Machine Learning and Earth System Modeling: from parameter calibration to feature detection

Katie Dagon

National Center for Atmospheric Research, Boulder, CO

KITP Machine Learning for Climate Conference

November 4, 2021

NCAR

U.S. DEPARTMENT OF ENERGY | Office of Science

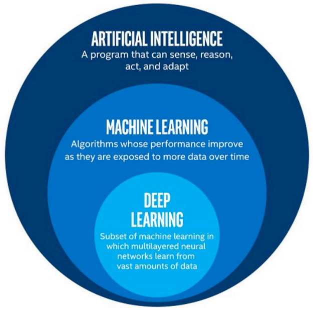
catalyst

NSF

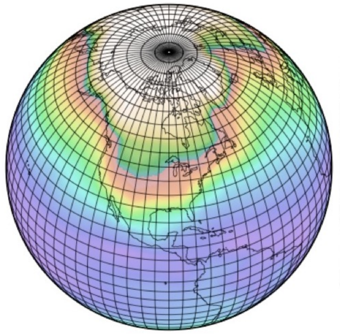
This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

Machine Learning for Climate Modeling

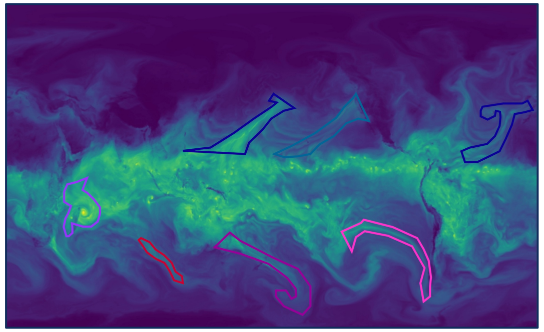
How can machine learning contribute to climate modeling?



1) Land model emulation and parameter calibration



2) Feature detection of extreme precipitation events



Parameter Calibration with Neural Network-Based Emulation of a Land Model

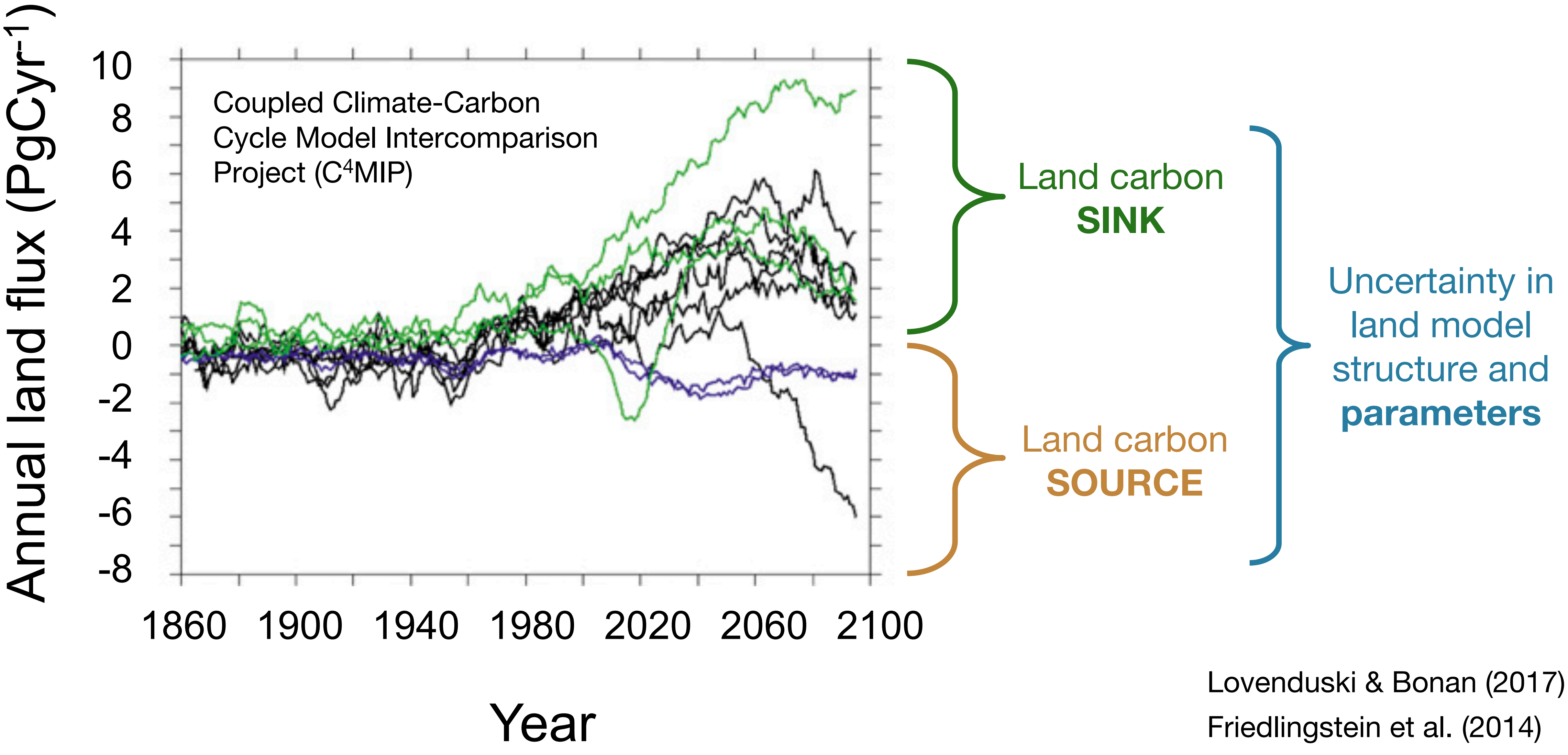
Katie Dagon (NCAR), Ben Sanderson (CICERO/NCAR), Rosie Fisher (CICERO), and Dave Lawrence (NCAR)

NCAR

NSF

This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

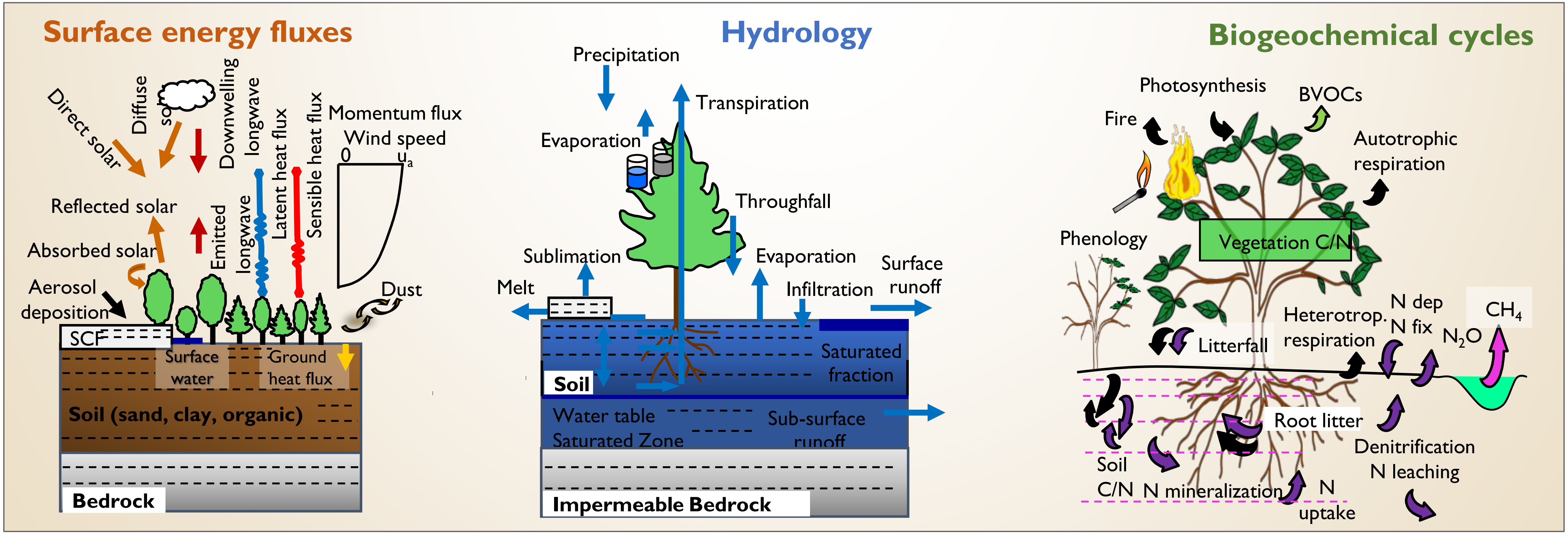
Uncertainty in Land Model Projections



Lovenduski & Bonan (2017)

Friedlingstein et al. (2014)

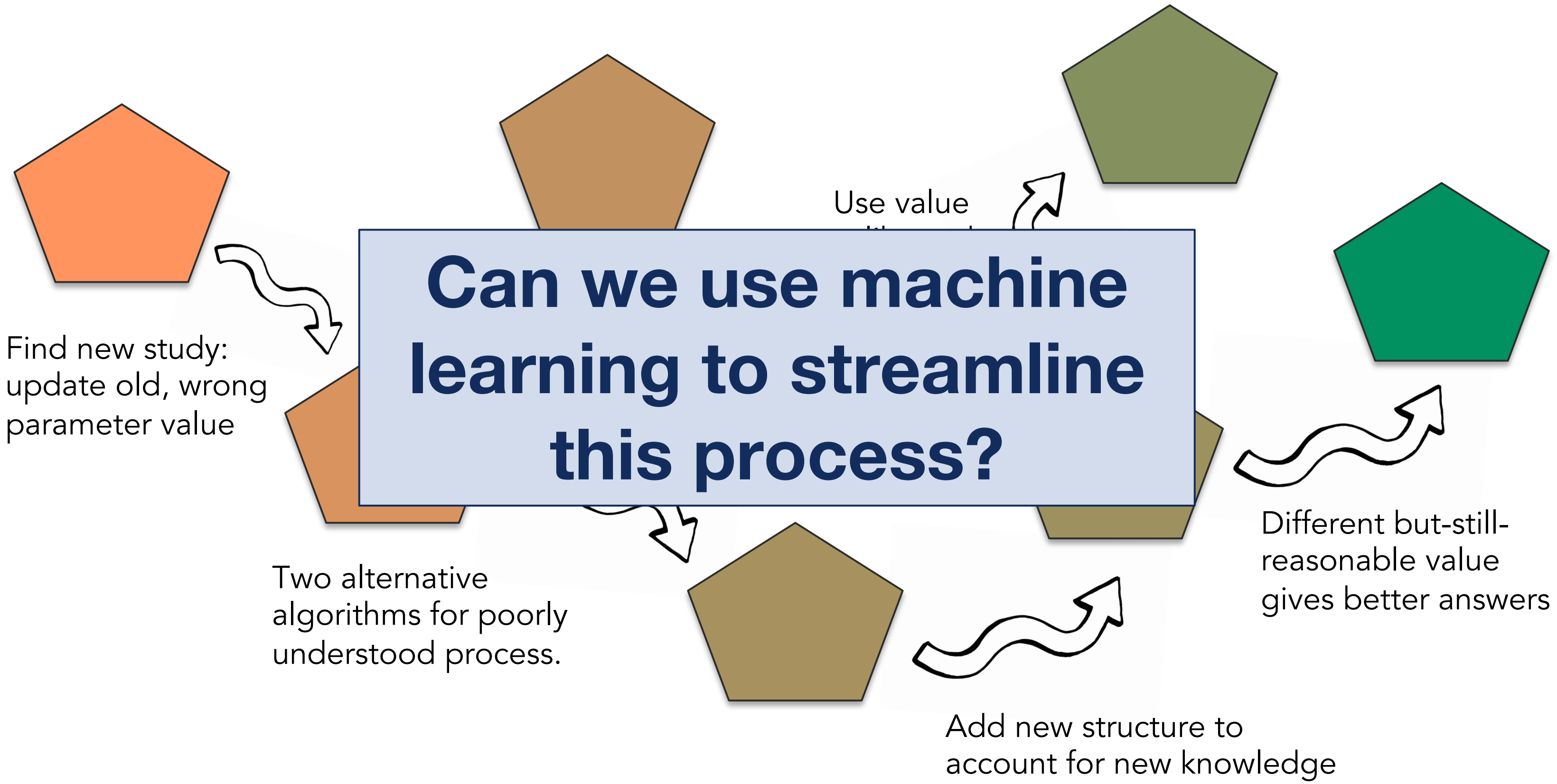
Uncertainty in Land Model Parameters



Schematic of NCAR's Community Land Model (CLM), version 5

Lawrence et al. (2019)

Hand-tuning parameter values takes a long time (many model runs, trial and error).

