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Comparing ScenarioMIP Drought Predictions using SPEI in the Central and Western U.S.

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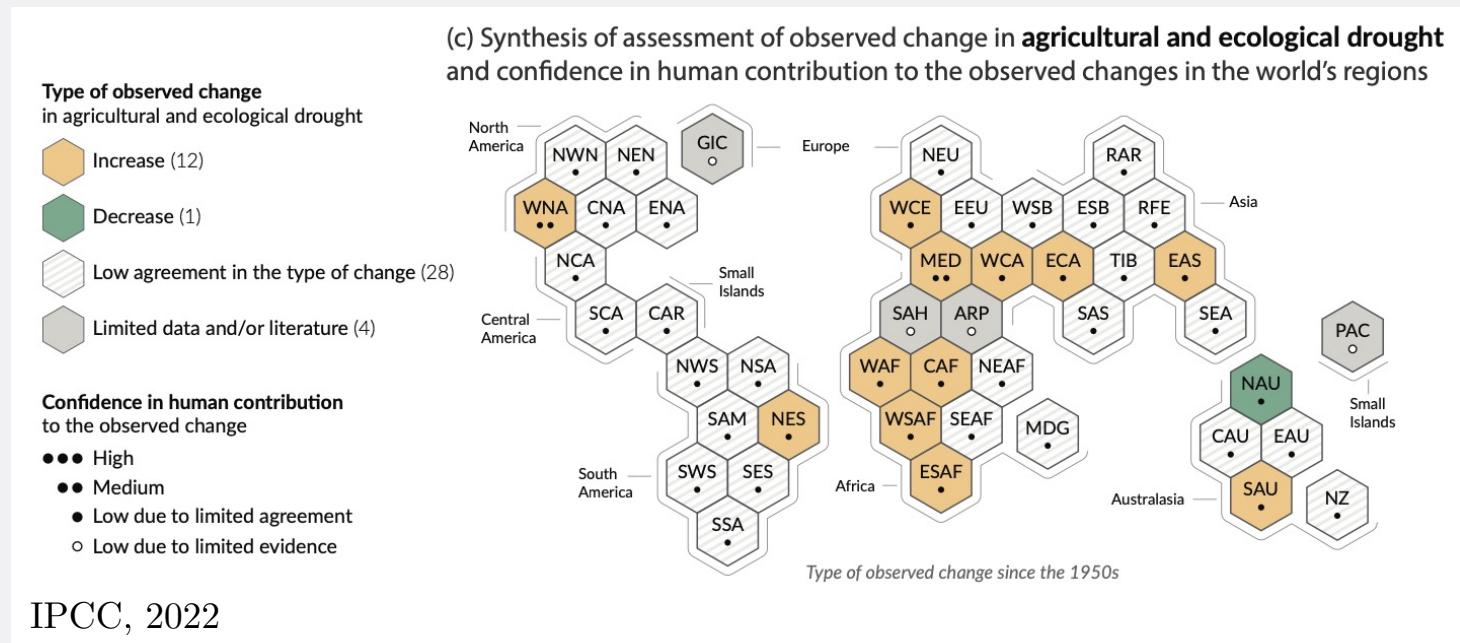
Project inspiration

- PhD research working on better understanding the drying period in the central Rocky Mountains during the Eocene-Oligocene transitional cooling using CESM 1.2
- Pivot this to the modern example of climate change, using accessible CMIP6 data from ScenarioMIP predictions until 2100



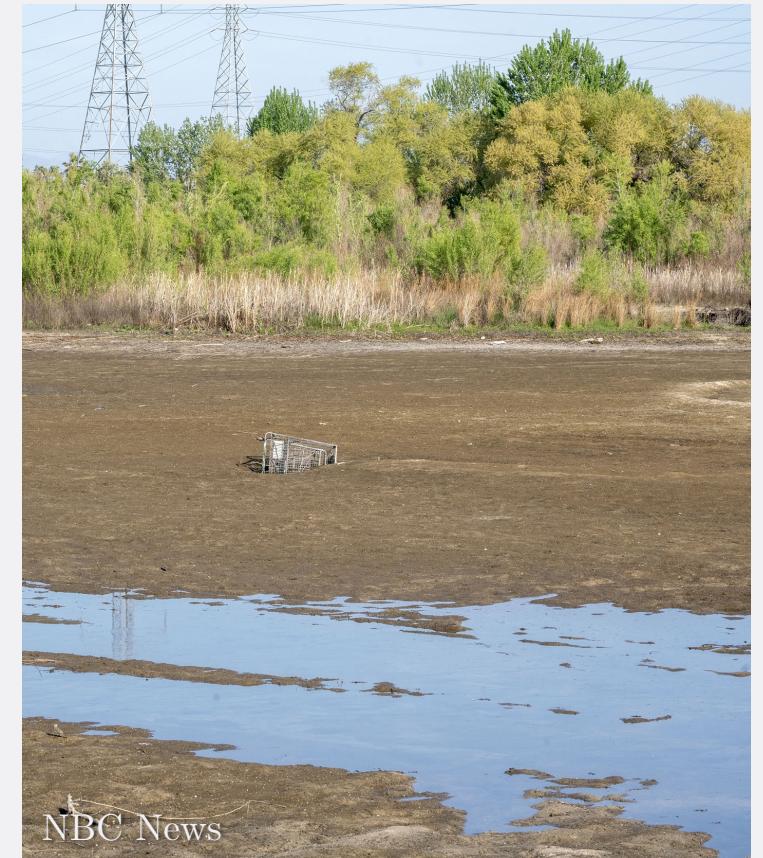
Existing literature

- IPPC's 6th Annual Report suggests little conclusive evidence about the future of drought in central U.S.
 - Western North America is one of only two regions with medium confidence



What is drought?

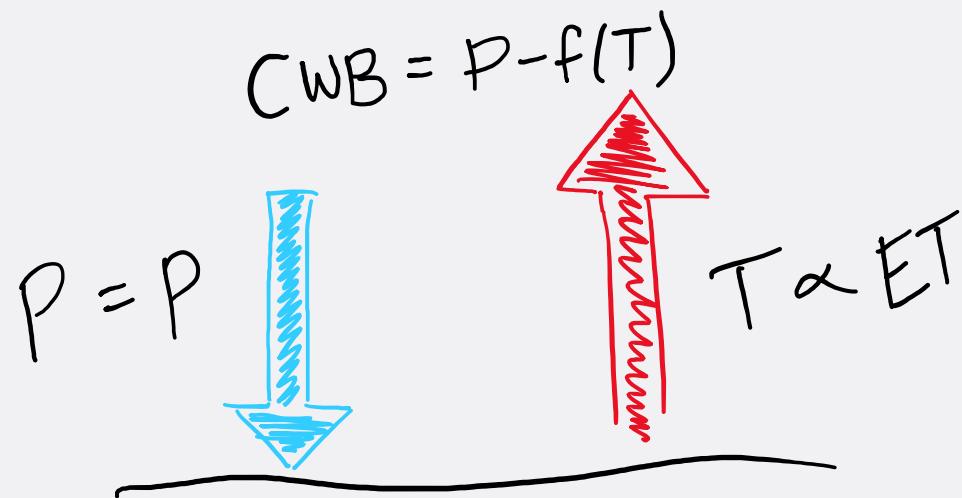
- While various types of drought exist, we will use the IPCC's definition of agricultural and ecological drought, defined as a "period with abnormal soil moisture deficit, which results from **combined shortage of precipitation and excess evapotranspiration...**" (IPCC, 2022)
- Increasing drought conditions can:
 - **reduce crop yield** (Basara et al., 2013; Vicente-Serrano et al., 2012)
 - **increase wildfire occurrence** (Stevens-Rumann et al., 2018)
 - **deplete drinking water sources** (Pasteris et al., 2005)
 - **threaten electricity supply in areas dependent on hydropower** (Wan et al., 2021)



But how do we measure it?

