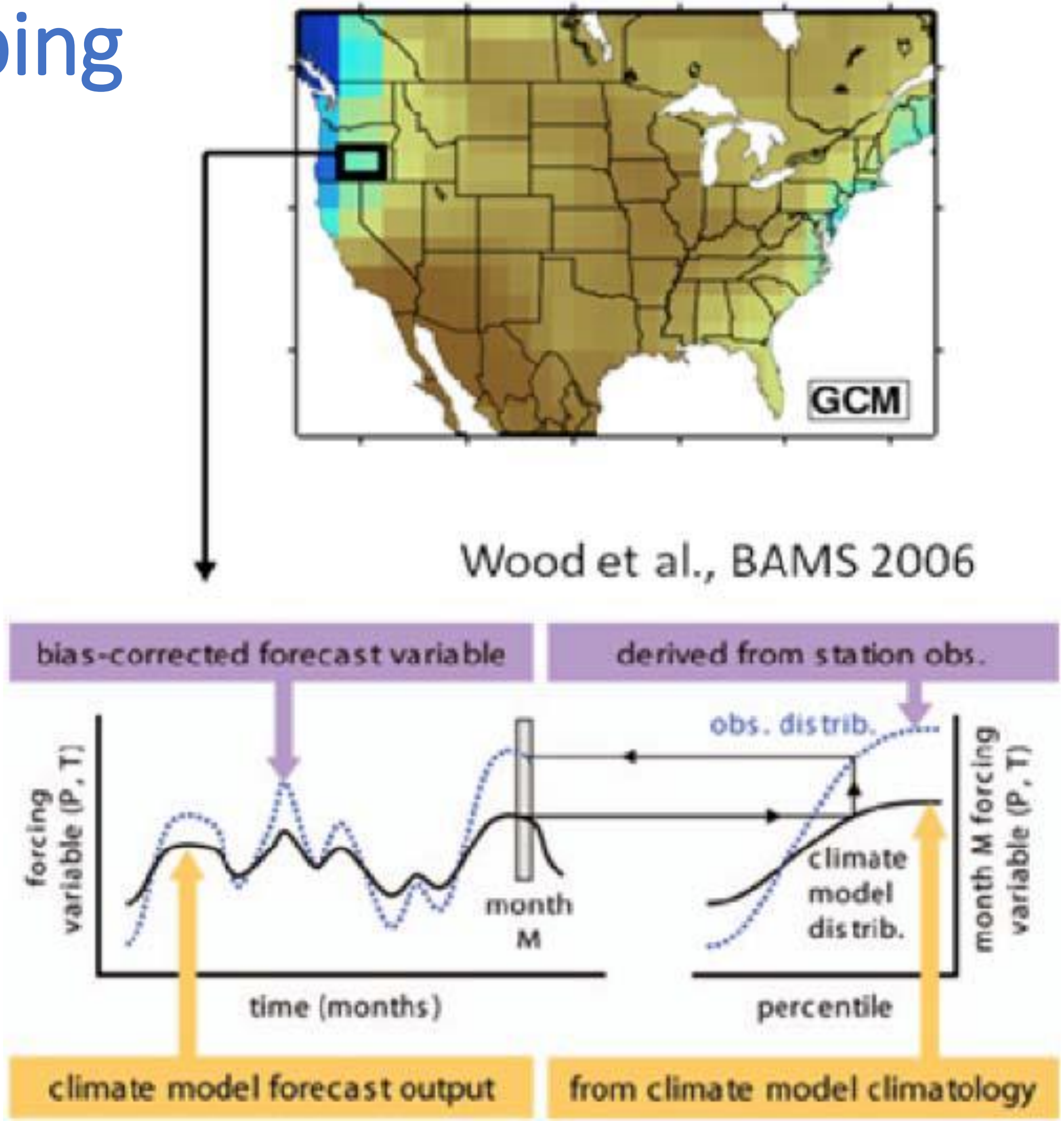


- Generate cumulative distribution functions (CDFs) of average monthly temperature by location (1° cell)
- CDFs generated for observational analysis (black), each GCM ensemble member (red)

Figure from Reclamation, 2013

Bias-correction: Quantile mapping

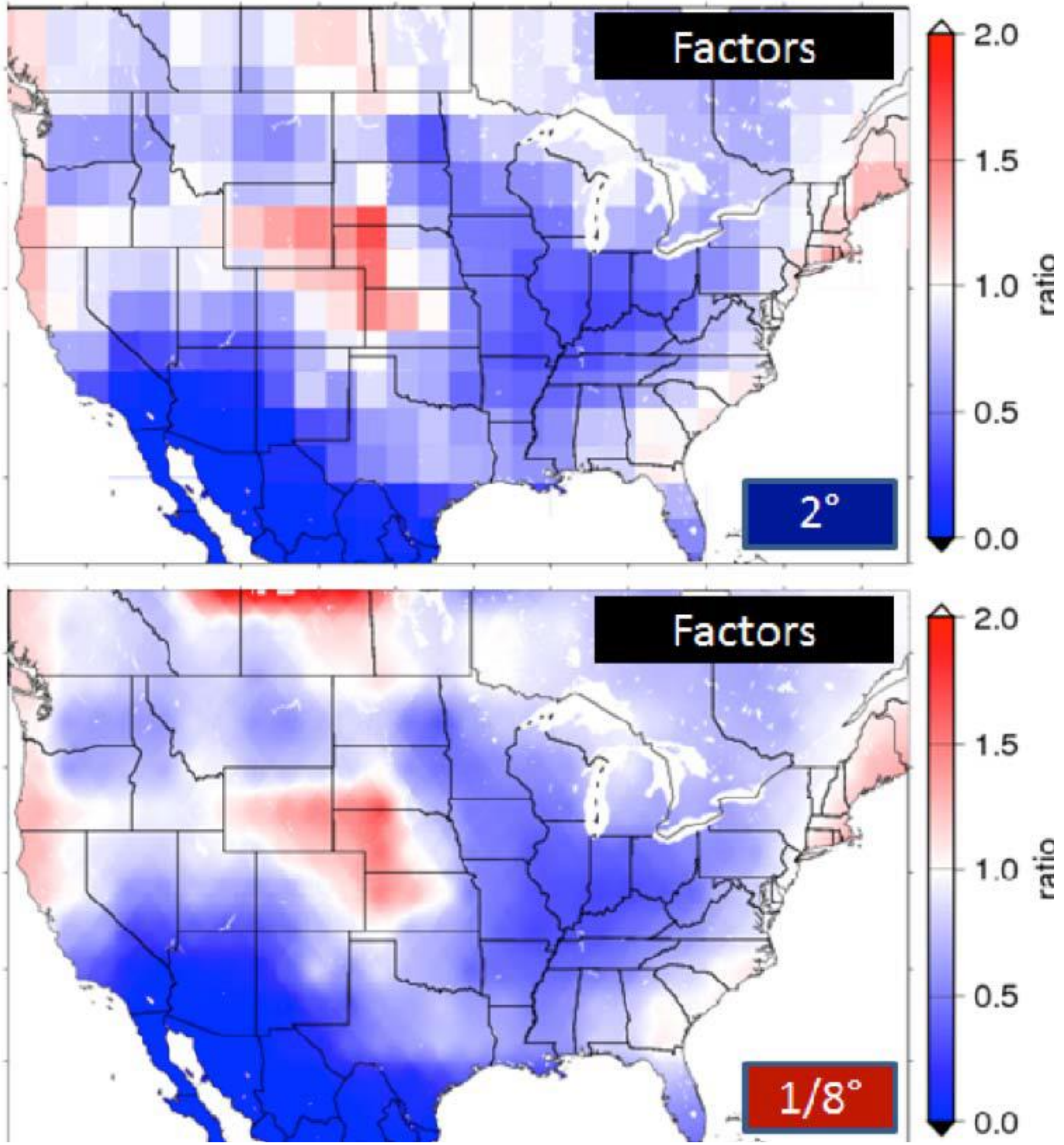
- For a GCM temperature, use the CDF for the given month and location to identify rank probability
- Match the rank probability of the observational analysis CDF and use its corresponding temperature as the adjusted GCM value