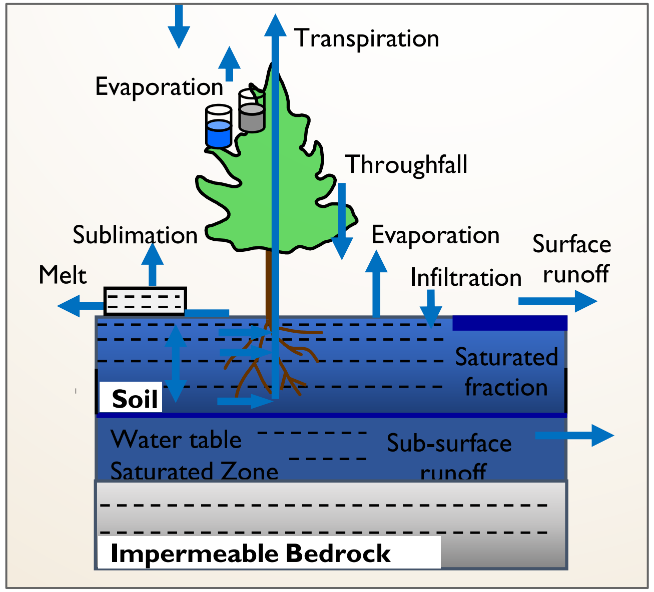


Can we use machine learning to streamline this process?

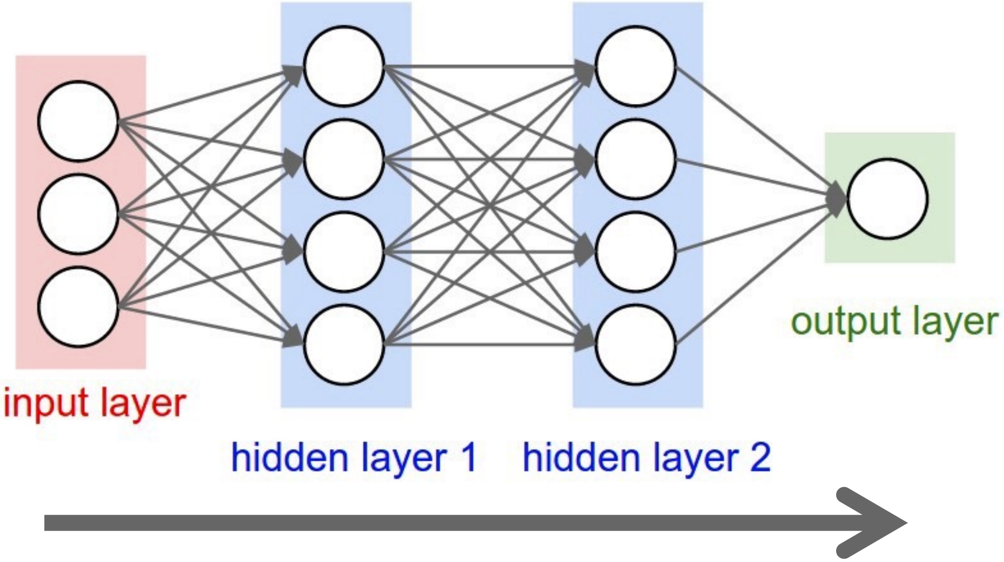
Figure from Rosie Fisher

Neural Networks as Land Model Emulators

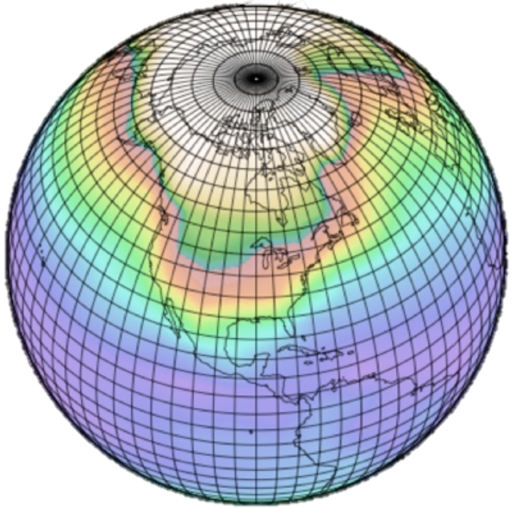
Input: land model parameter values



Neural network emulator



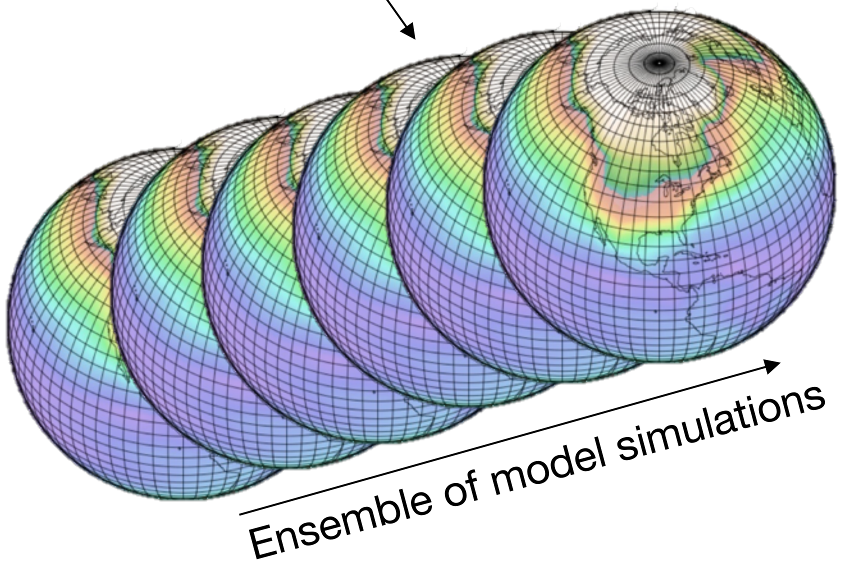
Output: land model predictions



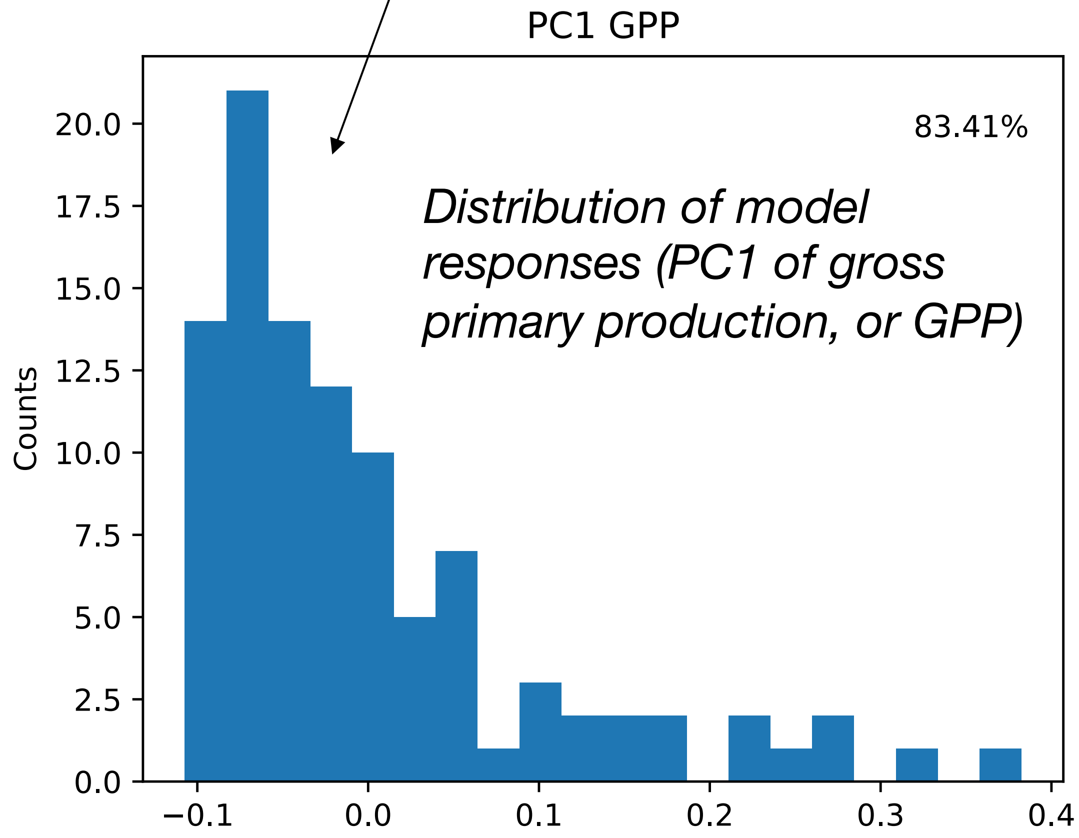
Network image: http://cs231n.github.io/neural-networks-1/

Generating the Training Data

Land model* perturbed parameter ensemble (PPE) using 100 parameter combinations generated with Latin Hypercube sampling



Use principal component analysis (PCA) to predict modes of variability of carbon and water fluxes



Distribution of model responses (PC1 of gross primary production, or GPP)

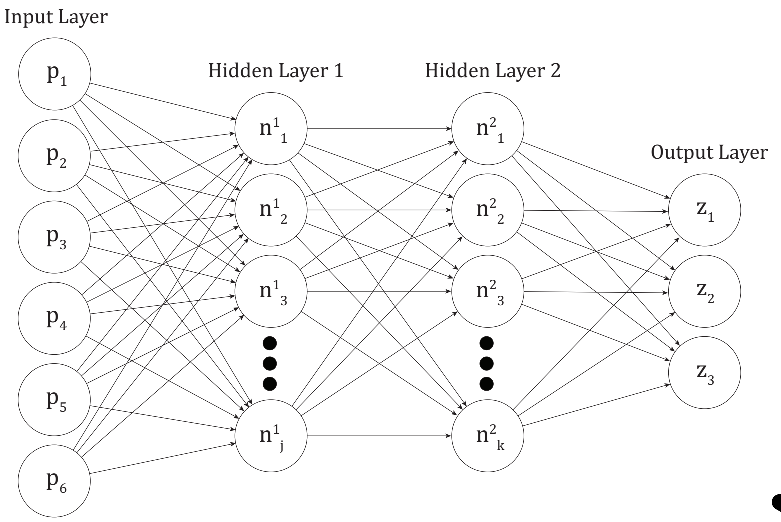
**Offline land-only simulations forced by atmospheric reanalysis data*