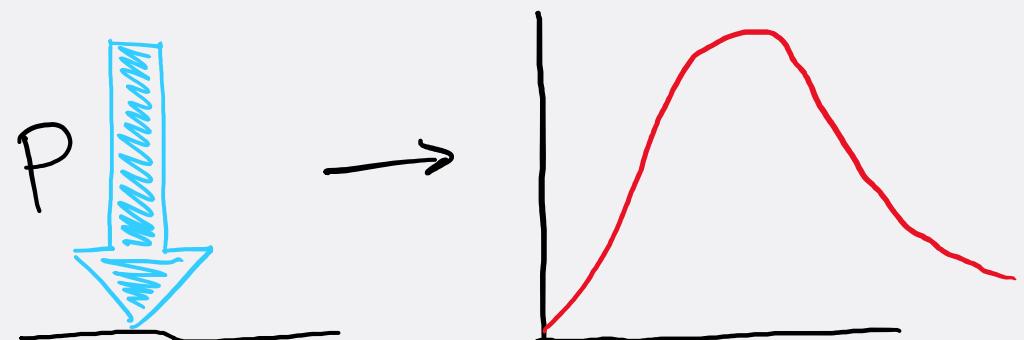
Palmer Drought Severity Index (PDSI)

- Uses temperature and precipitation data to make simplified estimates about climatic water balance
- Issues when comparing different climates



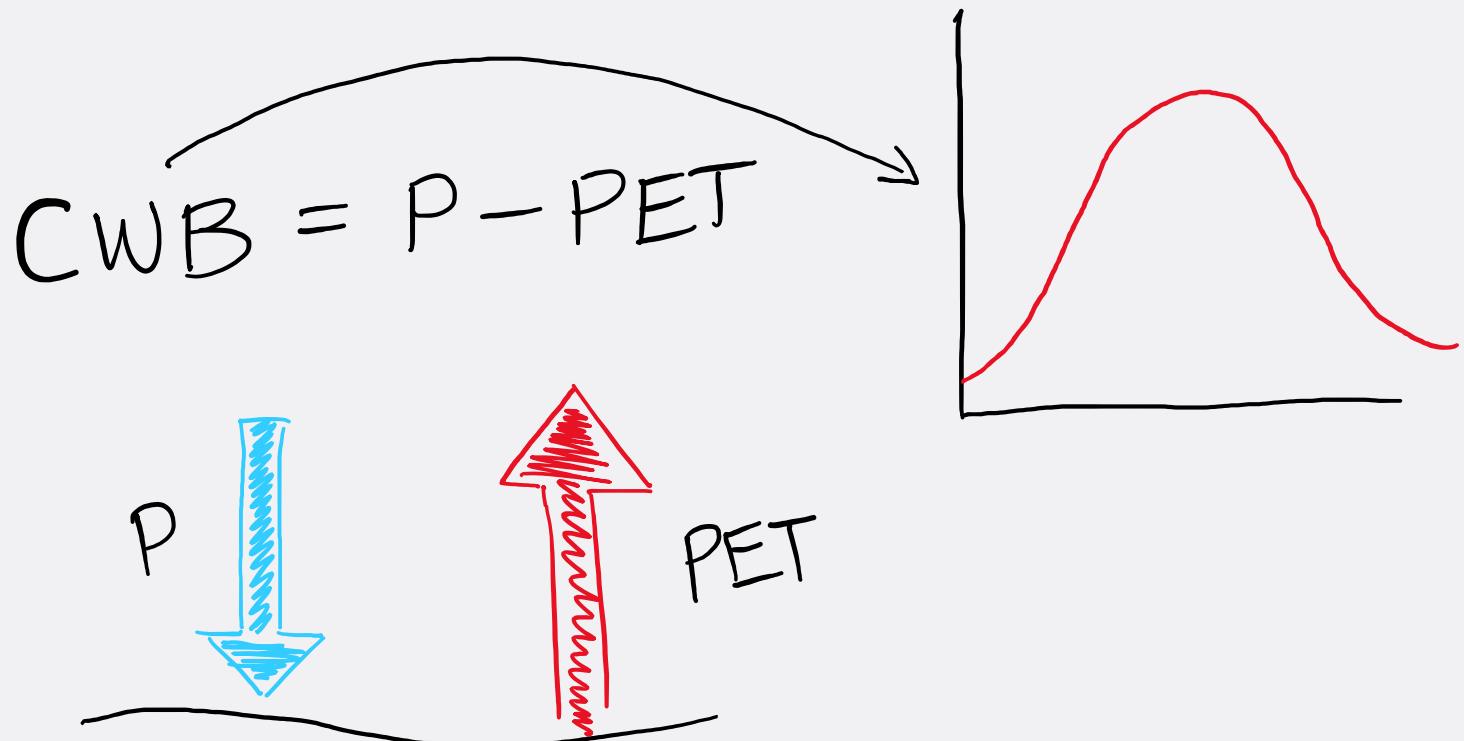
Standardized Precipitation Index (SPI)

- Statistical index that fits precipitation data to a probability distribution and then returns data as a standardized difference from mean values
- Calculations can be done at various monthly scales



SPEI...SPI, but better

- A revised and tweaked form of the SPI was introduced more recently, taking climatic water balance as an input
- Now we have a drought index that can be calculated over longer time scales, is more comparable across differing regions (Vicente-Serrano et al., 2010), and incorporates climatic water balance



PET calculations

- Potential evapotranspiration (PET) or latent heat flux, is rarely output in climate models, so we must determine this with another calculation.
- PET calculations use a variety of surface measurements with varying levels of complexity, but the **Penman-Monteith method** is generally considered the most robust formula for its incorporation of surface wind speed, net incoming radiation, and pressure

$$PET = \frac{0.408\Delta(R_n - G) + \gamma(\frac{C_n}{T} + 273)u_2(e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)}$$

where Δ = slope of the saturation vapor pressure curve, R_n = net incoming solar radiation, G = soil heat flux density, γ = psychrometric constant, C_n and C_d are constants fluctuating with vegetation type, T = mean surface temperature, u_2 = wind speed at 2 m above surface, and e_s and e_a are saturation and actual vapor pressures

ScenarioMIP data

- Part of the 6th Coupled Model Intercomparison Project (CMIP6), the ScenarioMIP experiment tasks various collaborating groups with running simulations to predict future climate scenarios according to five shared socioeconomic pathways (SSP; O'Neill et al., 2016)
- SSPs are CO₂ forcing schemes predicted to accompany five different paths that the international community may opt into based on future political and economic decisions
- We will use **SSP2-4.5**, commonly called the “middle of the road” pathway, where governments and businesses slowly but consistently reduce CO₂ concentrations

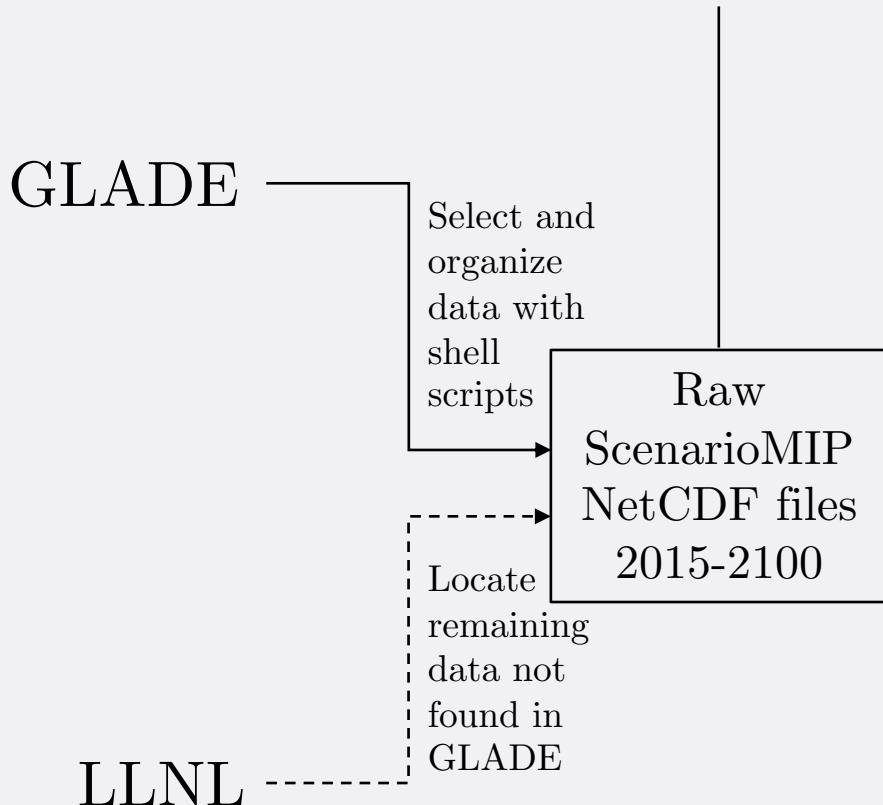


Equilibrium Climate Sensitivity!