Reclamation, 2013

Spatial Disaggregation

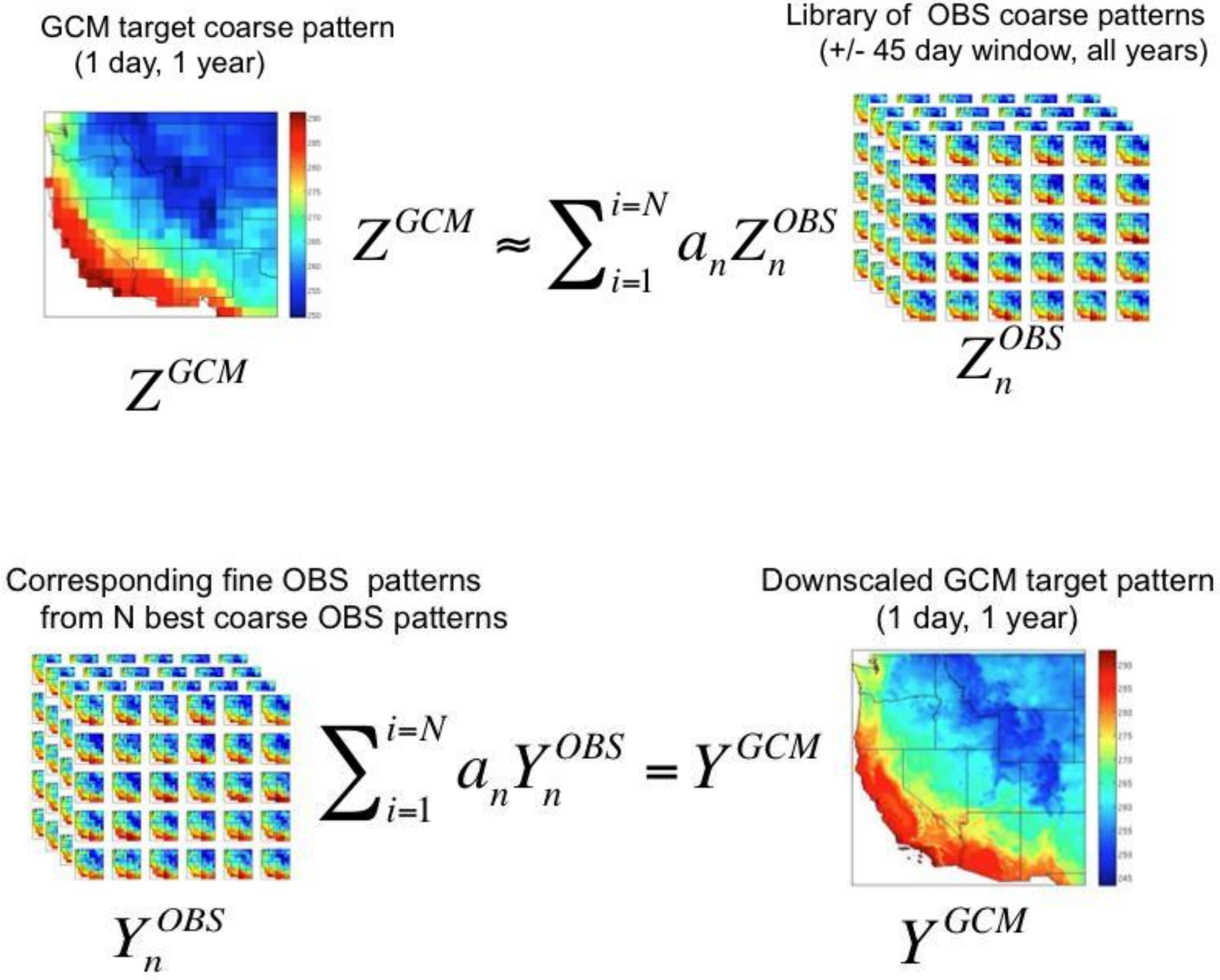
- Calculate "factor" as difference between monthly mean GCM and observational analysis precipitation data on coarse (1°) grid
- Interpolate "factors" to 1/8 ° grid using an inverse-distance-squared method
- Multiply interpolated factors with mean GCM 1° data to achieve 1/8 ° data



Reclamation (2013)

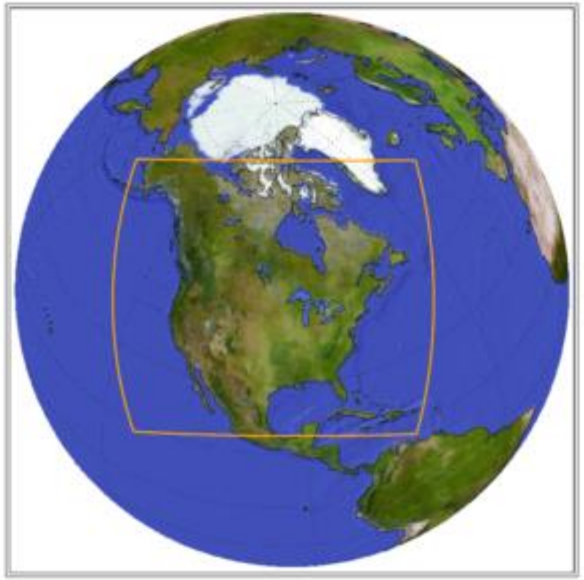
MACA

- Similar to BCSD method, bias-correction is based on quantile mapping using CDFs (based on 15-day period rather than monthly)
- Matches 1 deg GCM data with same spatial pattern from observed cases of previous years
- An analog "best" case matching the GCM is a superposition from 100 best observed cases using matrix inversion to estimate coefficients for each of the 100 cases
- The fine-scale (1/24°, 4 km) versions of the 100 observed cases along with their estimate coefficients are used to construct a down-scaled GCM