Training

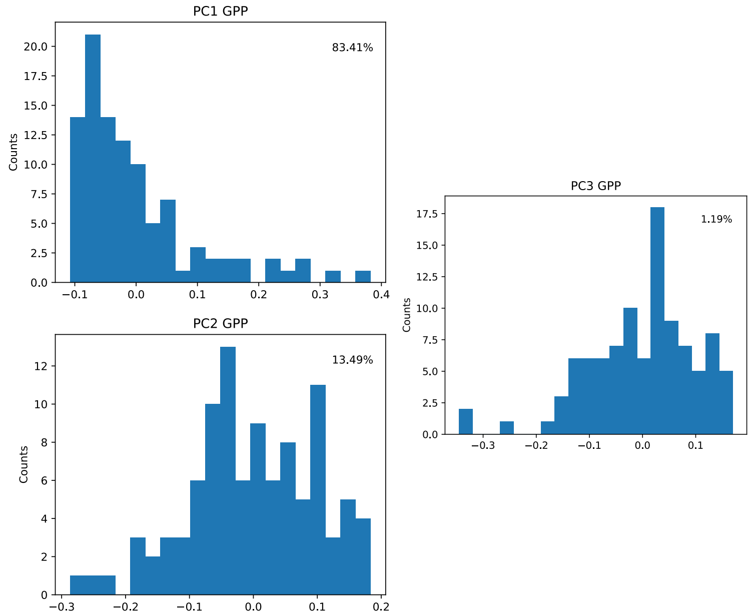
Input: land model parameter values

	P1	P2	P3	P4	P5	P6
S1	x1,1	x1,2	x1,3	x1,4	x1,5	x1,6
S2	x2,1	x2,2	x2,3	x2,4	x2,5	x2,6
S3	x3,1	x3,2	x3,3	x3,4	x3,5	x3,6
…	…	…	…	…	…	…
S100	x100,1	x100,2	x100,3	x100,4	x100,5	x100,6

2-layer feed-forward artificial neural network (ANN)



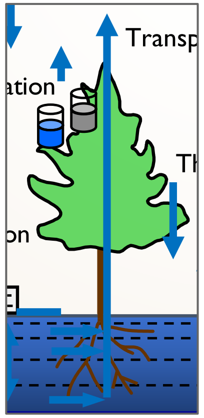
Output: land model perturbed parameter ensemble



Train to predict spatial variability (first 3 PCs) of gross primary production (GPP).

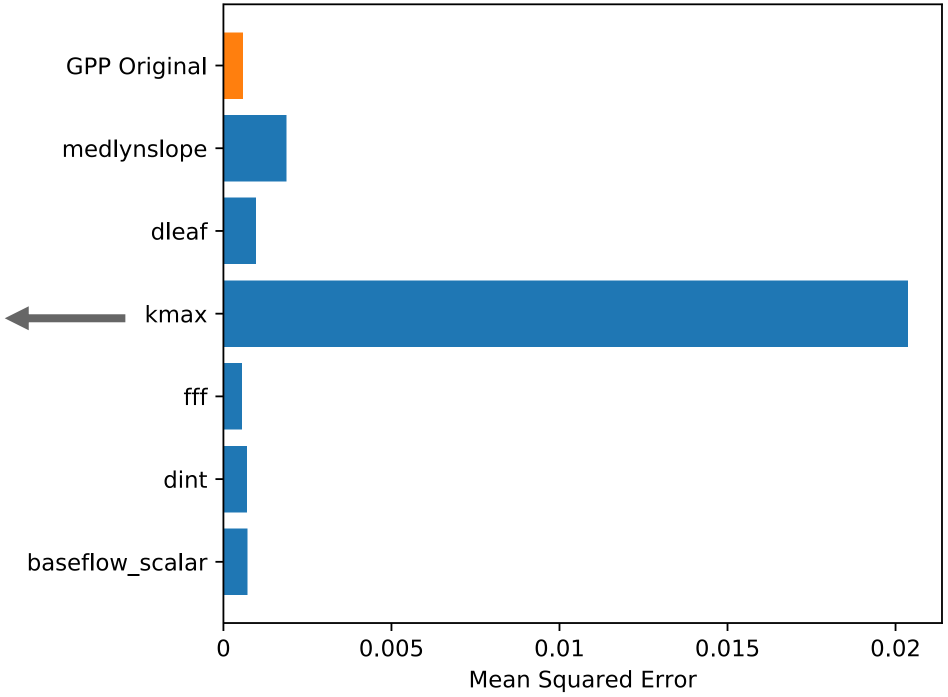
Separate emulator built for first 3 PCs of latent heat flux (LHF).

Machine Learning Interpretation: Variable/Feature Importance

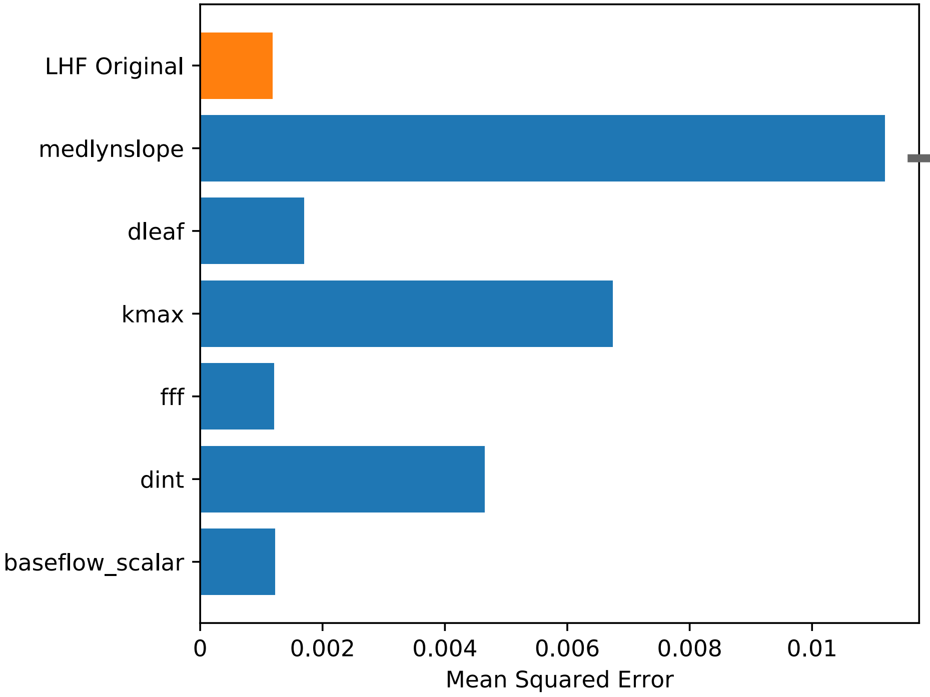


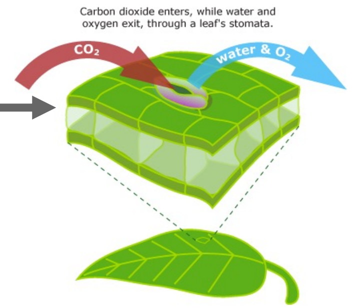
Kennedy et al. (2019)

PC1 Gross Primary Production



PC1 Latent Heat Flux





Medlyn et al. (2011)

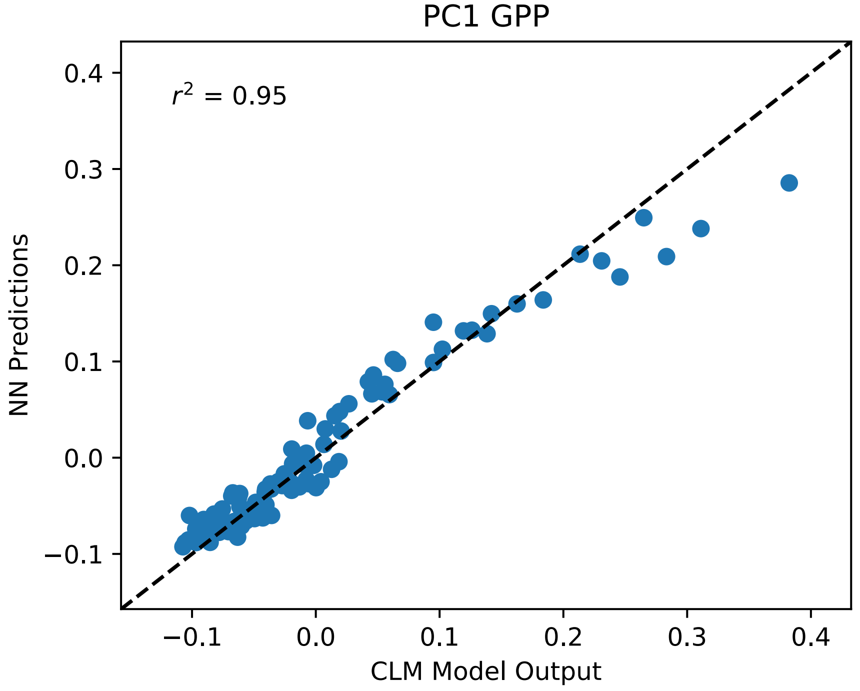
<u>Variable/Feature Importance</u>

- Randomly shuffle values of one parameter (preserving others) and test performance of emulator.
- Skill metric is mean squared error between predictions and actual values.
- Larger bar means the parameter is **more important to the predictive skill** of the emulator.

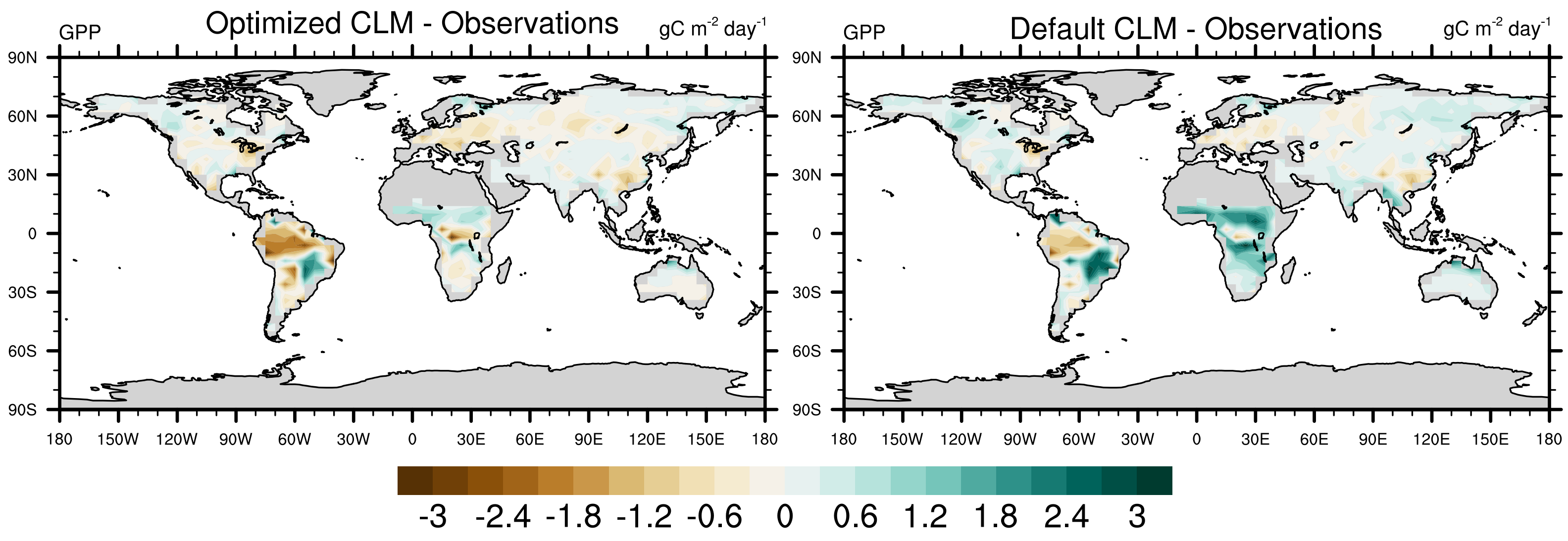
Land Model Emulation for Parameter Calibration

Approach: Emulate, calibrate, test.