- Two models (BCC and MRI) were selected for their output resolution
- Two models (CAN and MIROC) were selected based on their ECS variability

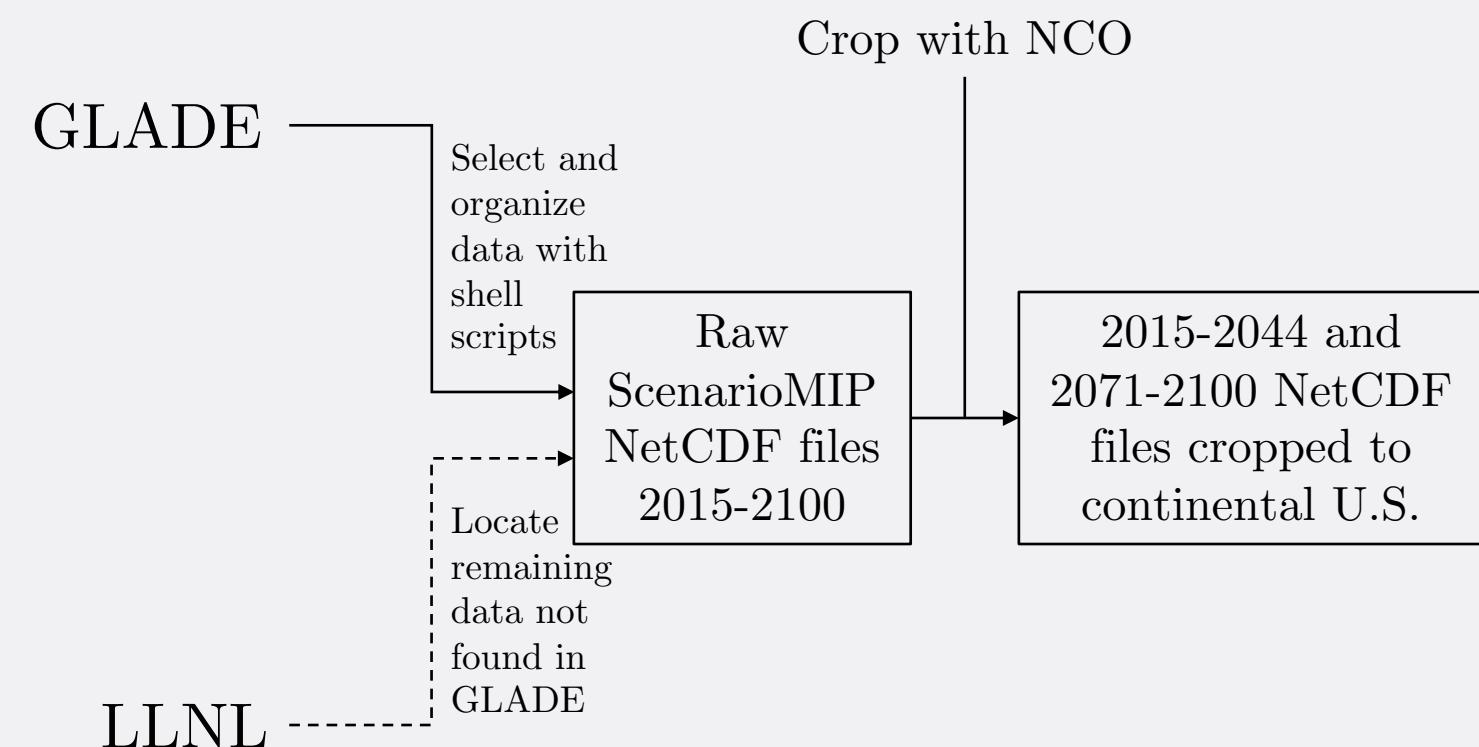
Model Name	Spatial Resolution	ECS
BCC-CSM2-MR (BCC)	160 × 320	3.02
CanESM5 (CAN)	64 × 128	5.64
MIROC6 (MIROC)	128 × 256	2.60
MRI-ESM2-0 (MRI)	160 × 320	3.13

Four models selected due
to variable availability and
data accessibility

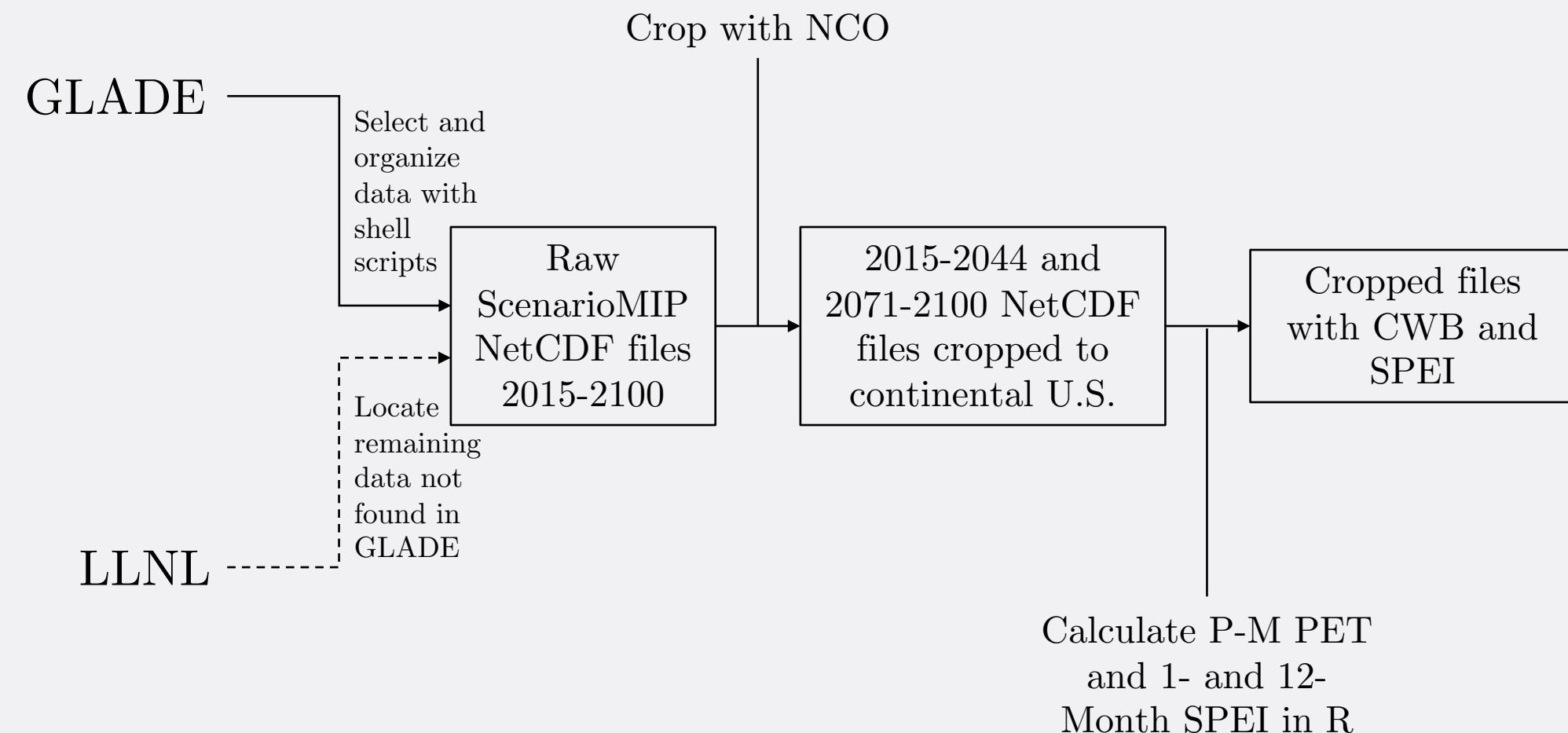


GLADE = Storage system for NCAR's high performance computing system;

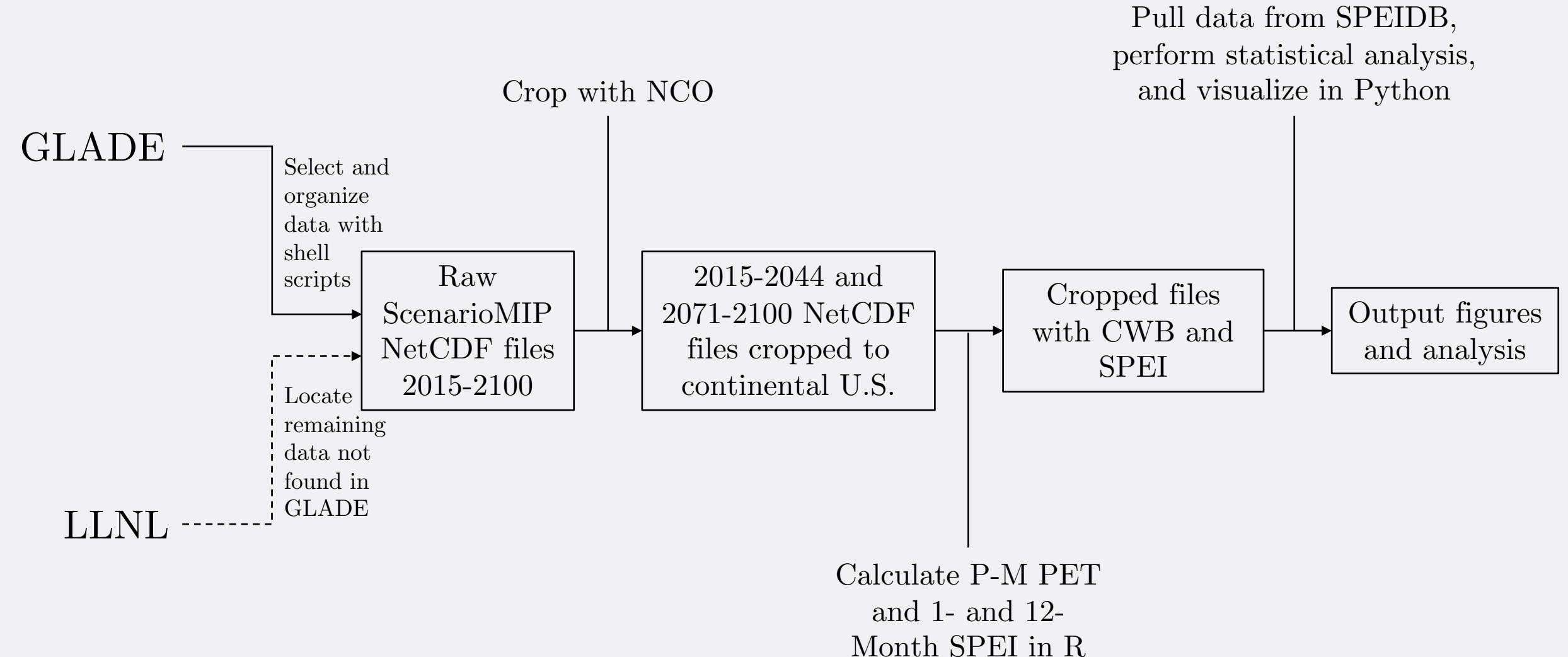
LLNL = CMIP6 repository hosted by Lawrence Livermore National Laboratory