Figures from https://climate.northwestknowledge.net/MACA/MACAmethod.php

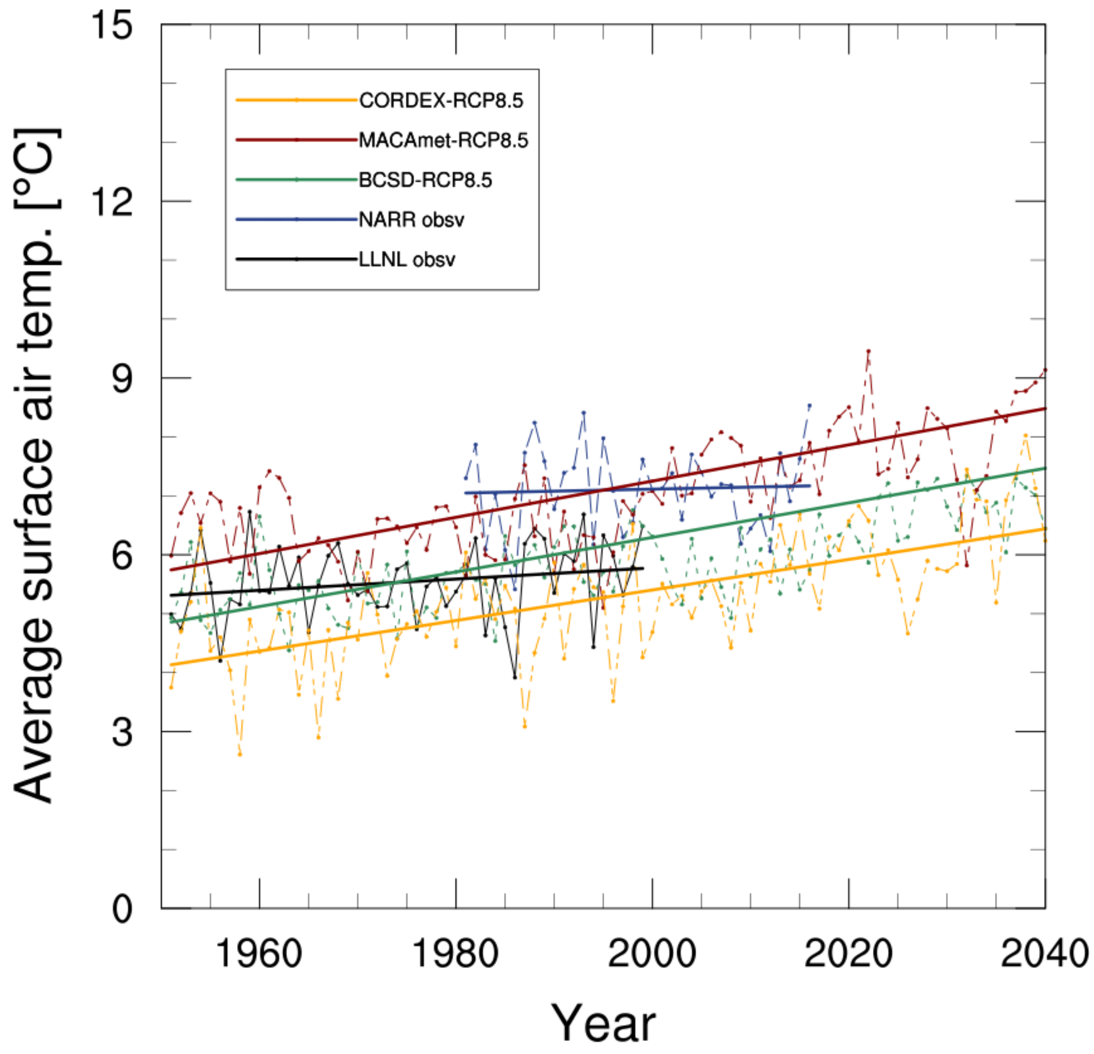
CORDEX



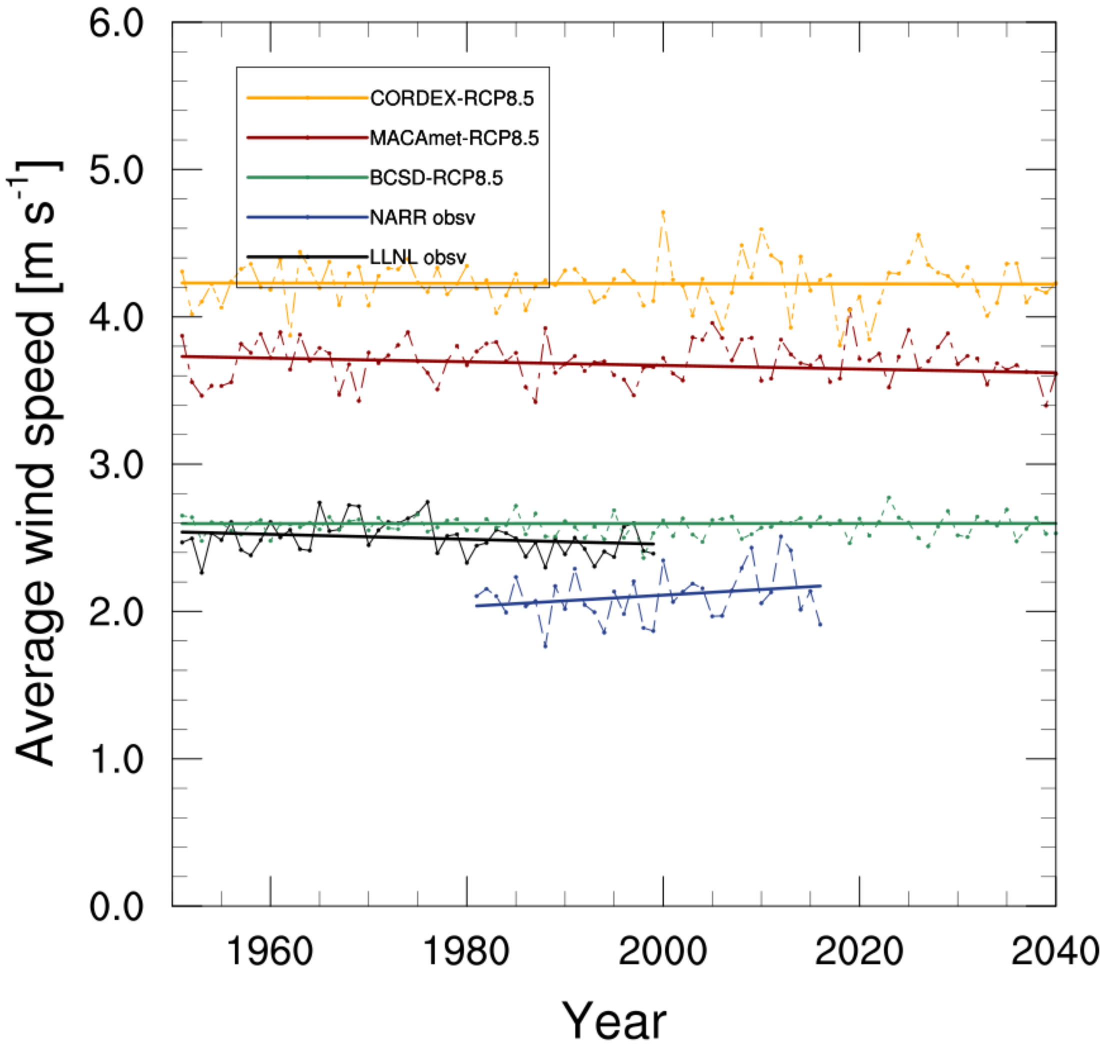
- Regional climate model using initial and boundary conditions from GCM
- Explicitly calculate weather variables at a relatively fine resolution (e.g. 0.44°), not statistically generated
- Computationally expensive
- Accounts for effects of local features such as terrain and land/vegetation type as well as relatively smaller-scale weather phenomena such as local storms

Domain of interest in the Pacific Northwest

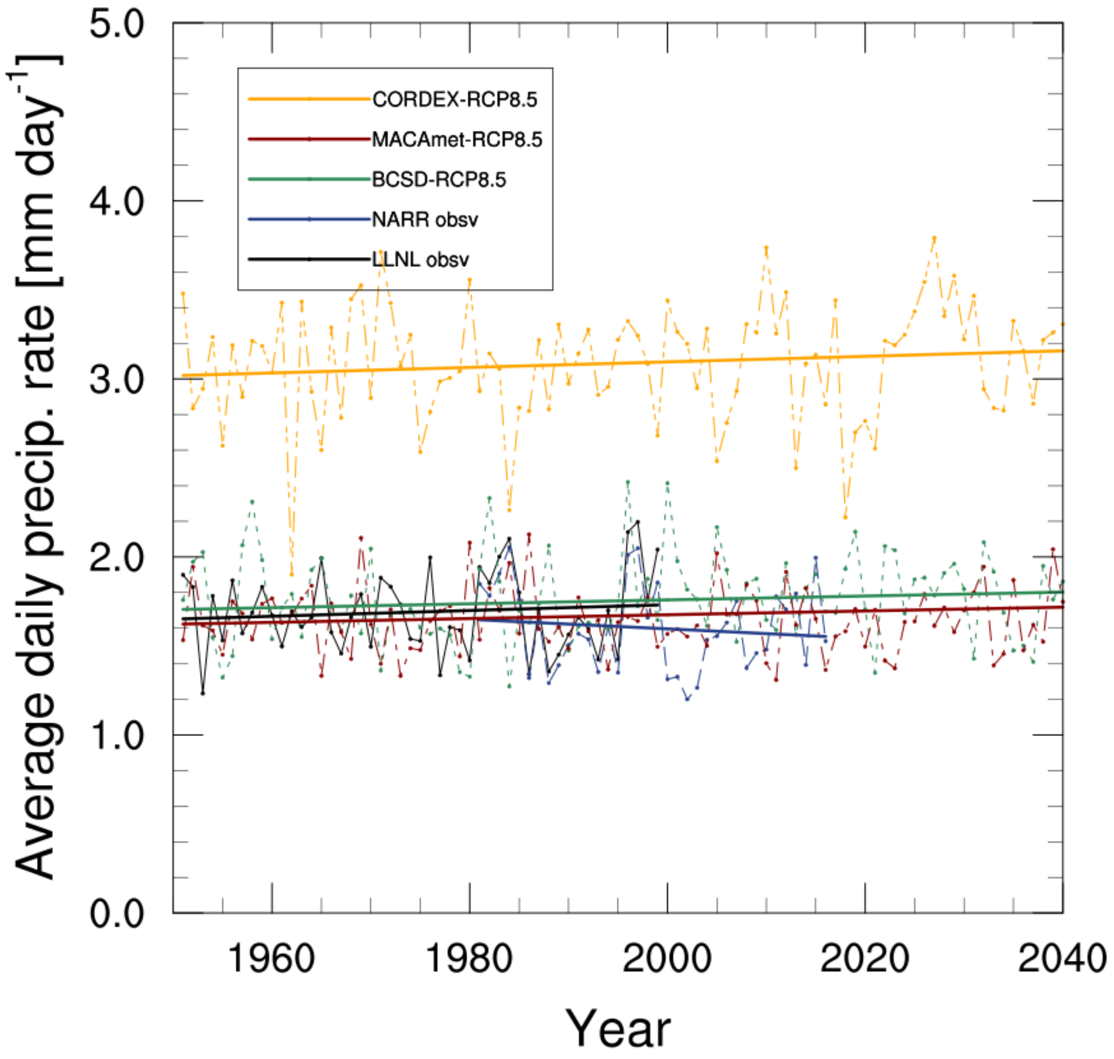
Annual average near-surface (2 m) temperature



Annual average near-surface (10 m) wind speed



Annual average daily precipitation rate



Identify the optimal regional climate dataset

- Method follows that given in Rupp et al. 2016, who evaluated GCM (i.e., not RDC data) performance over the PNW
- Calculate a normalized mean absolute error (MAE) by variable (mean temp., wind, precip.)