Emulator predictions vs. CLM output



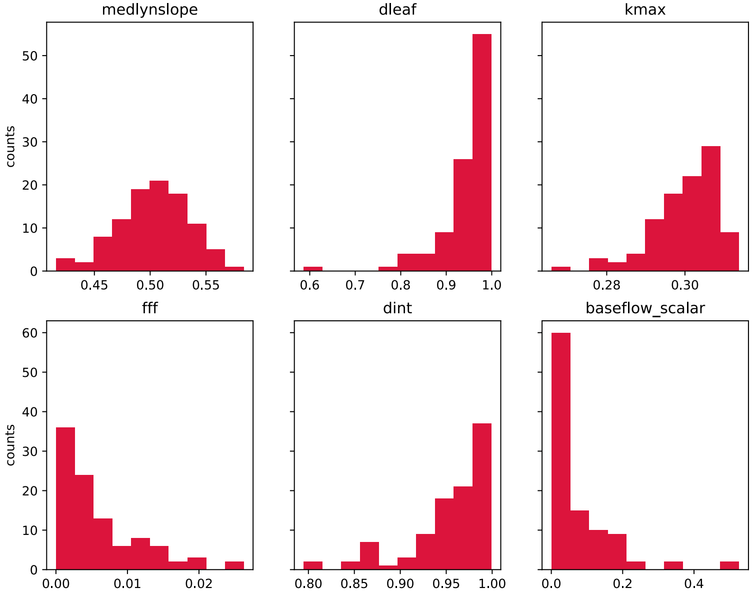
Comparing model bias with calibrated *(left)* and default *(right)* parameters



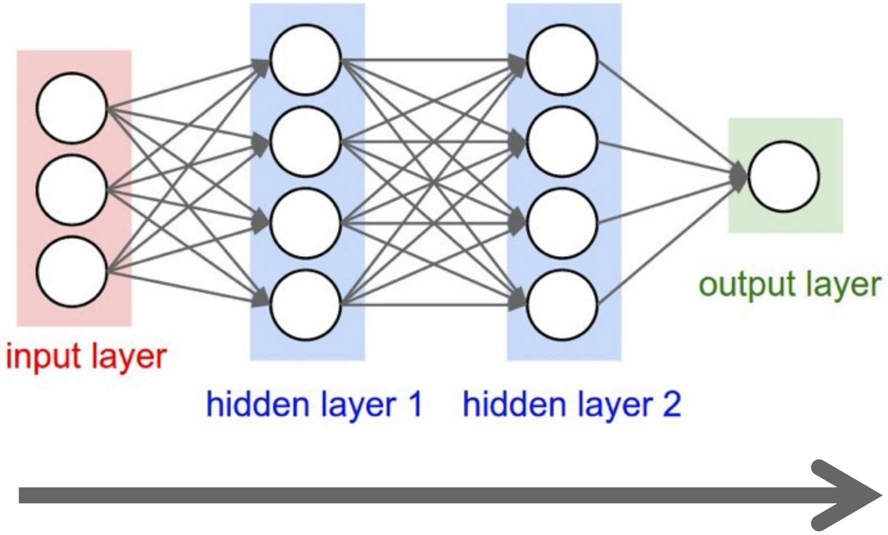
Dagon et al. 2020

Results in the Context of Climate Predictions

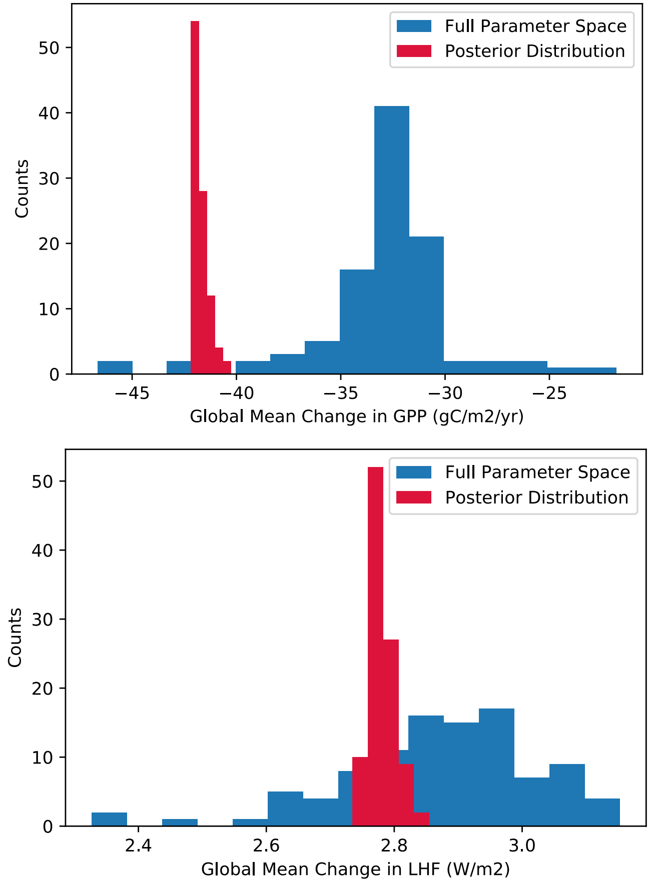
Input: Parameter posterior distributions



***DIFFERENT** neural network to emulate future climate response of land surface model*



Output: Predicted change in carbon/water fluxes accounting for parameter uncertainty



Machine learning-based feature detection to associate precipitation extremes with synoptic weather events

Katie Dagon (NCAR), John Truesdale (NCAR), Jim Biard (ClimateAI), Ken Kunkel (NC State), Maria Molina (NCAR), and Jerry Meehl (NCAR)

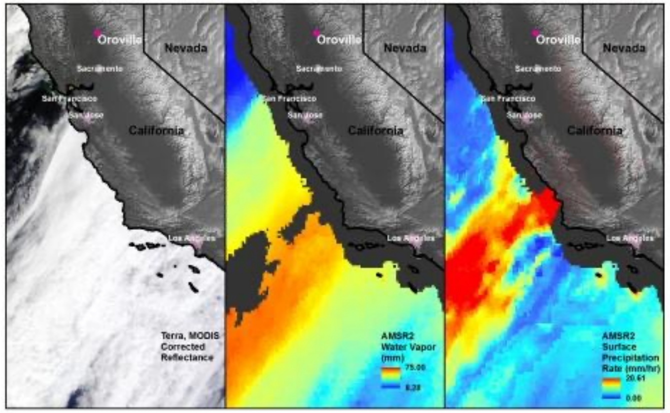
NCAR

NSF

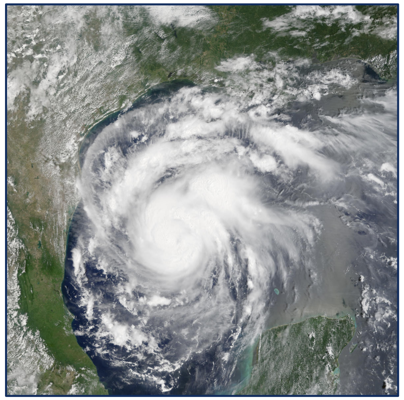
This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

Extreme Precipitation Has Significant Consequences

Oroville Dam spillway overflowing in February 2017 following an atmospheric river event in California.



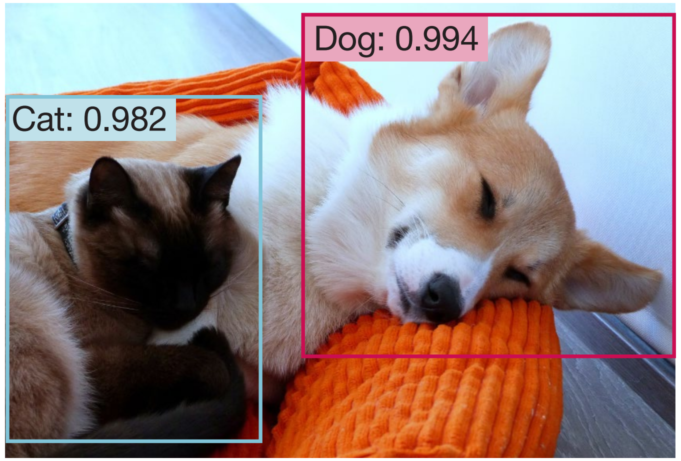
Flooding after Hurricane Harvey in August 2017.



Machine Learning for Feature Detection

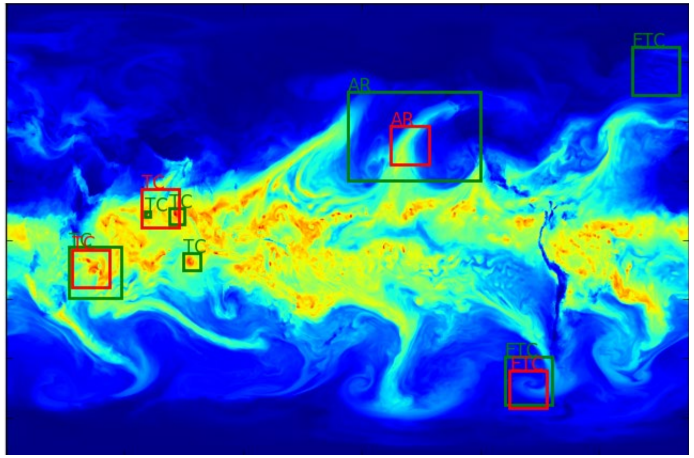
Machine learning tasks

a Object classification and localization



Earth science tasks

Pattern classification



Reichstein et al. (2019)

Project Goals:

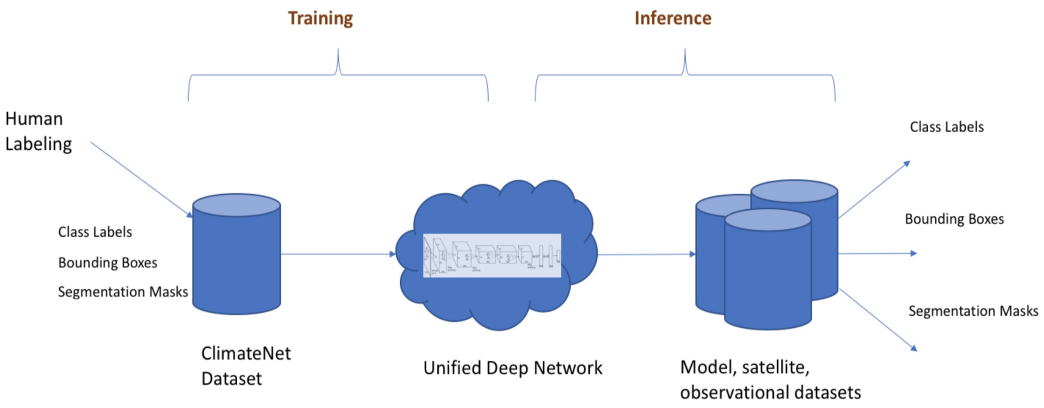
1. Apply and develop **machine learning-based detection algorithms** to automate the classification of synoptic weather features such as atmospheric rivers (ARs), tropical cyclones (TCs), mesoscale convective systems (MCSs), and fronts.