GLADE = Storage system for NCAR's high performance computing system; NCO = tools for modifying NetCDF files;
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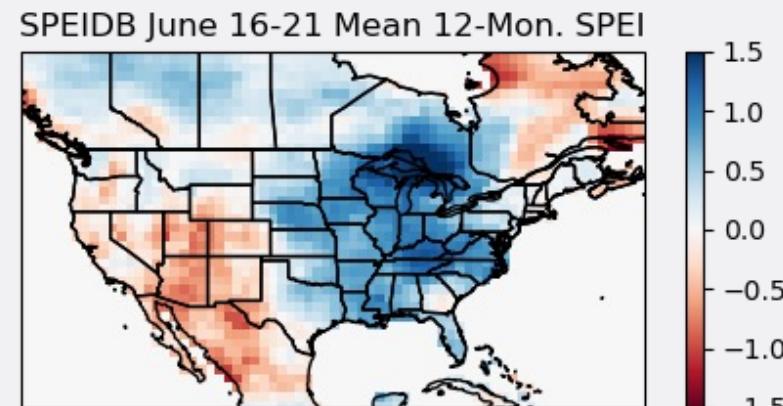
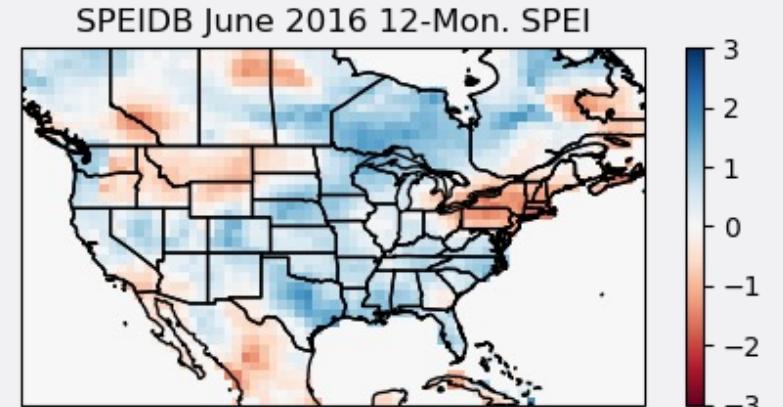
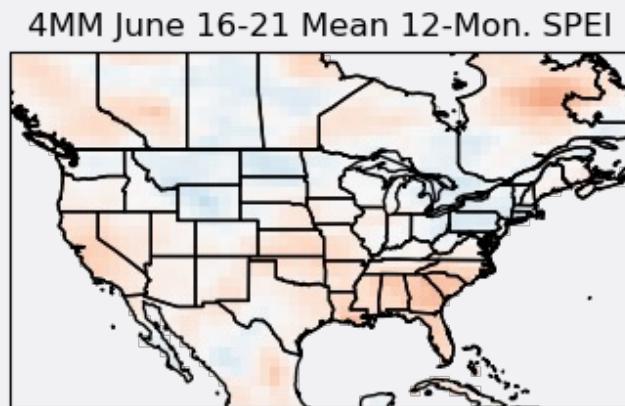
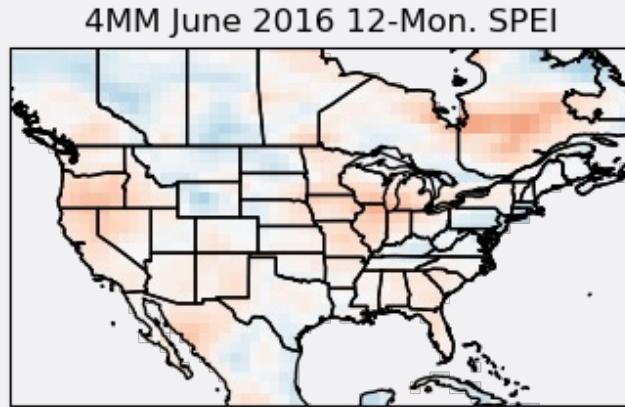
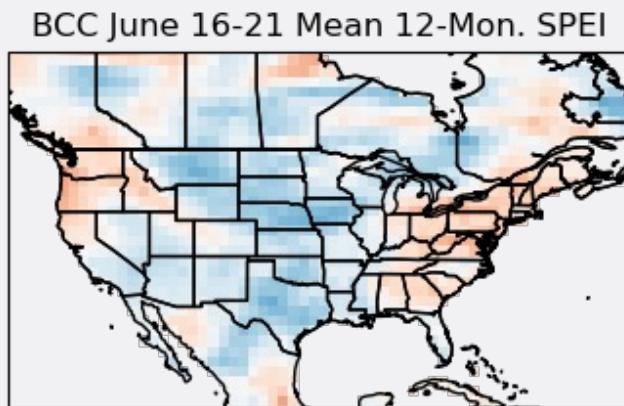
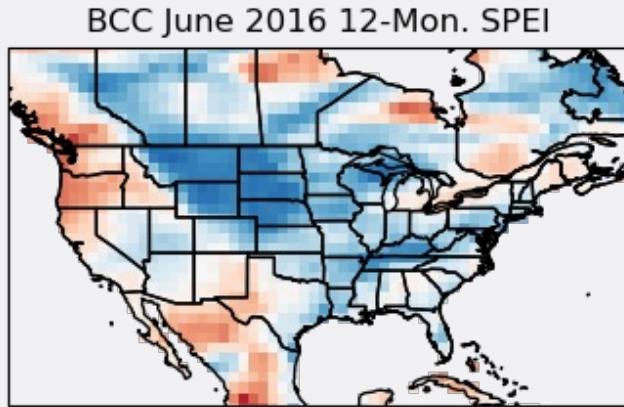


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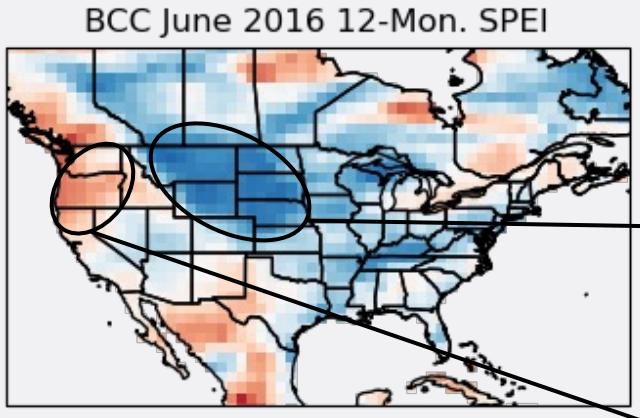
GLADE = Storage system for NCAR's high performance computing system; NCO = tools for modifying NetCDF files;
LLNL = CMIP6 repository hosted by Lawrence Livermore National Laboratory; SPEIDB = 1900-2021 observations