$$E = \frac{MAE - MAE_{\min}}{MAE_{\max} - MAE_{\min}}$$

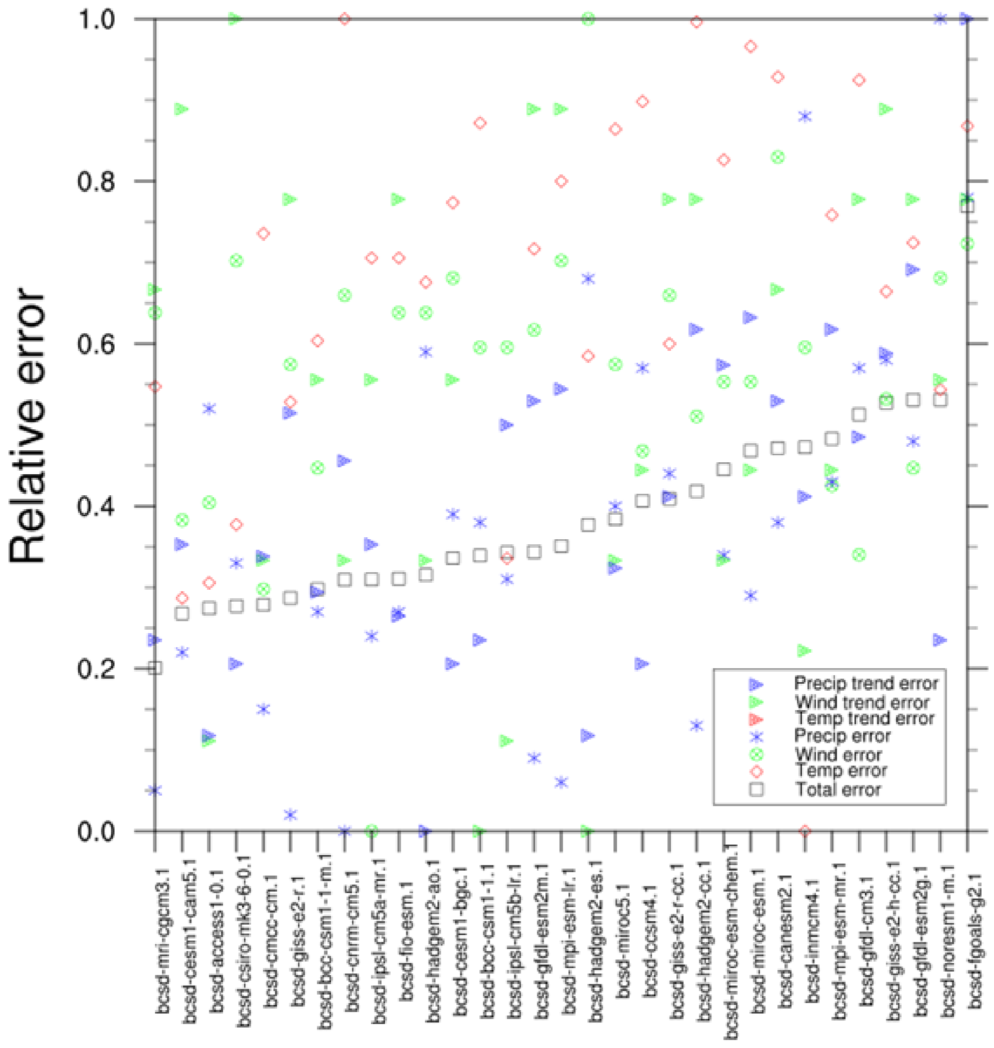
- Combine errors for all variables

$$E_{tot} = \sum_{var=1}^{m} w_{var} \, E_{var}$$

Weights by variable:

Precip.	0.7
Temp.	0.25
Wind	0.05

Identify the optimal regional climate dataset

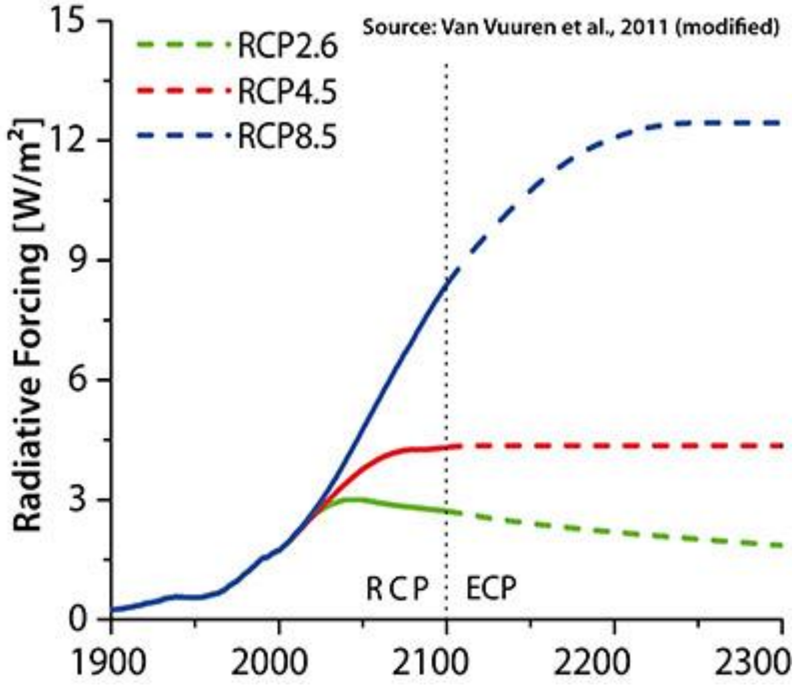


Identifying the optimal regional climate dataset

	Regional Climate Dataset	Associated Entity
Lowest total error (w/o trend error)	bcsd-cesm1-cam5.1	NCAR (USA)
Lowest total error (w/ trend error)	bcsd-mri-cgcm3.1	MRI (Japan)
Lowest temp. error	bcsd-inmcm4.1	RINM (Russia)
Lowest wind error	bcsd-ipsl-cm5a.mr.1	IPSAL (France)
Lowest precip. error	bcsd-cnrm-cm5.1	CNRM (France)
Lowest temp. trend error	bcsd-giss-e2-r.1	NASA (USA)
Lowest precip. trend error	bcsd-hadgem2-ao.1	Met Office (UK)

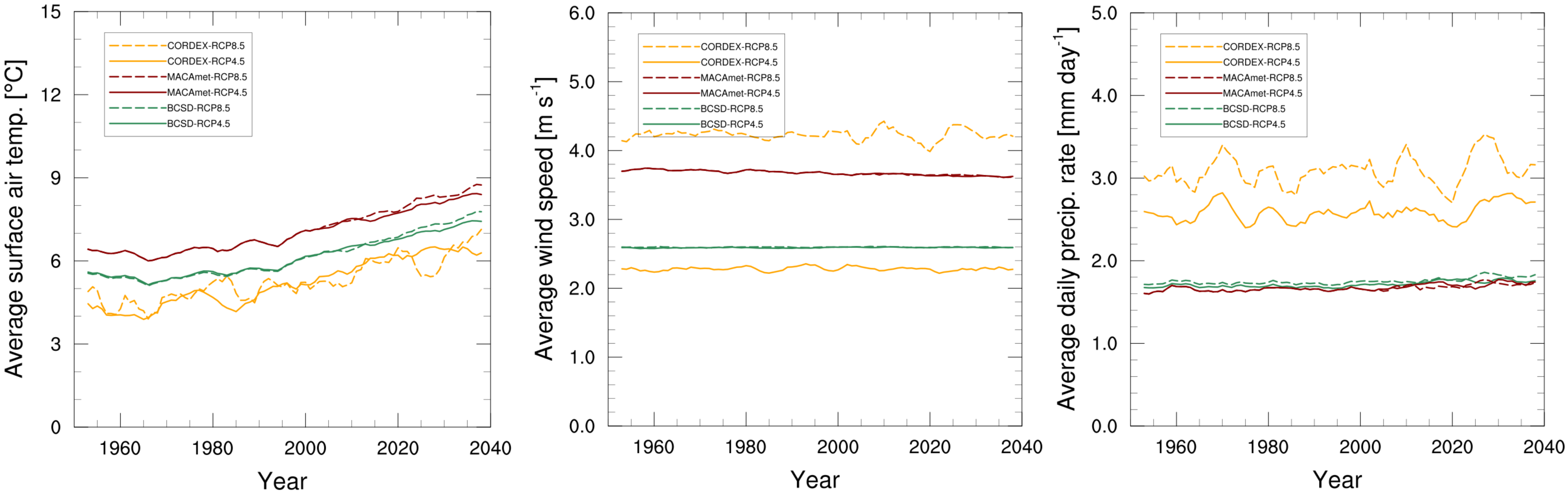
Results for different climate scenarios: RCP 4.5, 8.5

- Representative Concentration Pathways (RCPs) represent projected greenhouse gas (GHG) concentrations
- Dependent on population growth, energy production, land use, etc.
- GCMs run with different RCP scenarios



Source: portal.enes.org/data/enes-model-data/cmip5/datastructure

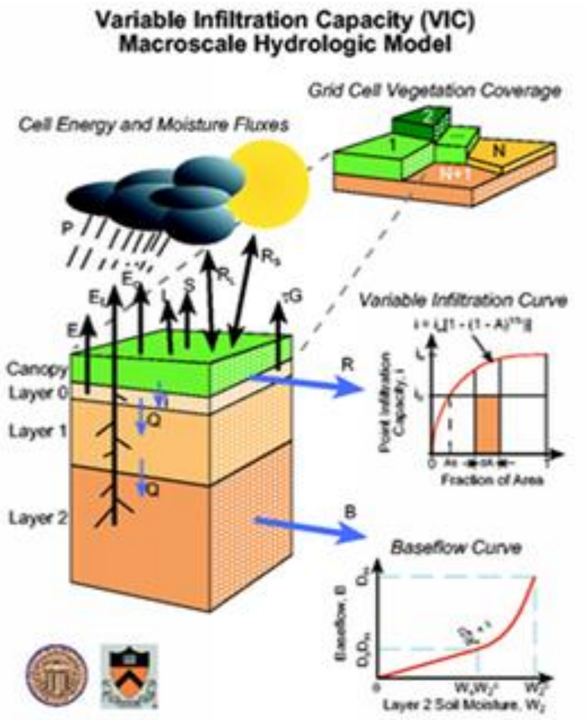
Results for different climate scenarios: RCP 4.5, 8.5