2. Study the **causes of extreme precipitation** by associating features with extreme precipitation events.

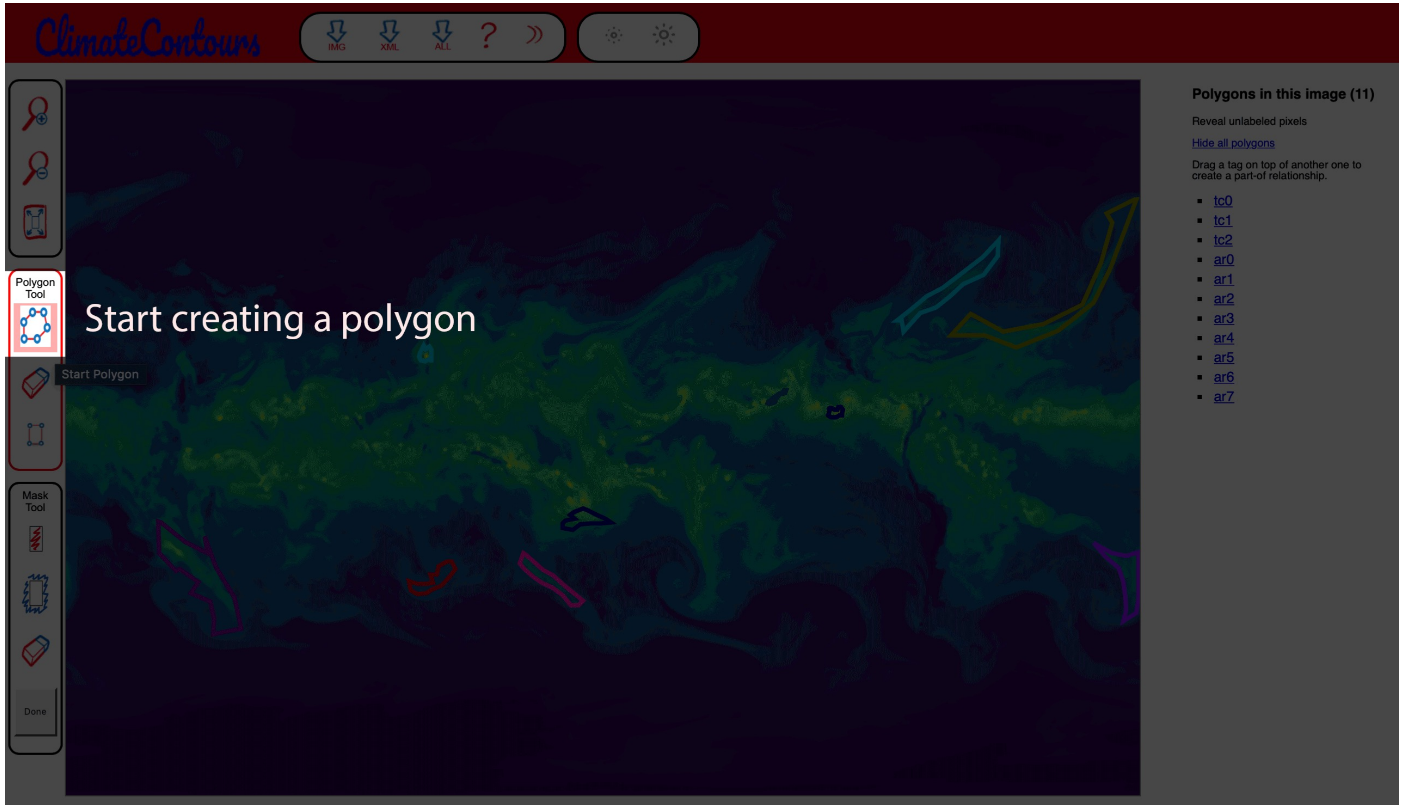
Detection of Atmospheric Rivers and Tropical Cyclones

ClimateNet: a community-sourced expert-labeled dataset to improve and accelerate machine learning applications in weather and climate

- ➢ *Focus on detecting atmospheric rivers (ARs) and tropical cyclones (TCs).*



Prabhat et al. (2021)

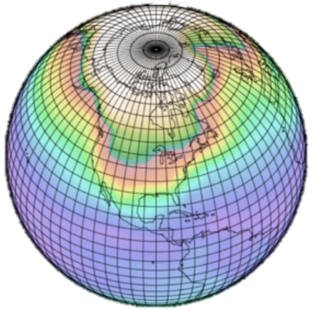


https://www.nersc.gov/research-and-development/data-analytics/big-data-center/climatenet

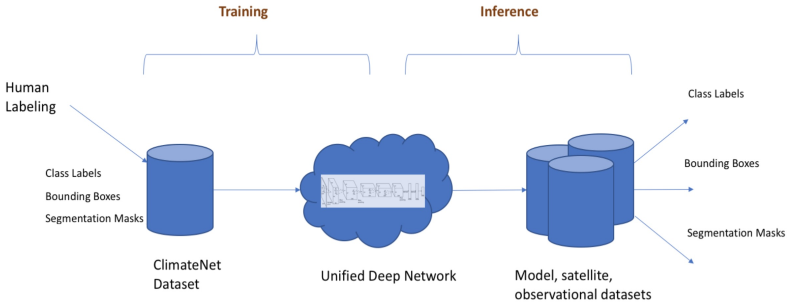
Collaborators: Karthik Kashinath (NVIDIA) and Arvind Nayak (LBNL)

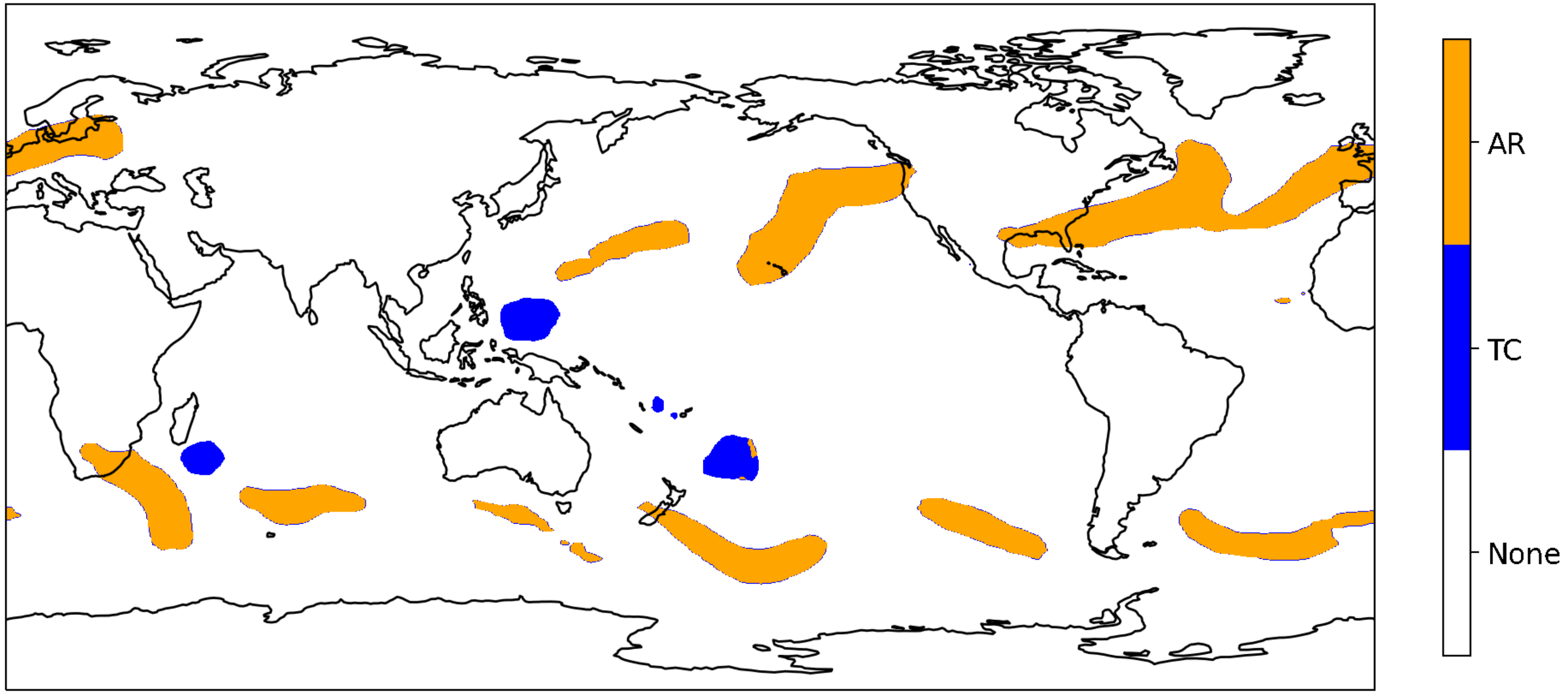
Detection of Atmospheric Rivers and Tropical Cyclones

Can we use the pre-trained ClimateNet algorithm applied to climate model output to detect ARs and TCs?



Specifically, fully coupled Community Earth System Model (CESM) simulations at high spatial and temporal resolution.





Input fields: vertically integrated precipitable water, sea level pressure, and u/v winds at 850mb
Output fields: 3 labels (AR, TC, and none)

Atmospheric River Detection

"The **Atmospheric River Tracking Method Intercomparison Project (ARTMIP)** is an international collaborative effort to understand and quantify the uncertainties in atmospheric river (AR) science based on detection algorithm alone."

- *Shields et al., 2018*

➢ **Integrated water vapor transport (IVT)** is often the only field used to detect ARs, though detection methods vary in other ways (e.g., relative vs. absolute thresholds).

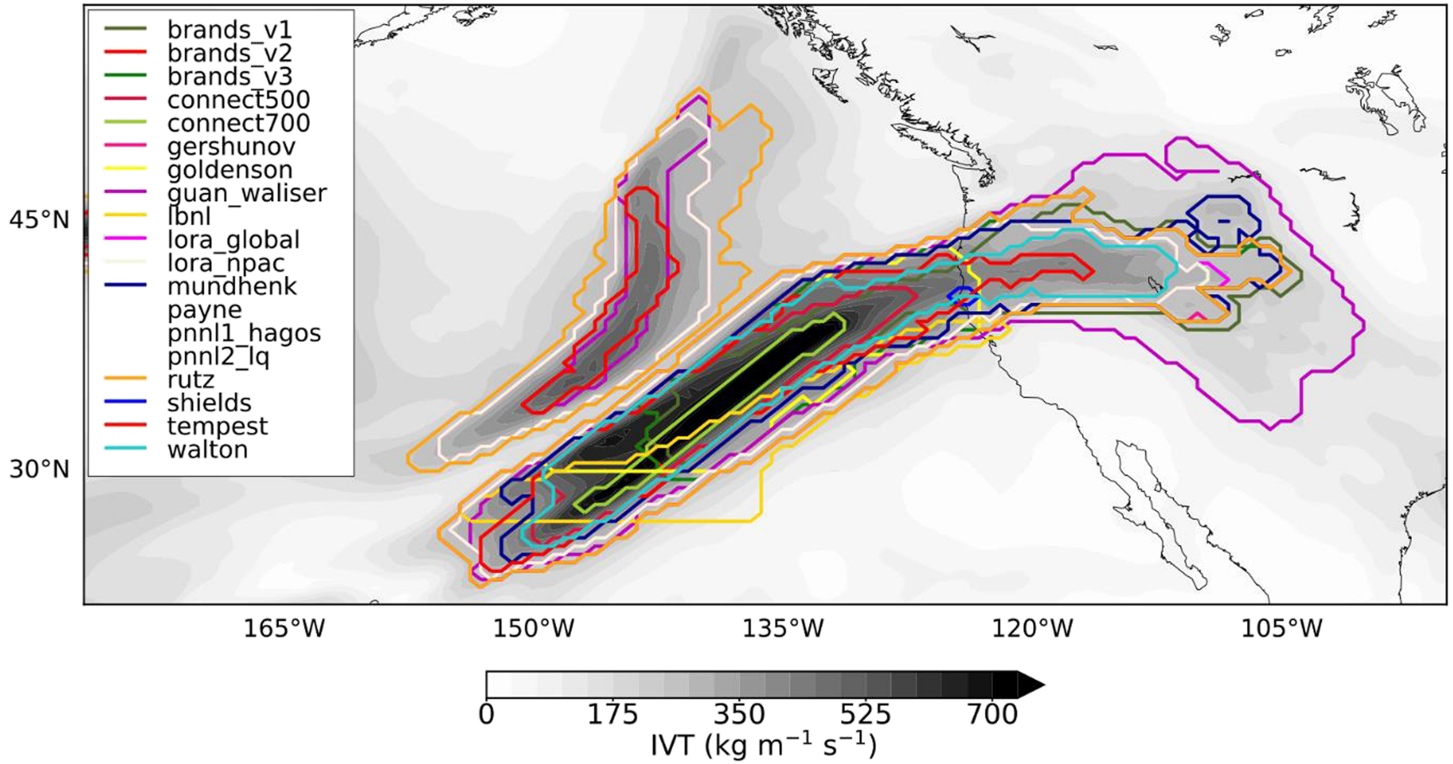
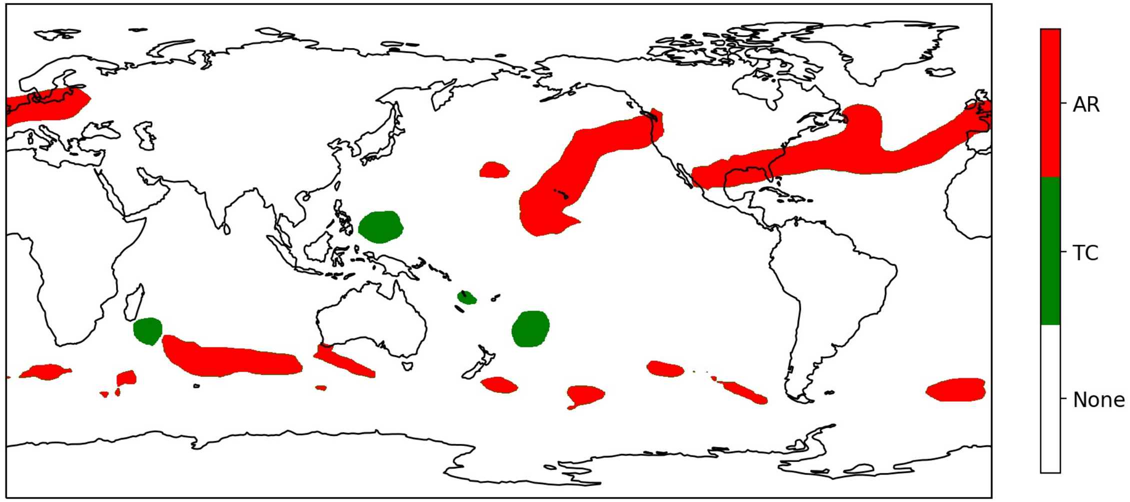