Checking SPEI calculations

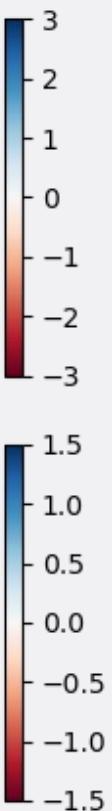
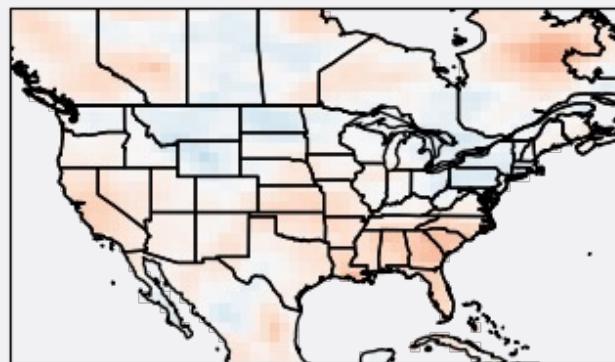
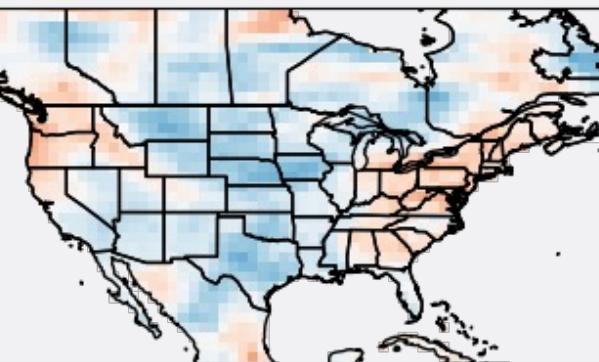
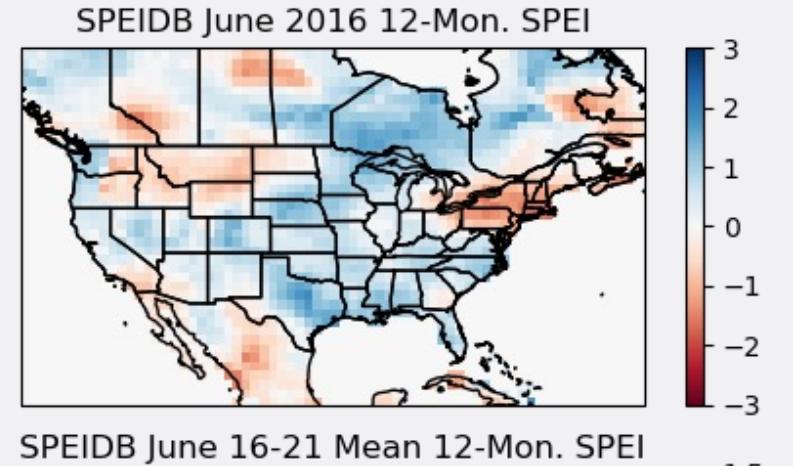
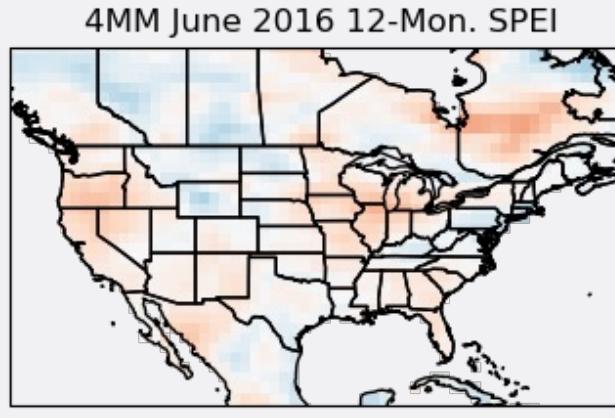


4MM = four model mean; 16-21 = 2016-2021; color bars shared across rows

Checking SPEI calculations

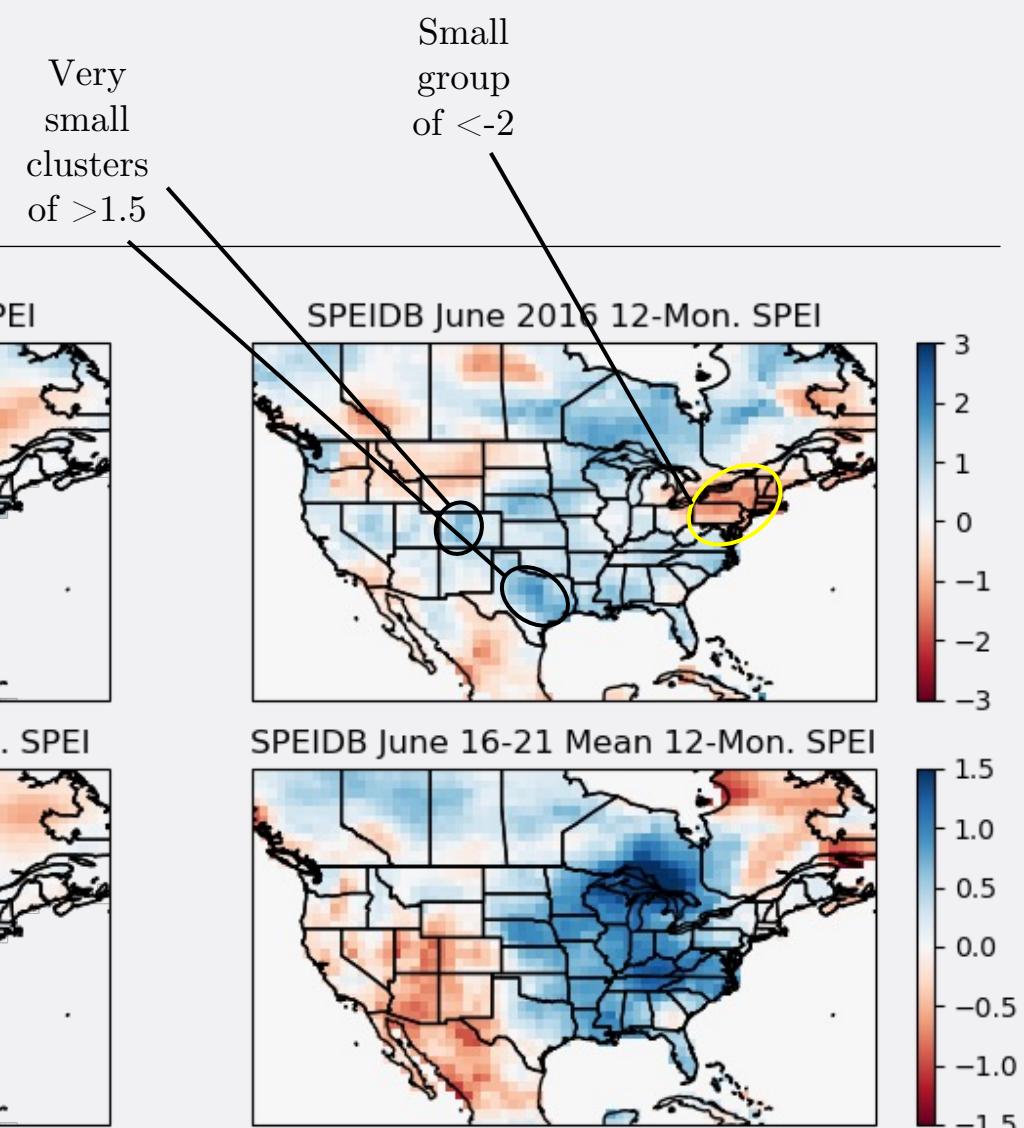
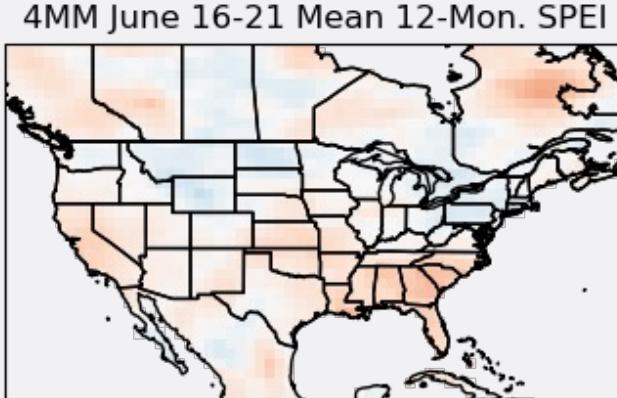
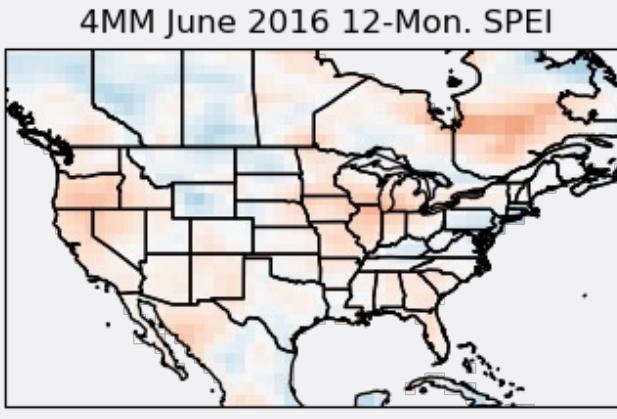
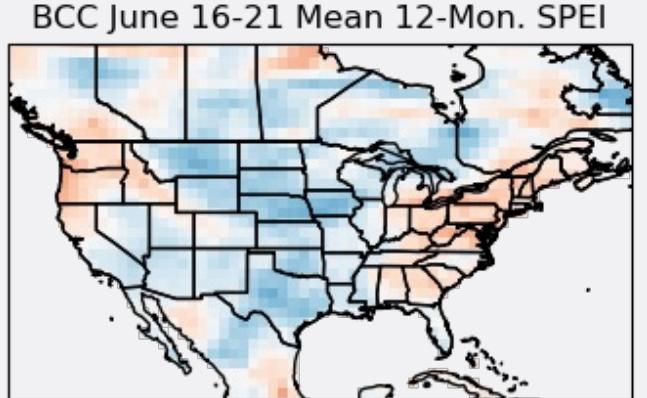
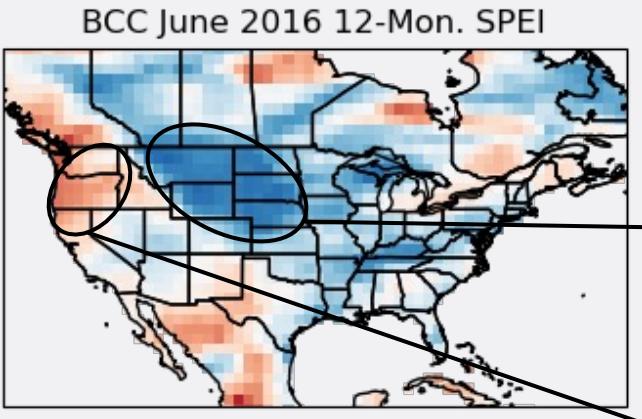