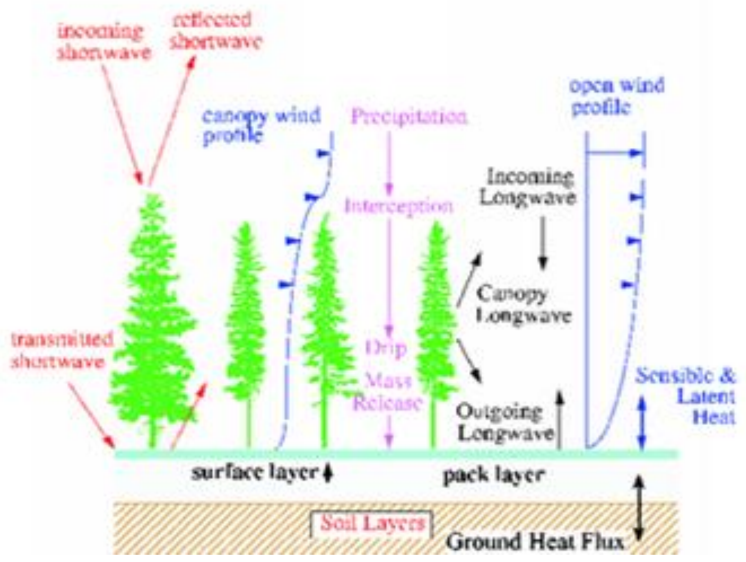


Shown are 5-year running averages

Hydrology Modeling

- Collaborators are the same as listed for the CMIP5 RDC datasets (LLNL, Bureau of Reclamation et al.)
- Variable Infiltration Capacity (VIC) Model
- Developed at the U. of WA
- Solves the water balance for each model grid cell
- Inputs include: precip., temp., wind speed, solar rad., RH, vapor pressure, veg. type, soil type
- Maintains states of soil moisture and snow
- Produces evapotranspiration, baseflow, sublimation, runoff

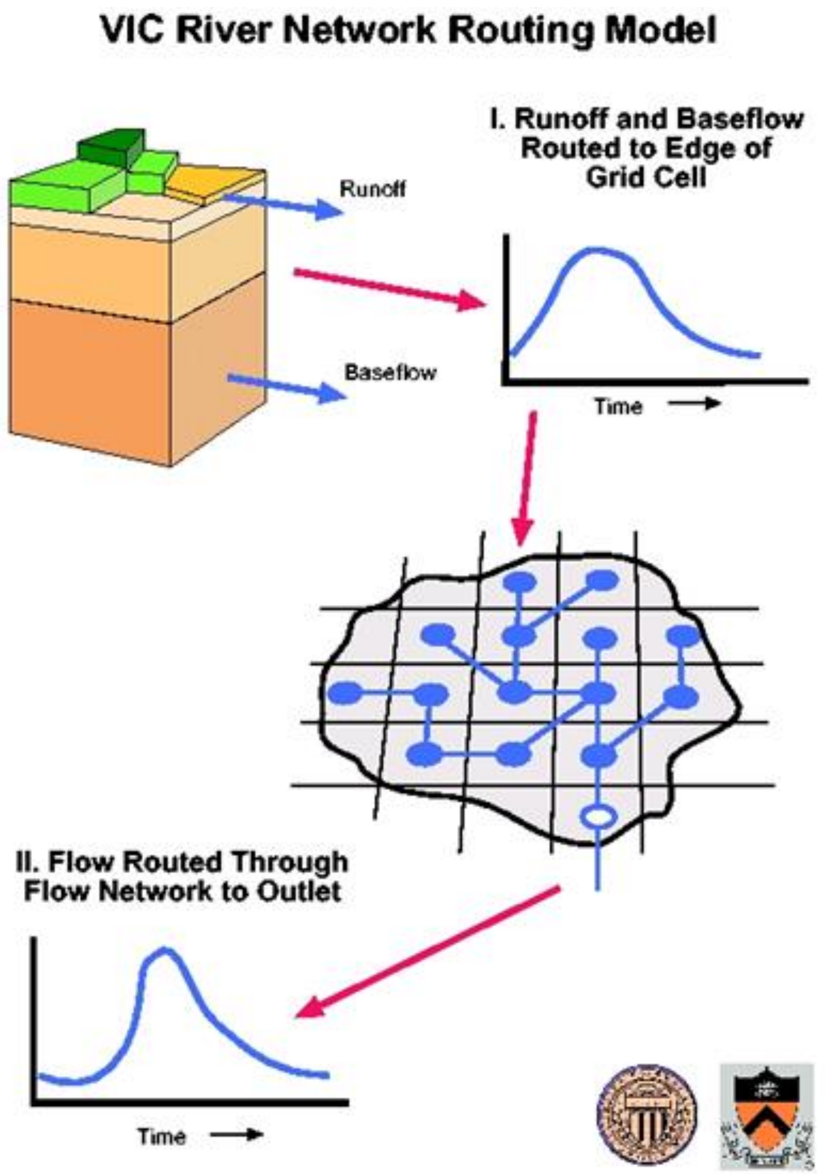




Reclamation (2014), Wood and Mizukami (2014)

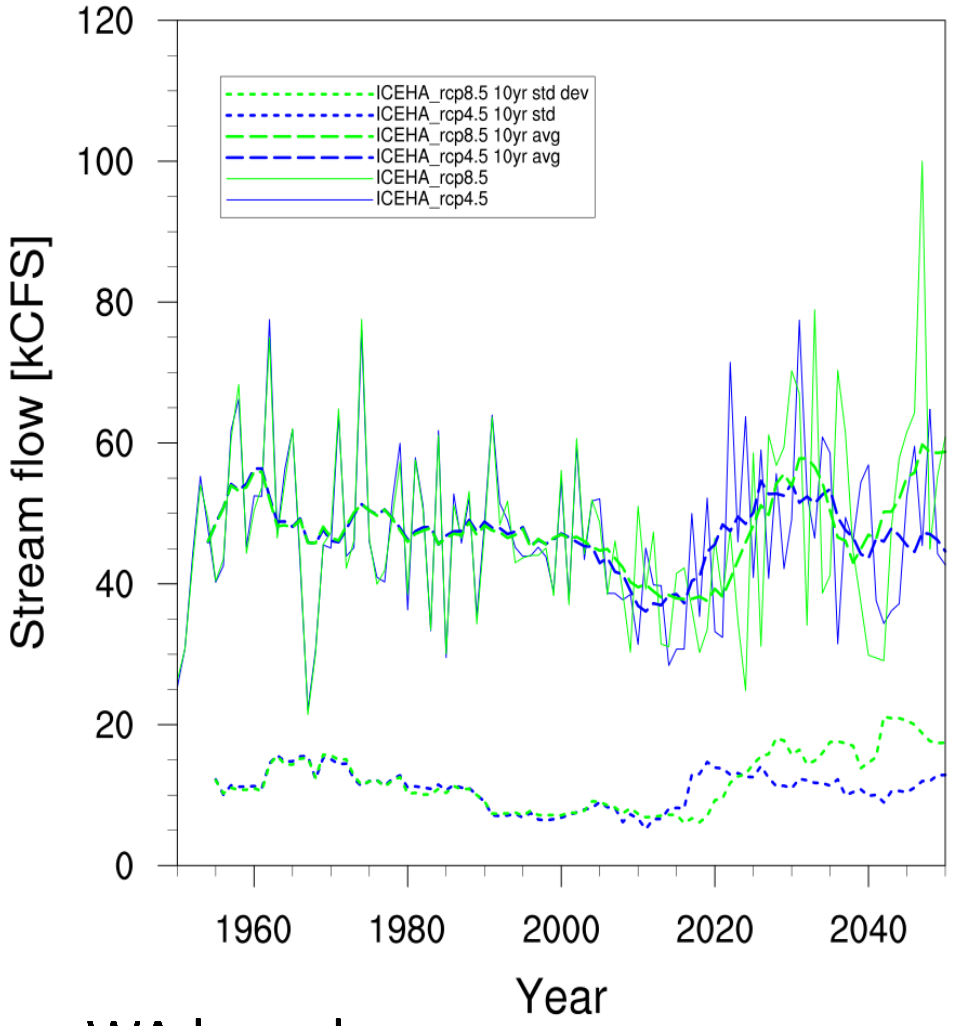
Hydrology Modeling

- VIC river network routing model that aggregates runoff and baseflow from each cell identified with a given tributary to give streamflow
- Hydrology projections based on CMIP5 BCSD RDC datasets



Reclamation (2014)