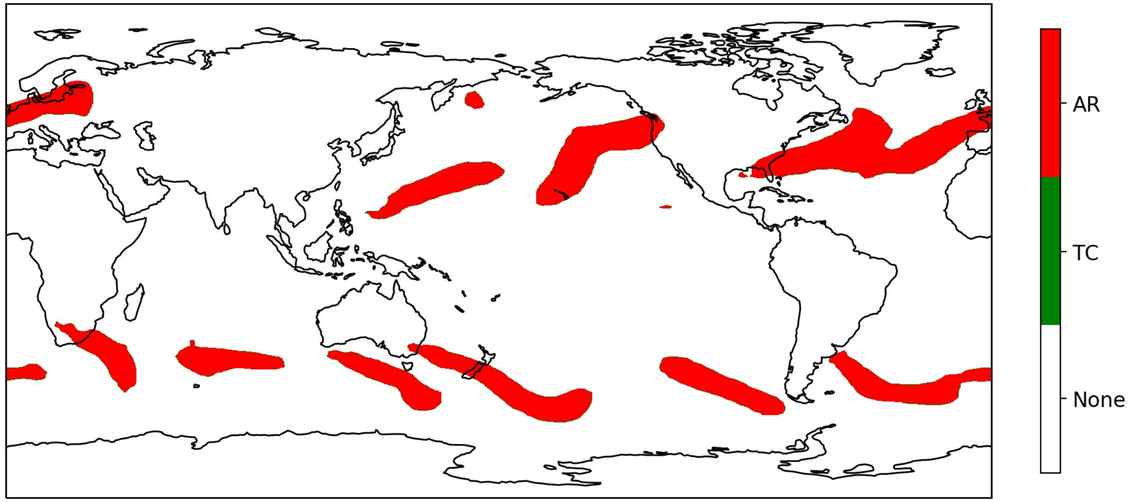
Figure 2. Example of how AR identification and tracking methods differ over the northeastern Pacific, based on MERRA Version 2 data from 0000 UTC 15 February 2014. Gray shading represents IVT (kg m^{-1} s^{-1}), and colored contours represent the spatial regions designated as ARs by the various methods. Note that only algorithms available in this region are shown.

Rutz et al. (2019)

Atmospheric River Detection

ClimateNet was trained on four input fields. Do the results change when altering input fields?





Trained on 4 fields:
vertically integrated precipitable water, sea level pressure, and u/v winds at 850mb

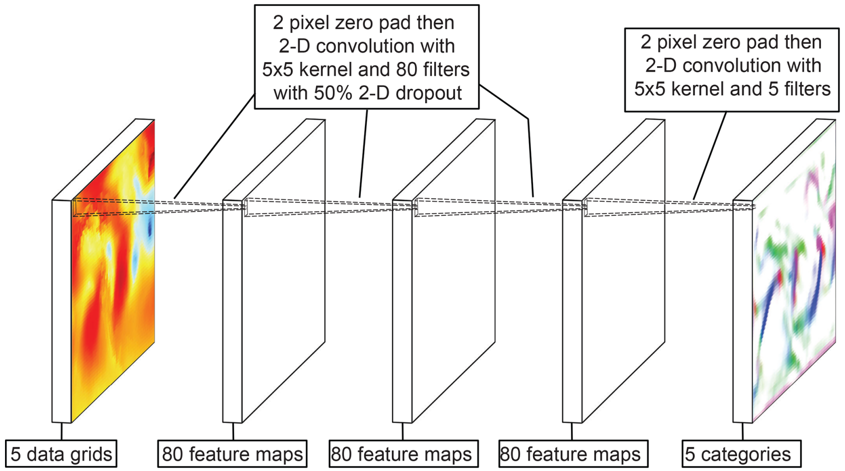
Trained on 1 field:
vertically integrated precipitable water

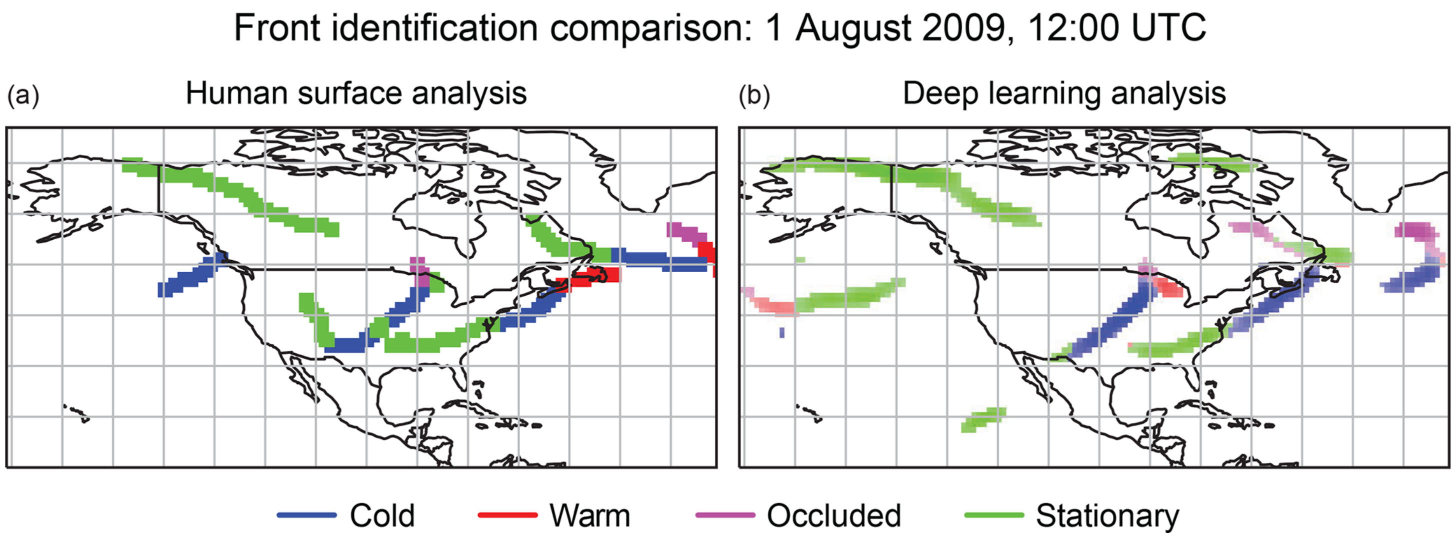
Unable to detect TCs, but able to **detect ARs with similar spatial/temporal representation as model trained on all 4 input fields.**

Thanks to John Truesdale (NCAR) for his work training ClimateNet.

Detection of Fronts

DL-FRONT: Machine learning-based frontal detection algorithm (Biard and Kunkel, 2019)





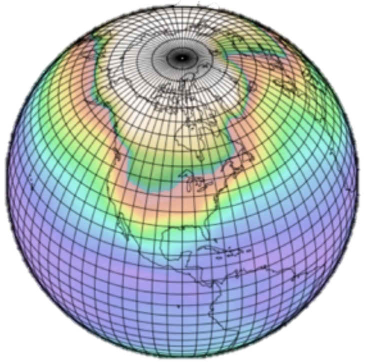
DL-FRONT is able to detect ~90% of manually labeled fronts over North America.

Input fields: surface temperature, sea level pressure, specific humidity and u/v winds
Output fields: 4 frontal categories (cold, warm, occluded, stationary) and none type

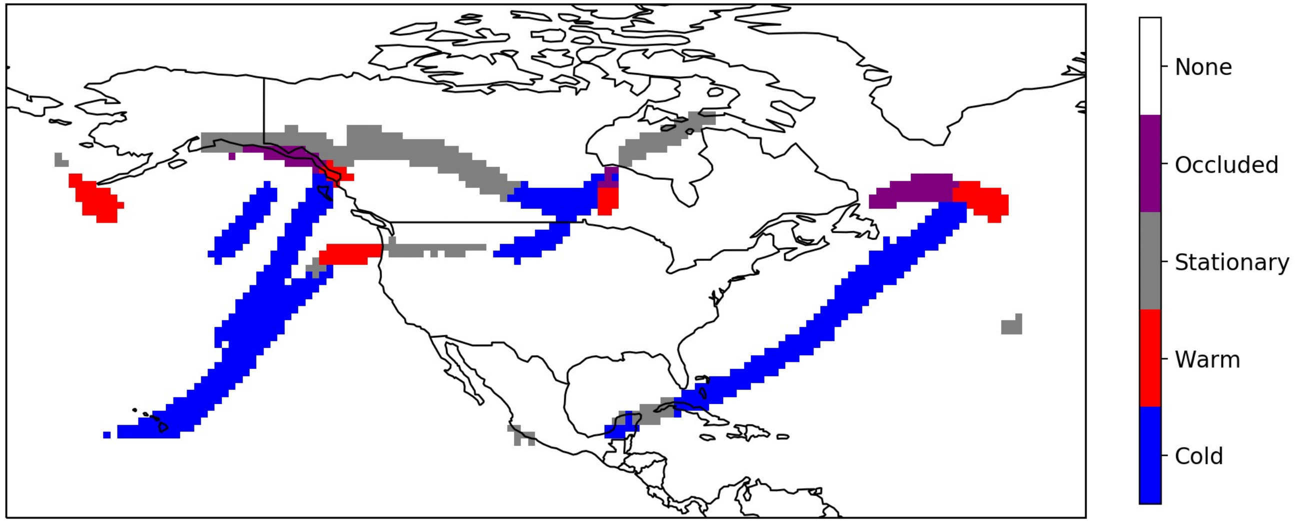
Collaborators: Jim Biard (ClimateAI) and Ken Kunkel (NC State)

Detection of Fronts

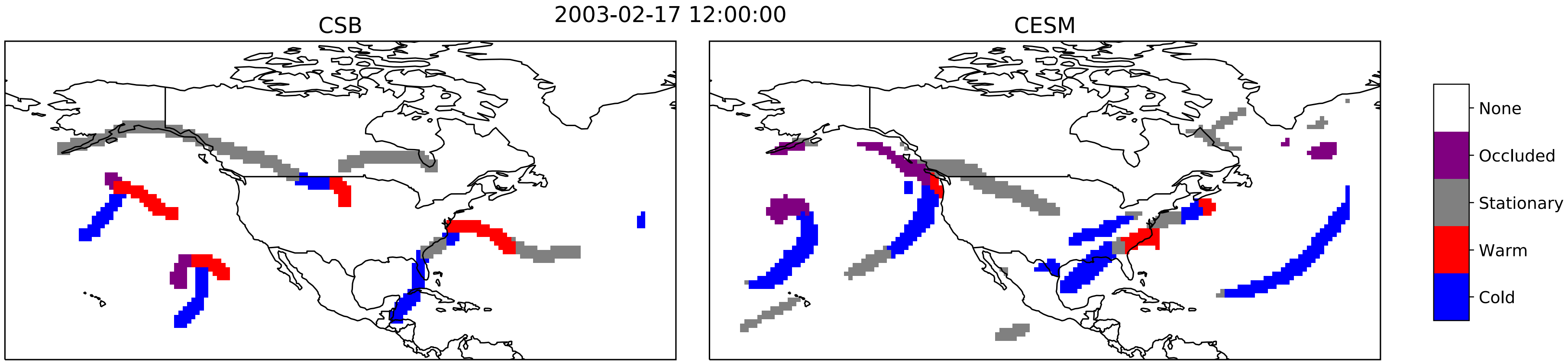
Can we use the pretrained DL-Front algorithm applied to climate model output to detect weather fronts?