Large group of >2
Smaller cluster of <-1.5



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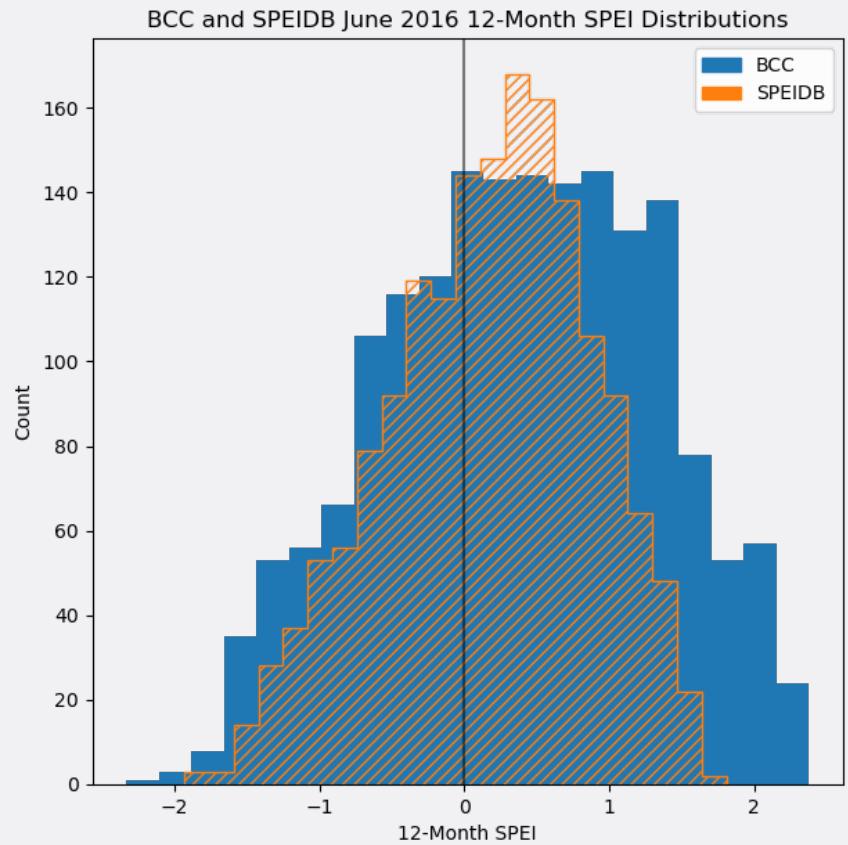
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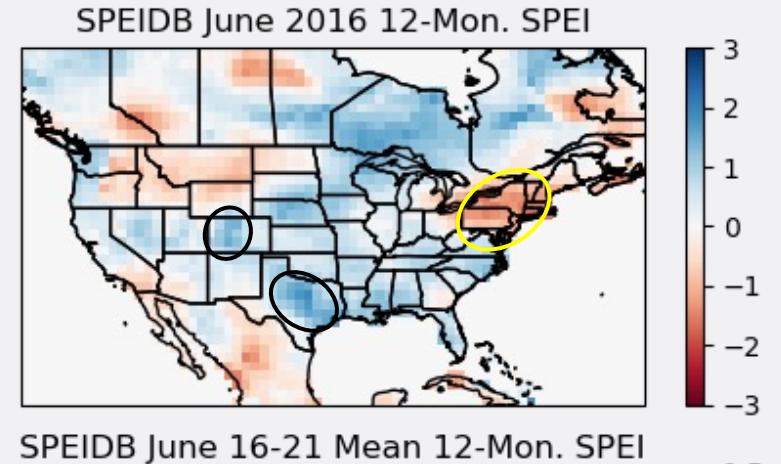
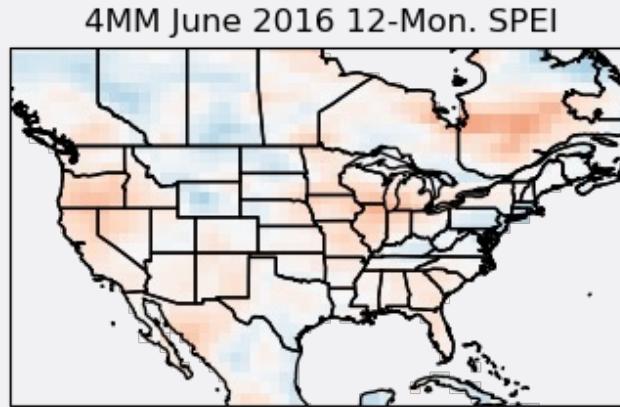
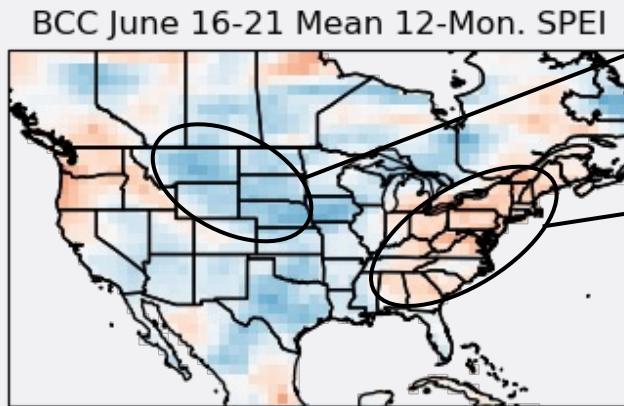
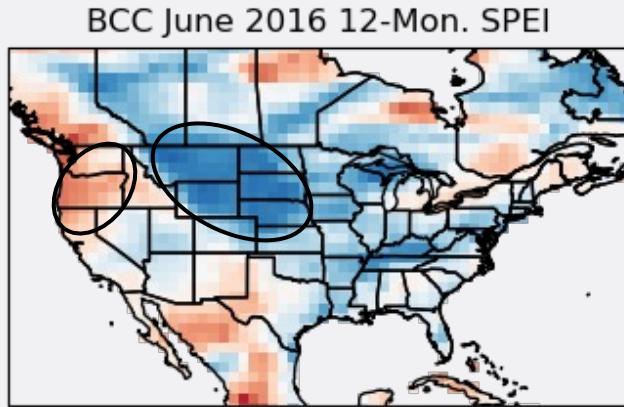
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Checking SPEI calculations

- Histograms of BCC and SPEIDB SPEI values confirms our visual inspection:
 - Larger size of wetter cluster in BCC plot means BCC distribution is pulled to the right with higher amounts of values >1
 - Drier conditions are closer to parity, with drought clusters generally being smaller in this simulation