Streamflow Projection



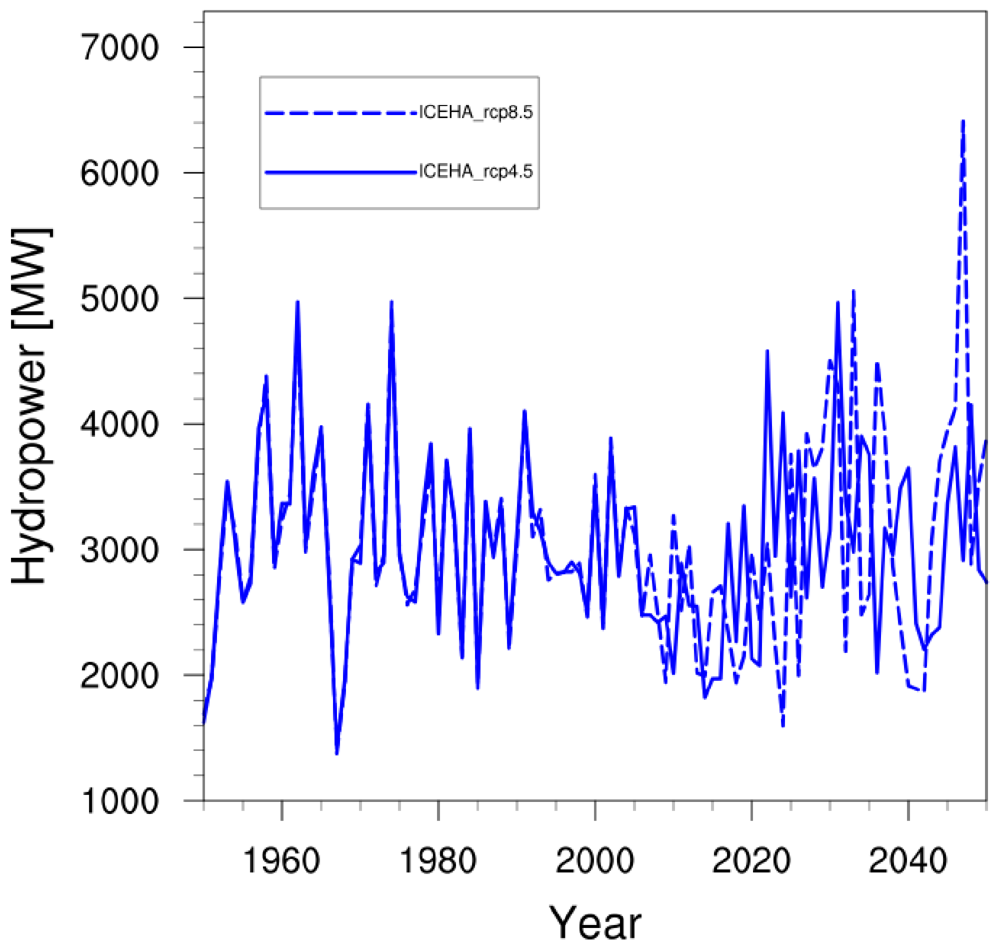
Forecast streamflow and std. dev. at Ice Harbor, WA based on one RDC projection (NCAR's bcsd-cesm1-cam5)

Calculating hydropower

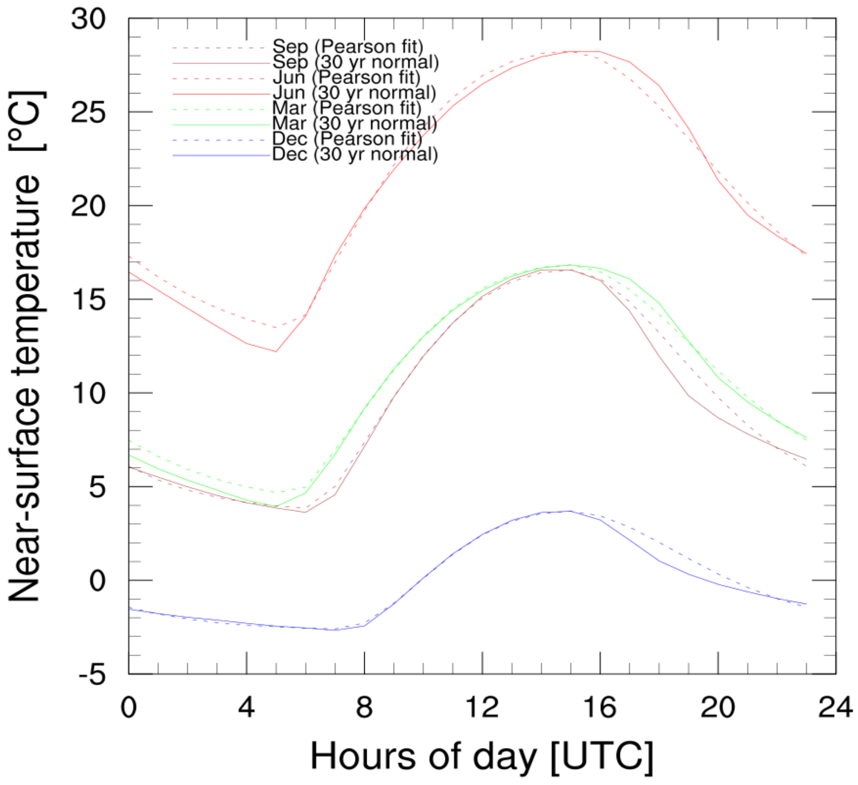
$$P_{hydro} = g\rho\eta QH$$

Q = streamflow [m^3 s^{-1}]
H = height of water above turbine [m]
ρ = density of water [1000 kg m^{-3}]
η = efficiency coefficient = 0.9

$$H = \frac{P_{hydro-capacity}}{g\rho\eta Q_{capacity}}$$



Diagnosing diurnal variation of mo. mean temperature



30 year normal diurnal curves by month for Yakima, WA from the National Centers for Environmental Information (www.ncdc.noaa.gov).

$$T(t) = T_{\min} + (T_{\max} - T_{min})\Gamma_P(t)$$

$$\Gamma_P(t) = e^{-t\gamma}\left(1 + \frac{t}{a}\right)^{\gamma a}$$ Pearson type III distribution

t = number of hours either prior to ($t < 0$) or after the normal curve maximum ($t > 0$)
a = time in hours from the normal curve minimum to its maximum
γ = empirically-defined for a given normal curve by iteratively varying its value to generate a Pearson-fit function that fits the given 30-year

Follows method of Satterlund et al. (1983).

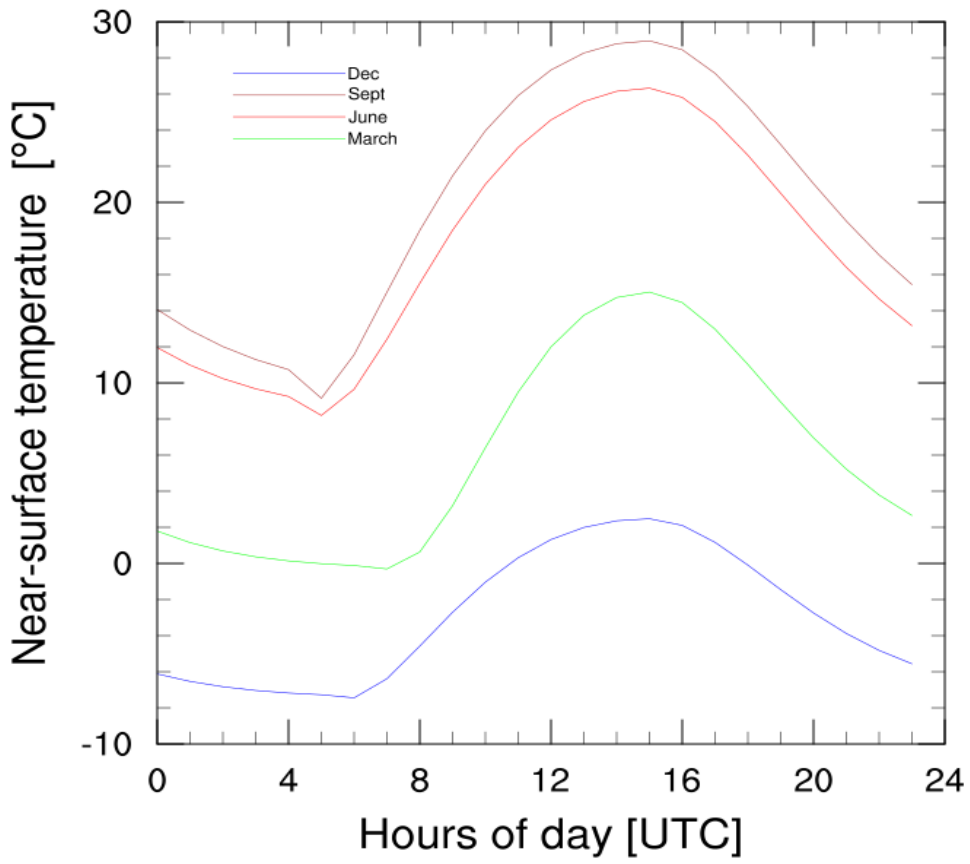
Diagnosing diurnal variation of temperature

$$T(t) = T_{\min} + (T_{\max} - T_{min})\Gamma_P(t)$$

Diurnal variation of average monthly near-surface temperature using Pearson III distribution curves for Yakima, WA and for designated months of year 2015.

Used average monthly max/min temperature projection of bcsd-cesm1-cam5.1 (NCAR).

Useful for projecting daily load in the future.