Specifically, fully coupled Community Earth System Model (CESM) simulations at high temporal resolution.



Applying trained DL-FRONT algorithm to CESM output to detect front types.



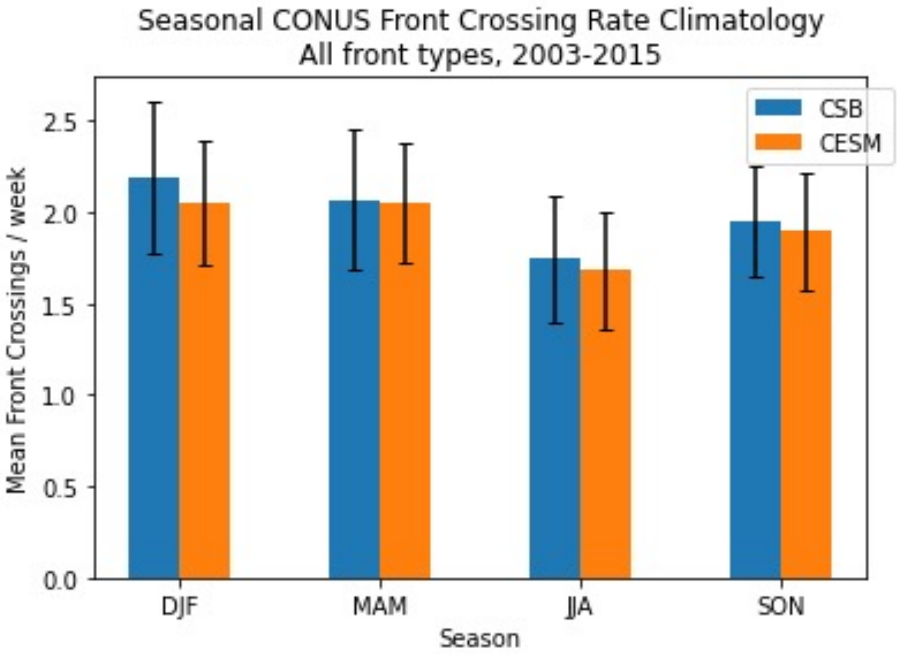
How do we validate the climate model results?

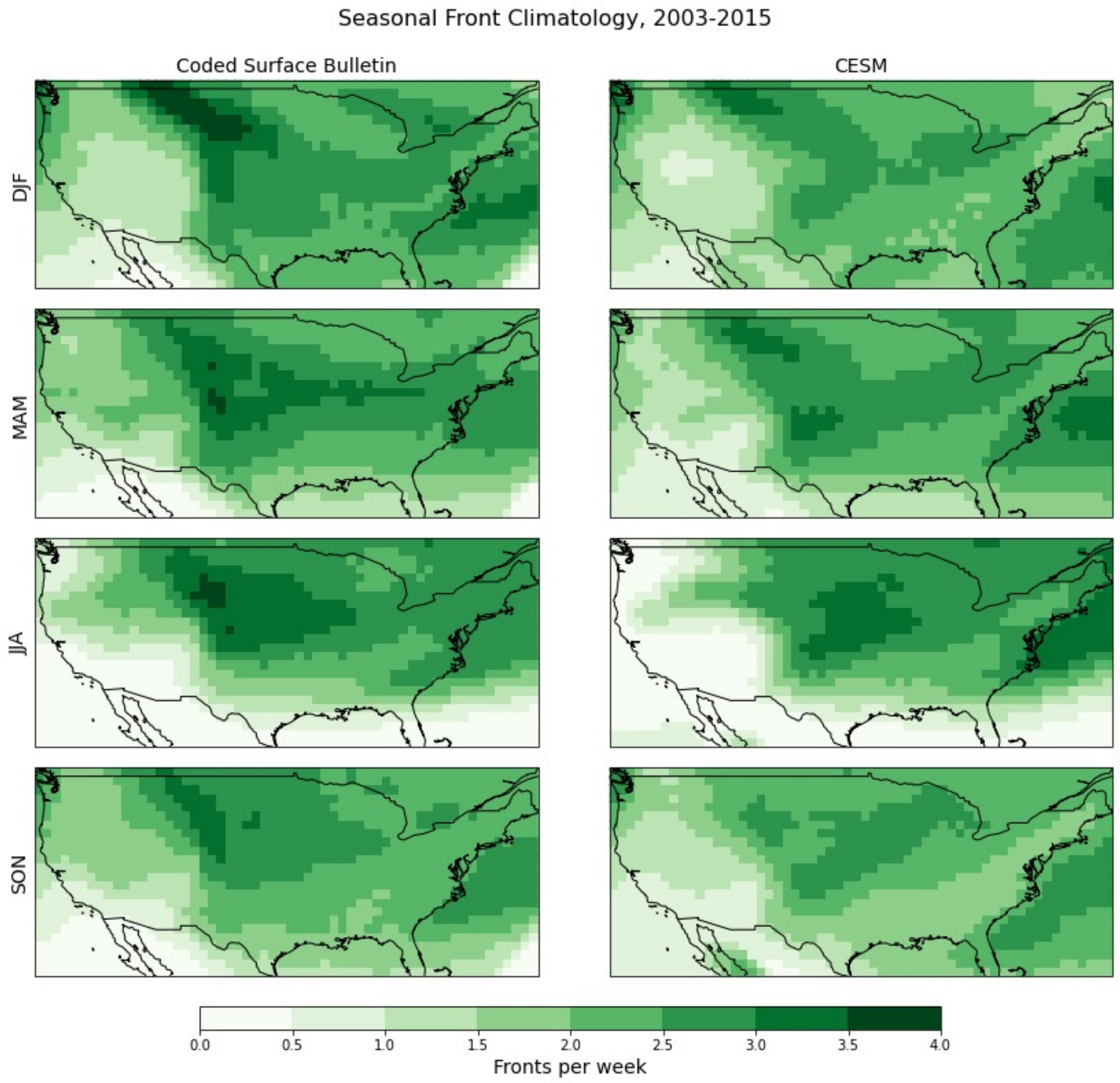
Comparing CESM output with NWS Coded Surface Bulletin (CSB) front locations for a random time point.

Validating Frontal Detection

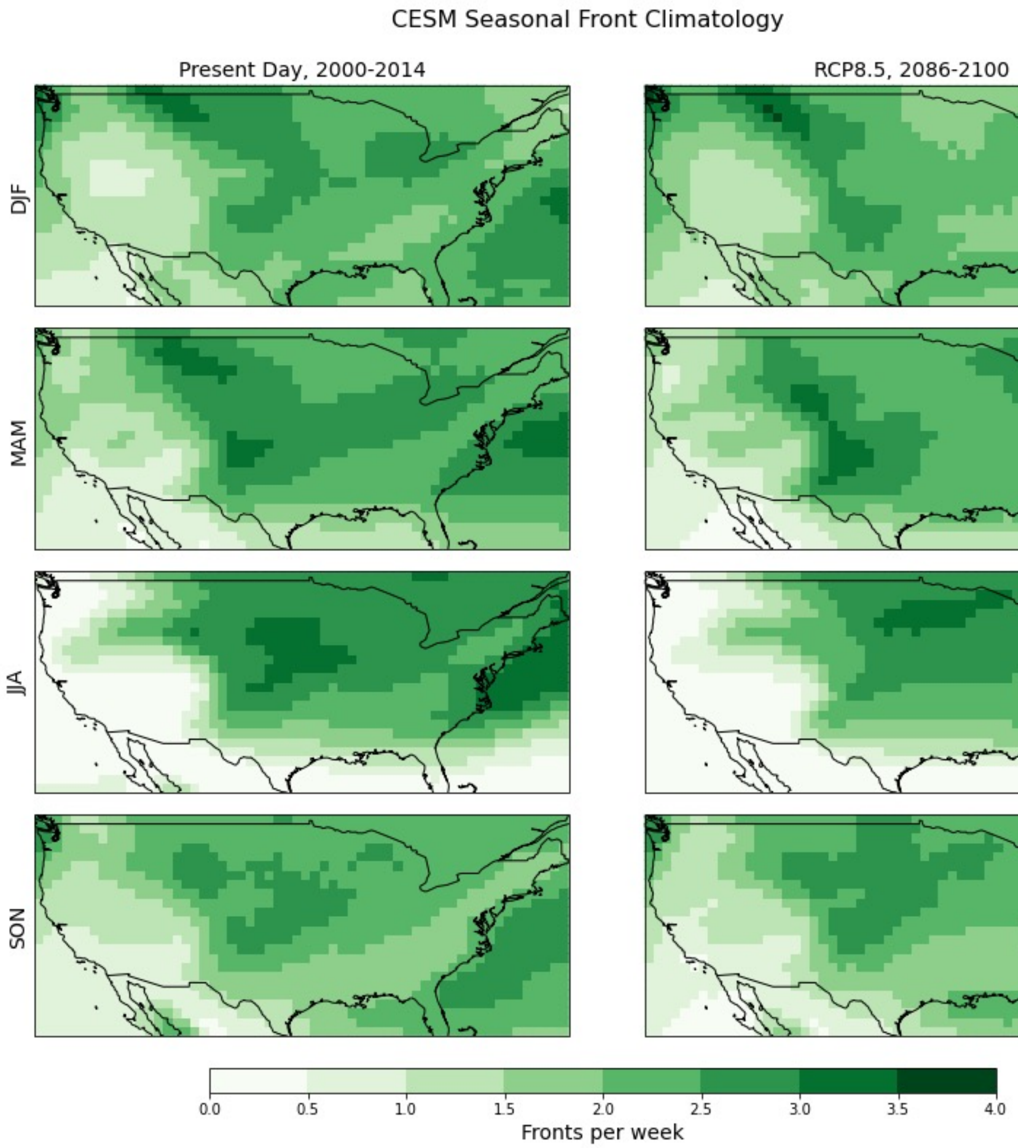
Validation using **seasonal front crossing rate climatologies** (fronts/week) at each grid point.