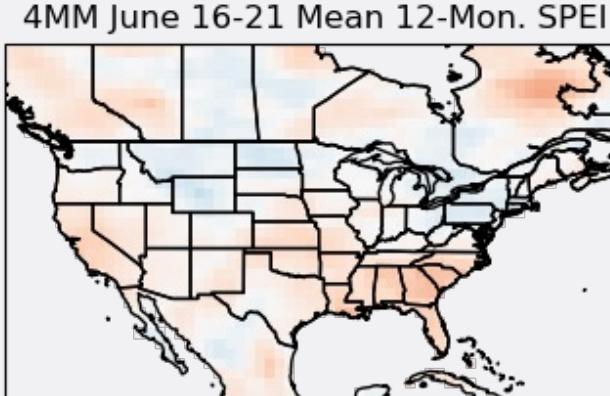
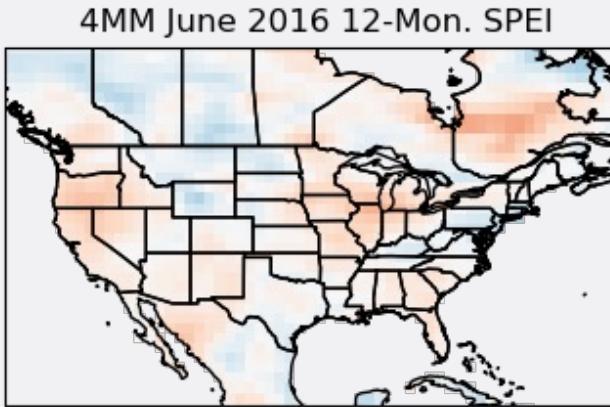
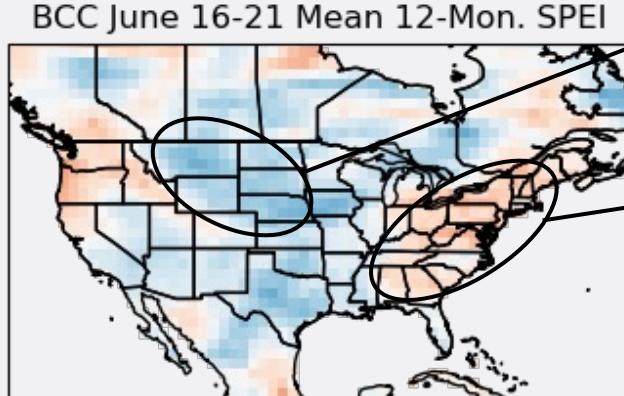
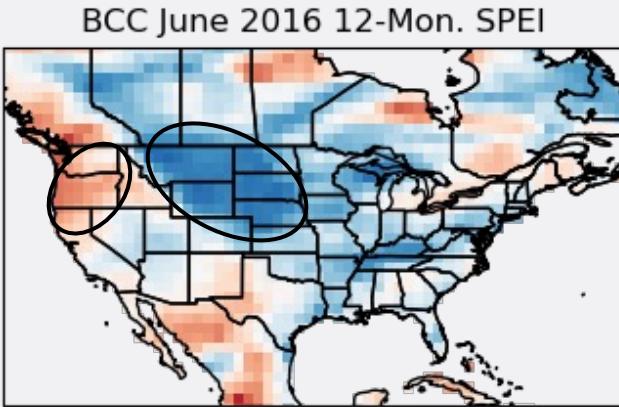


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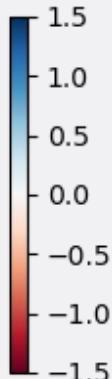
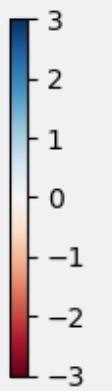
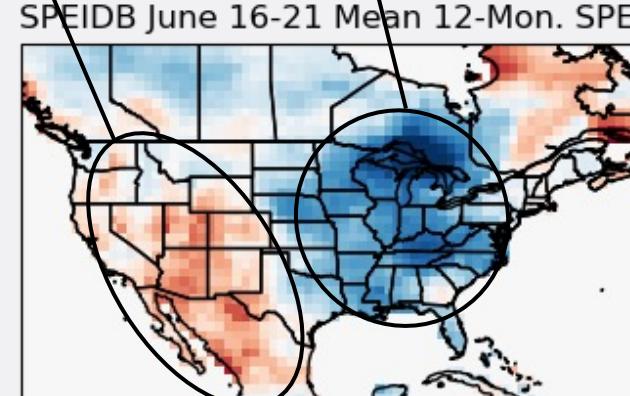
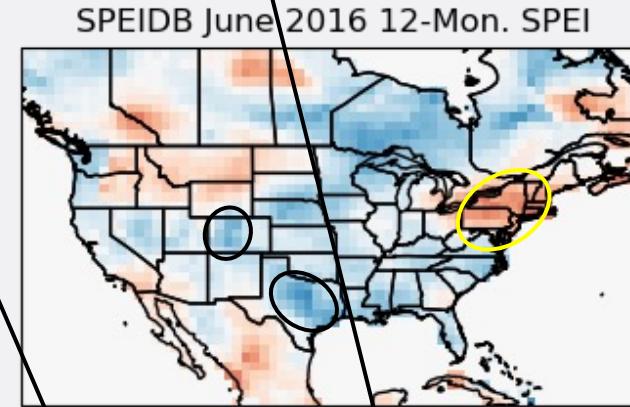
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Checking SPEI calculations



Very large group of <-1

Very large cluster of >1.5



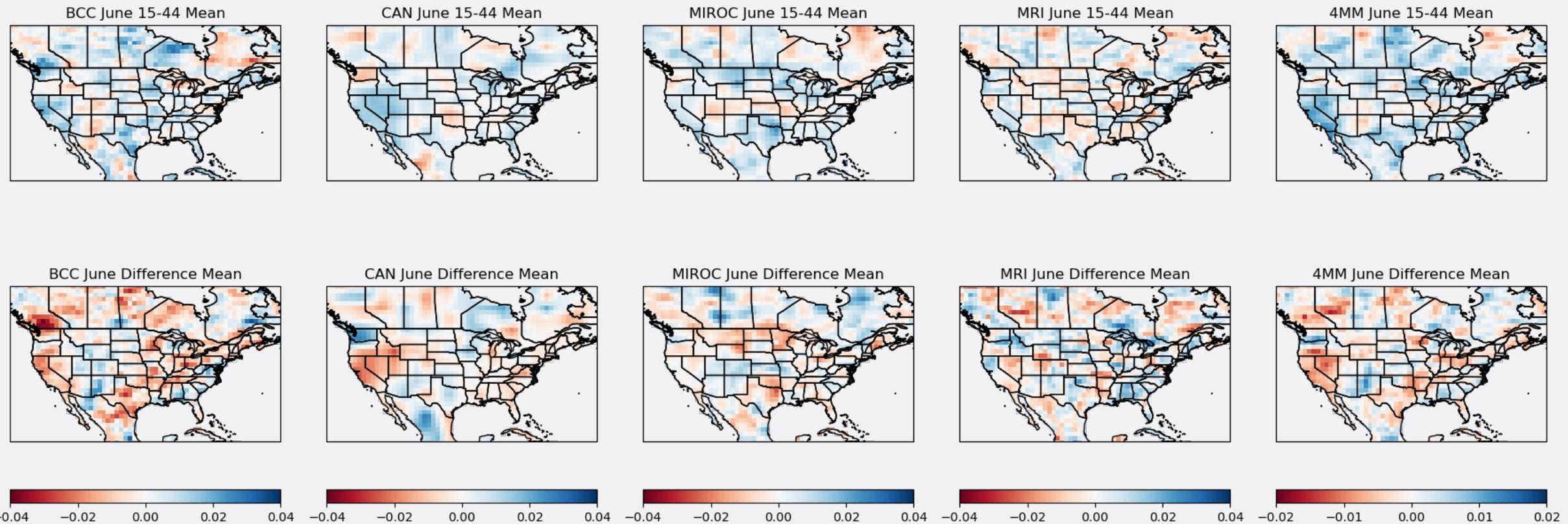
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Checking SPEI calculations

- While model-derived SPEI distributions look reasonable with our calculations generally achieving normal distributions that match observations, a clear issue remains with spatial matching between models and observations
- Different mechanisms could be at fault for these differences:
 - Short, 6-year span of tested climatologies do not smooth out variability from periodic events like ENSO
 - 2016-2021 was an especially unforgiving time to compare with observations due to massive CO₂ output drop due to COVID-19 shutdowns