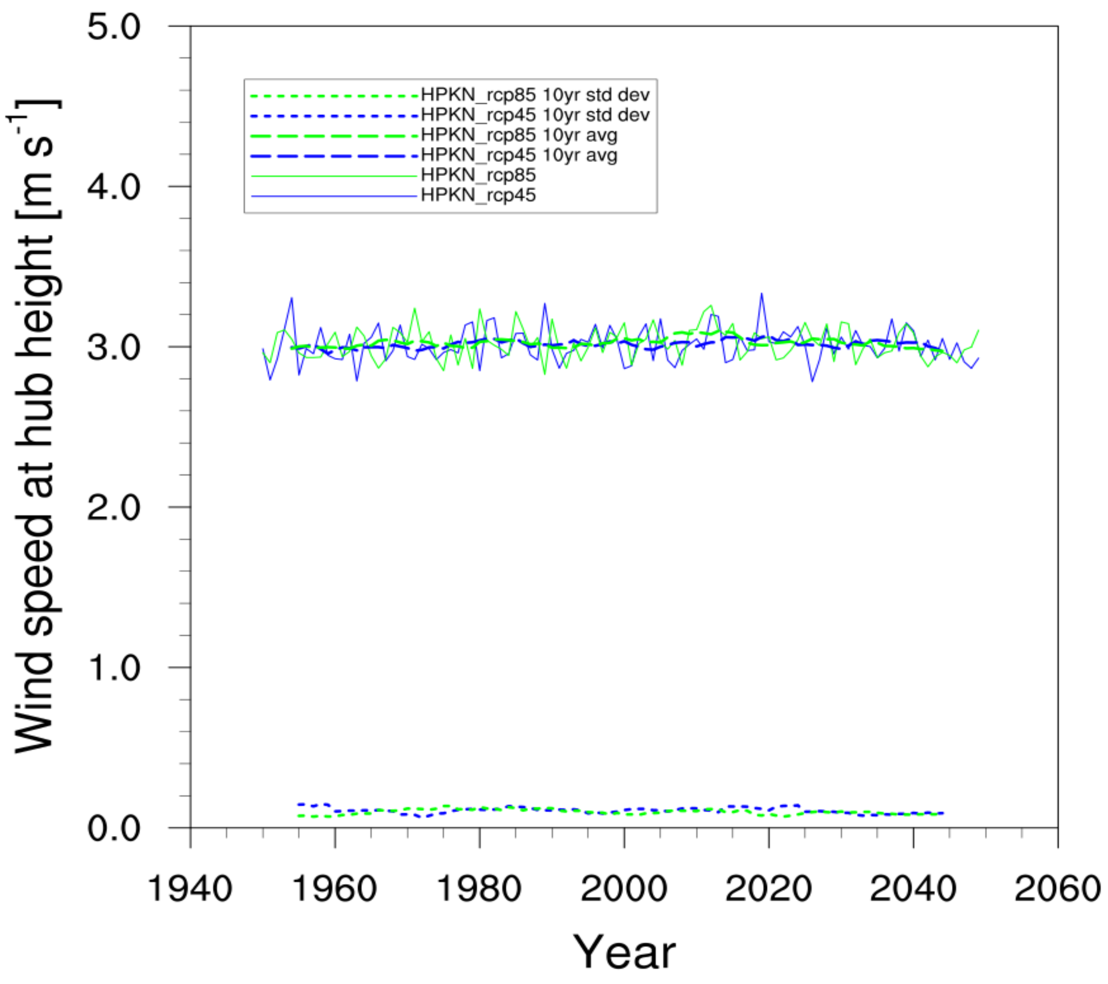
Calculating wind power

Extrapolate near-surface wind to turbine height.

$$v_{hub} = v_{10m}\left[\frac{\ln\left(\frac{z_{hub}}{z_o}\right)}{\ln\left(\frac{10}{z_o}\right)}\right]$$

z_o= roughness length = 0.3
(consistent with broad open areas)

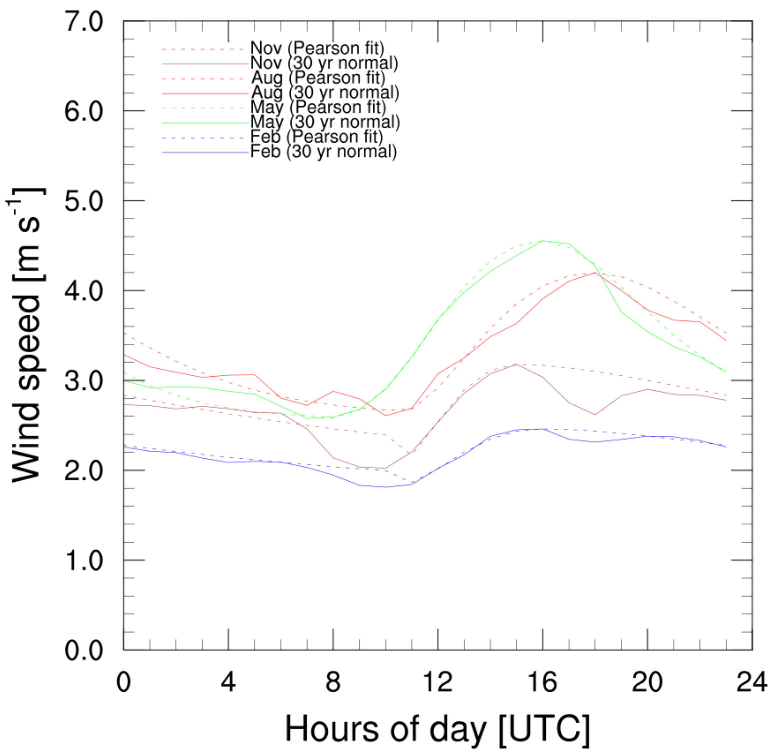
Wind speed projections from mri-cgcm3.1 model (Japan).



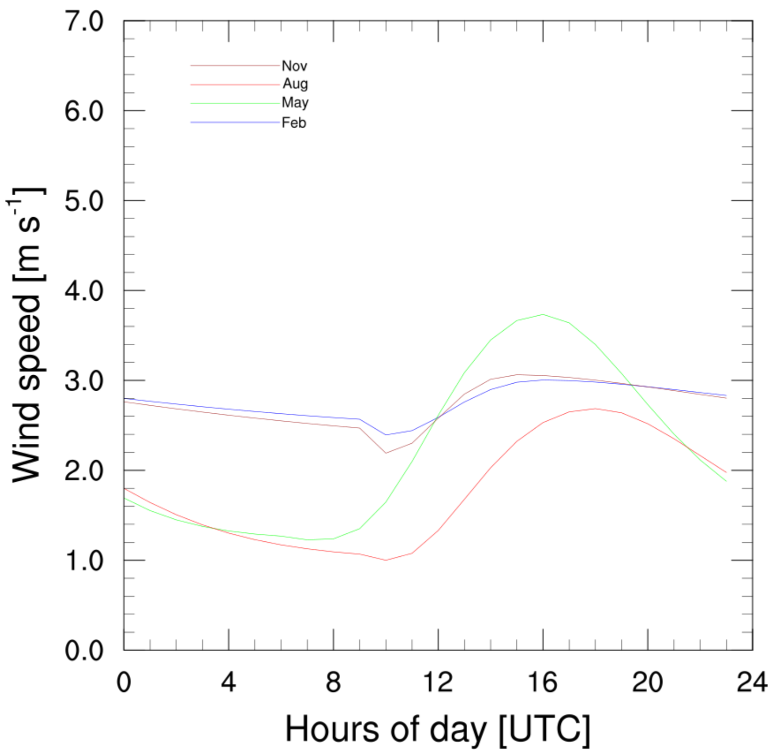
Forecast annual average hub height wind speed at Hopkin Ridge, WA

Generate monthly-averaged diurnal curves

30-year normal curves



Derived wind curves for 2015



- 30-year normal and monthly 2015 derived curves from Yakima, WA (close to but not at Hopkins Ridge)
- For Hopkins Ridge, do not have max/min projected winds, only mean wind

Calculating wind power: Hopkins Ridge Wind Facility

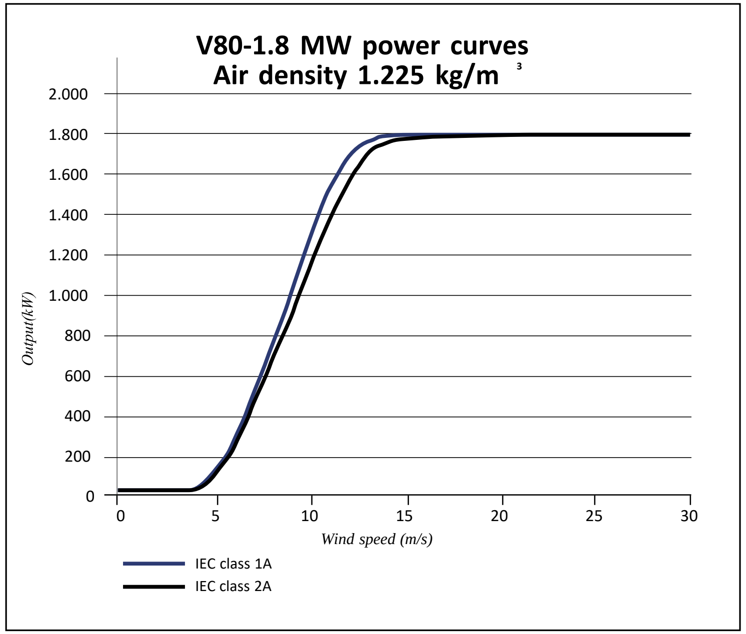
$$P_{wind} = 0.5\, \eta\, \rho\, A\, u^3$$

- NE of Dayton, WA (46.38, -117.81)
- Total 157 MW capacity from 87 turbines
- Vestas V80 1.8 MW turbines
    - 80m diameter, 5027 m2 sweep area
    - Hub height 67m
    - Cut-in/cut-out wind speed: 4, 25 m/s
- Assume 0.4 efficiency
- Account for wake effect

$$U_{cell} = C_{wake} \times U_{Met}$$ (NREL Tech Rpt 2014)

$$C_{wake} = 1 - \frac{1}{140}(N_{turbines} - 1)$$

- Adjust for forecast low wind speed bias



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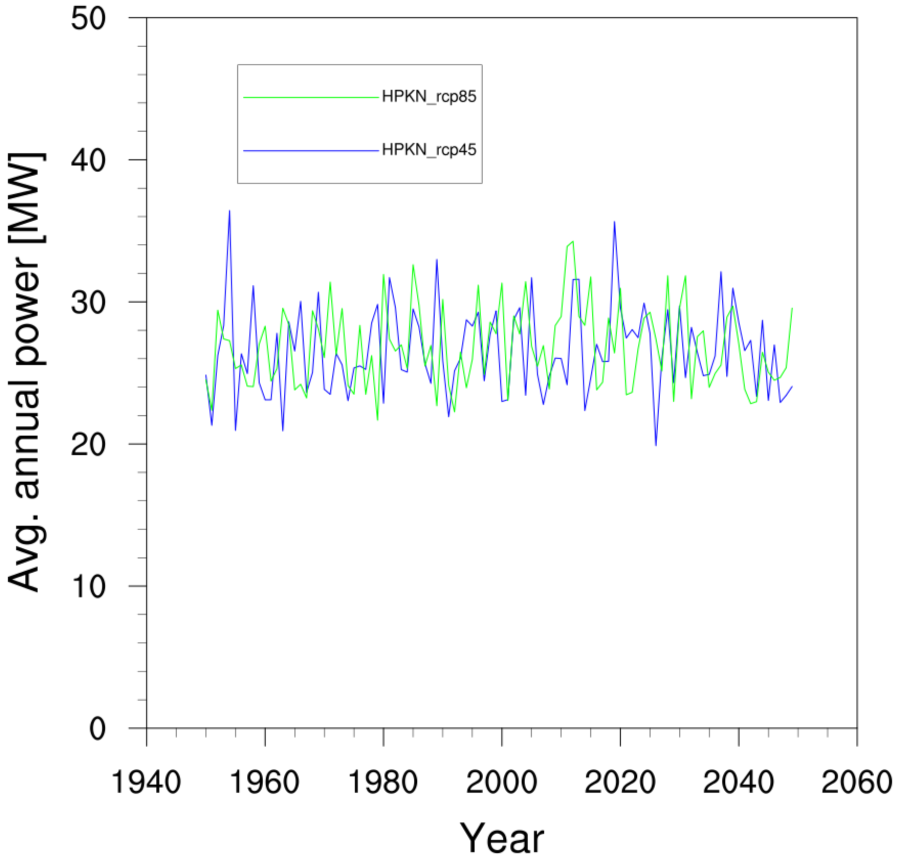
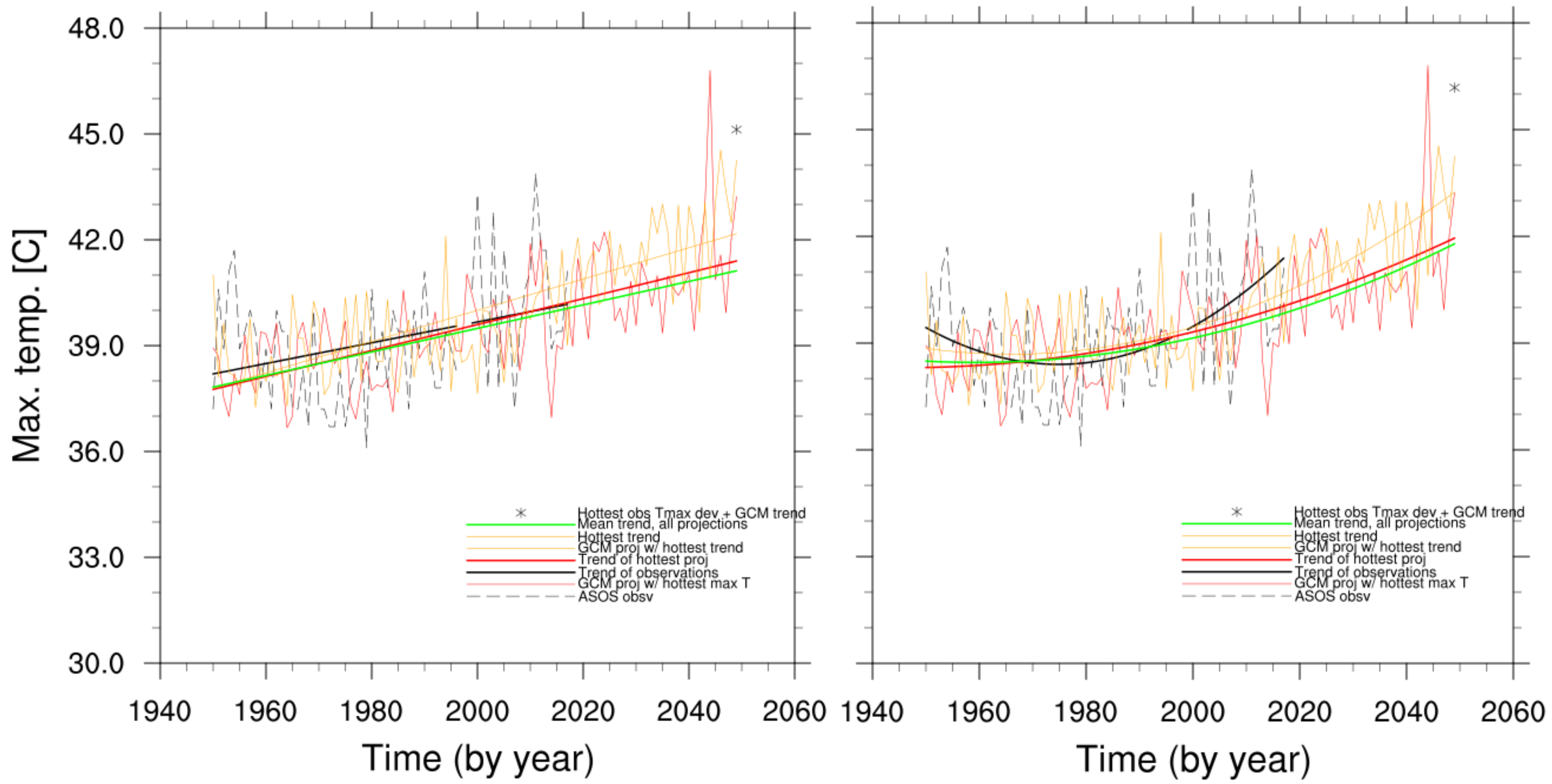


Power across entire wind farm

What about forecasting climate extremes?

Trends of observations and "hottest" projections (RCP8.5 data for Austin)



- Year 2011 gives the largest observed departure from mean temperature trend (~5 deg.)
- Identify reasonable future extreme event by adding observed extreme departure (5 deg) to projected future mean at 2050.
- BUT, what is appropriate means of extrapolating mean temperature to 2050?

Forecast extremes: consistency among temp., wind, pcp.

- For example, to consider the range of plausible extreme events would give a matrix of scenarios:
  - High temp/high pcp/low wind
  - Low temp/high pcp/high wind
  - Low temp/low pcp/high wind … etc.
- Could investigate correlations among temp., wind, precip. extremes in the historical data
- Models would impose physical constraints such that certain scenarios would not occur:
  - Extreme high temp/high pcp would not occur, because it takes more energy to heat moist air vs. dry air (heat capacity of water vapor is nearly double dry air), thus extreme heat events occur only in cases of low pcp

Overview of Results

- There is projected an increase of 0.5 C in average annual temperature in the PNW by 2040
- Average annual wind speeds and precipitation will remain nearly the same over the PNW through 2040
- These trends are consistent among the RDC ensemble sets (even if actual magnitudes of temp., wind, and precip. rate differ among the RDC ensembles)
- Using LLNL observational dataset to determine RDC error, the bcsd-cesm1-cam5.1 (NCAR, US) and bcsd-mri-cgcm3.1 (MRI, Japan) datasets scored overall the best

Future work

- More work can be done to identify an appropriate observational data for RDC validation (such as considering PRISM)
- More observations are needed at wind farm locations for validation of wind power forecasts
- More precipitation observations needed in remote areas as well as data on water use in the PNW to aid validation of hydro power forecasts
- In evaluating optimal RDC datasets, consider observational datasets for validation other than LLNL and NARR, and, depending on end-use application, reconsider arbitrary weights per variable for normalized total error
- Evaluate RDC data on a seasonal basis

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