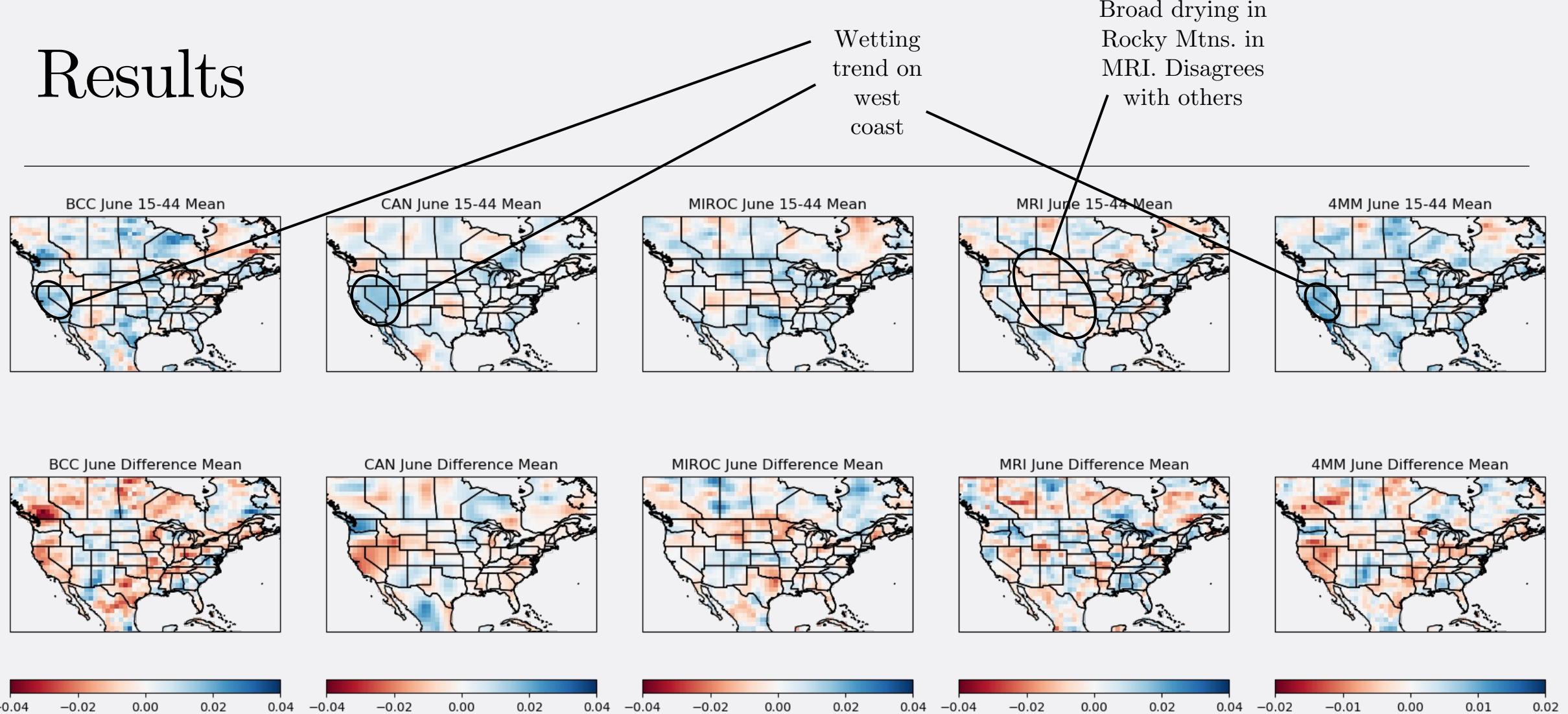


Results



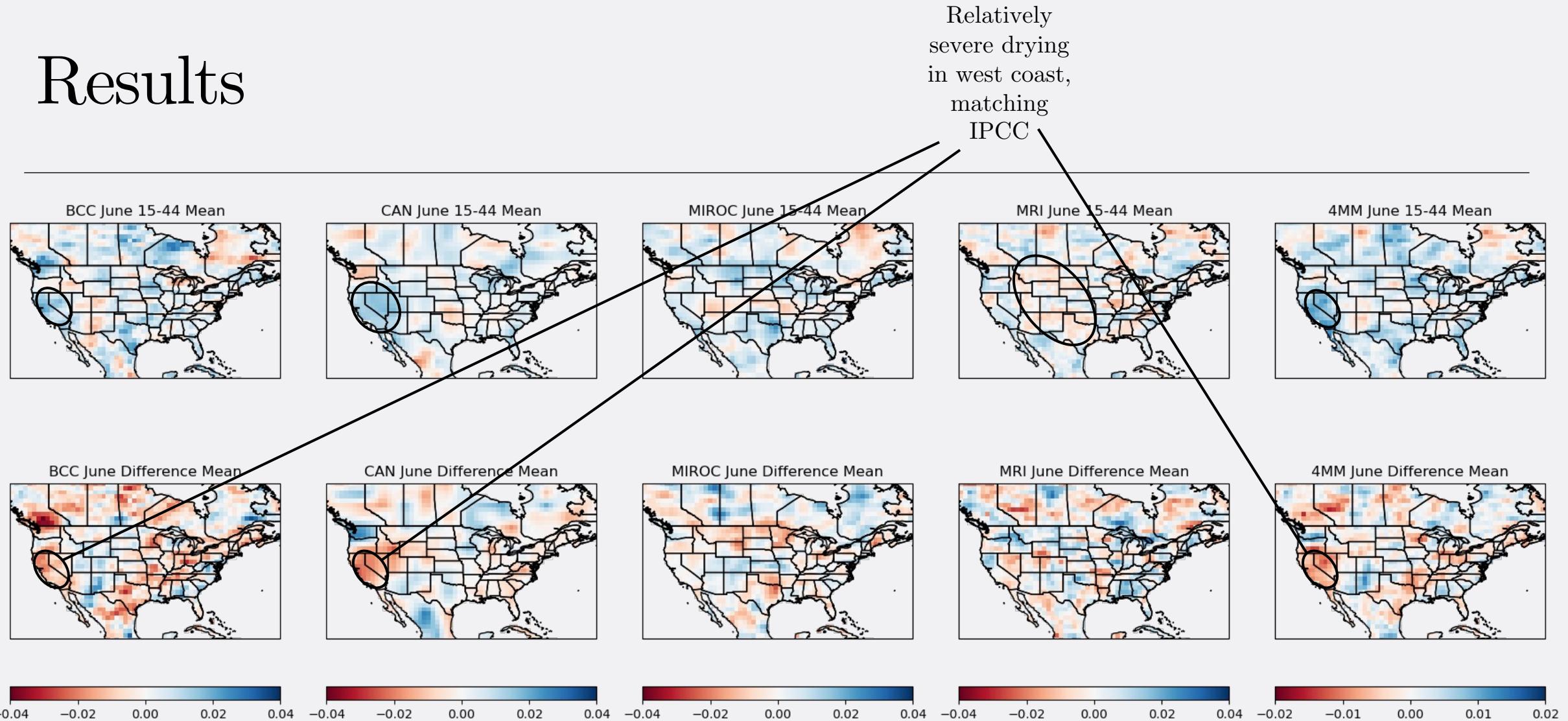
*all models still mean 12-month SPEI; 15-44 = 2015-2044

Results



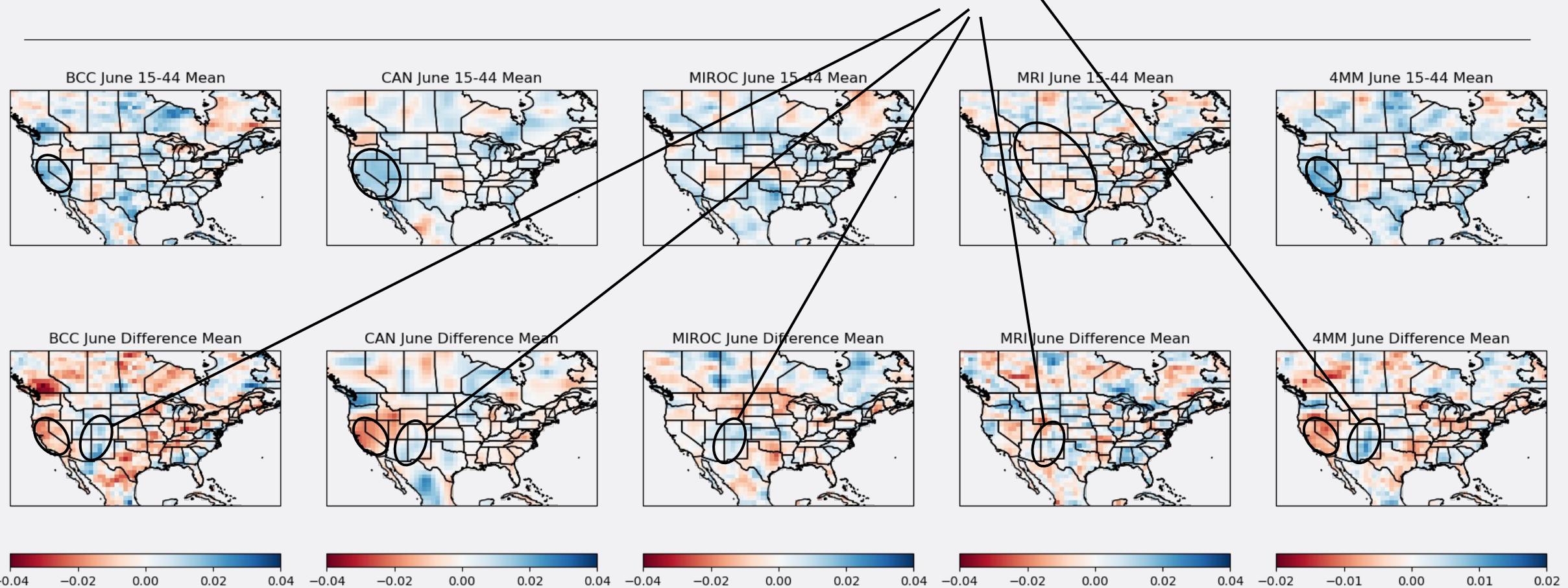
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Results



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Results



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Putting it all together

- Despite the spatial inconsistency of our initial testing results and the variability of model data, we were able to reproduce the western United States' drying trend predicted by the IPCC
- Wetting region in southwest U.S. also leaves potential questions about NAM
- ScenarioMIP models still fail to arrive at spatially consistent results



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