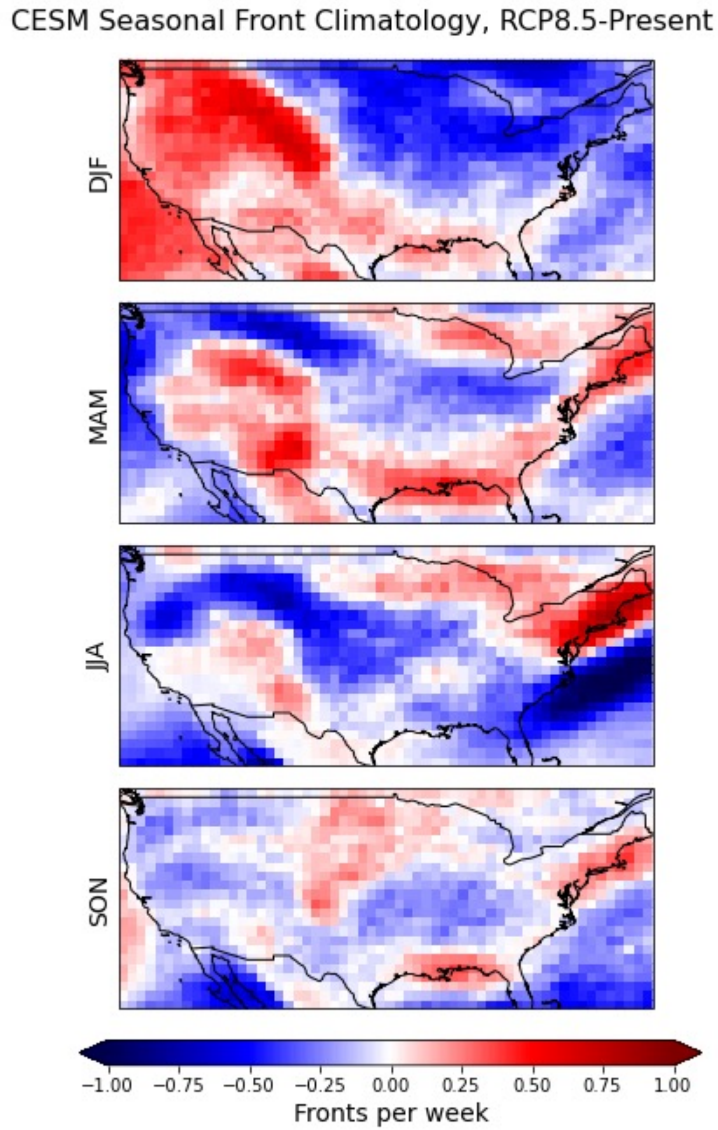
*Comparing **climate model results (CESM)** with validation data from NWS **Coded Surface Bulletin (CSB)**.*





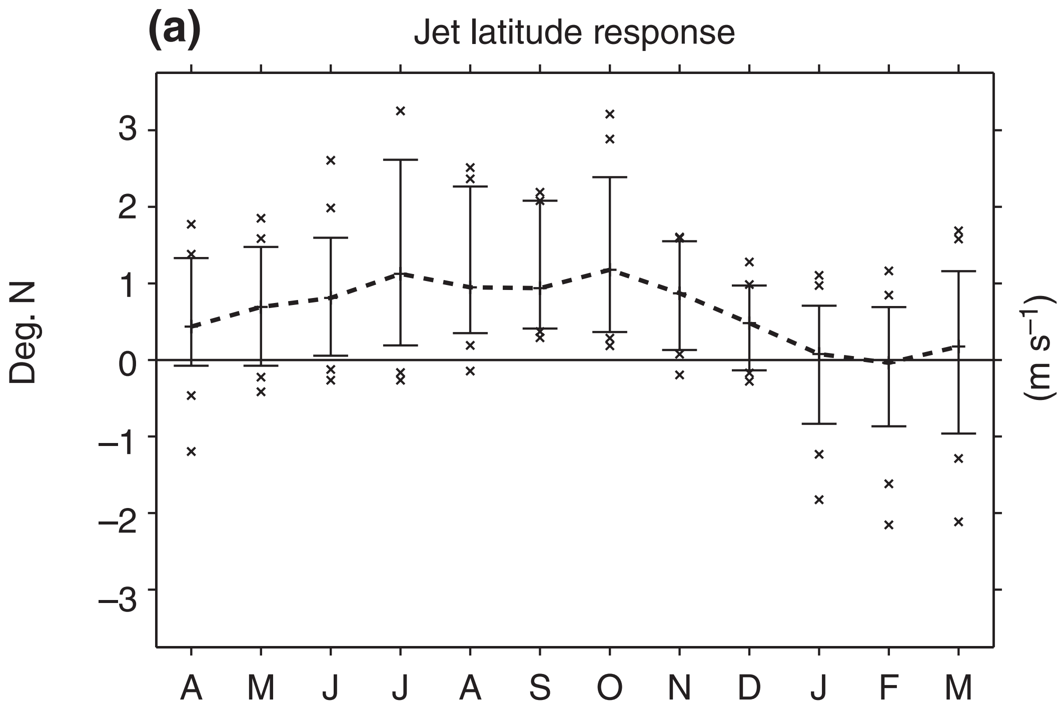
Front Detection Response to Climate Change





Spatial maps show **westward shift in DJF/MAM** and **northward shift in JJA/SON** fronts under RCP8.5.

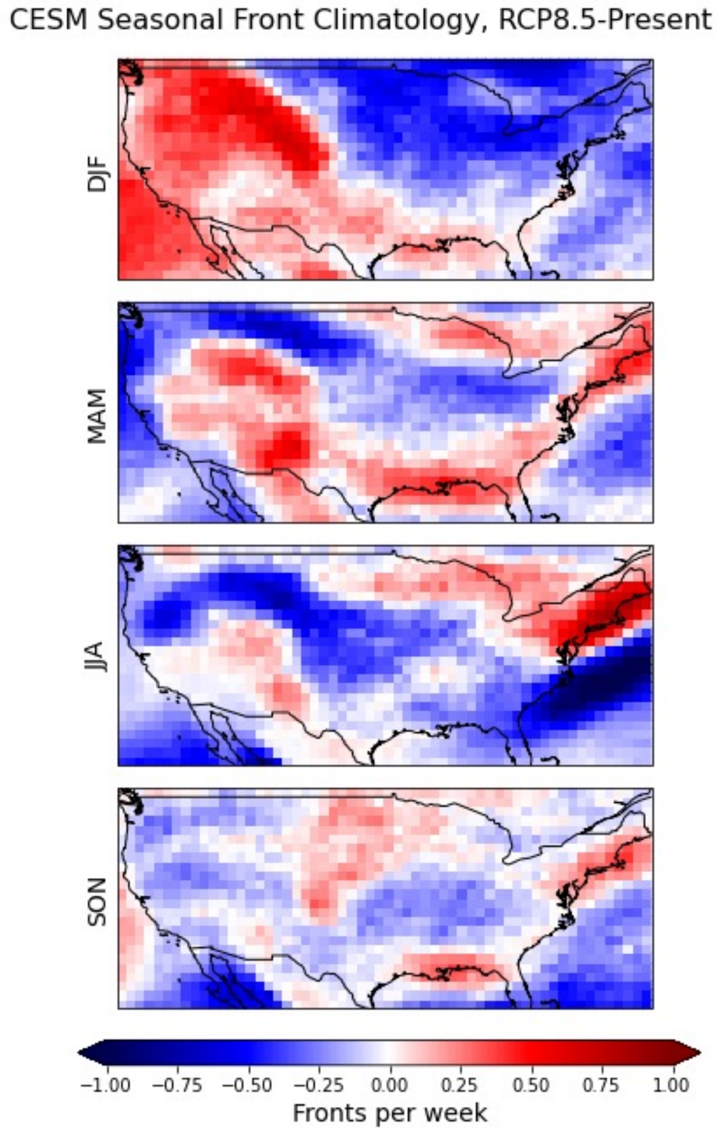
Possible Mechanism: Jet Response to Climate Change



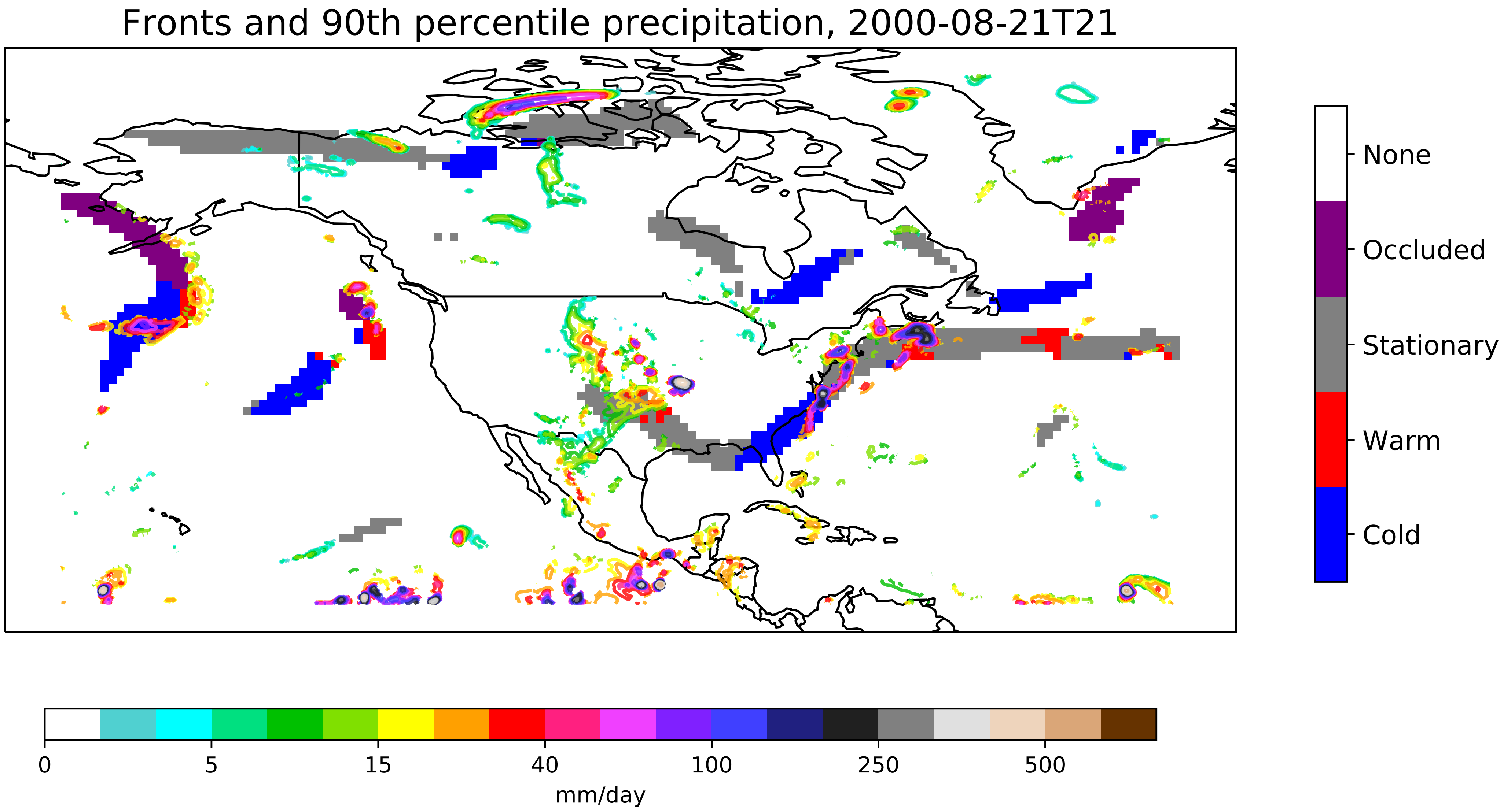
"North Atlantic jet latitude response as a function of month between 2076–2099 and 1980–2004 under RCP8.5 for 21 CMIP5 models. Bars signify the 10th–90th percentile range and crosses denote model responses outside of this range."

- *Barnes and Screen, 2015*

Decreases in JJA/SON driven by **northern retreat of jet stream?**

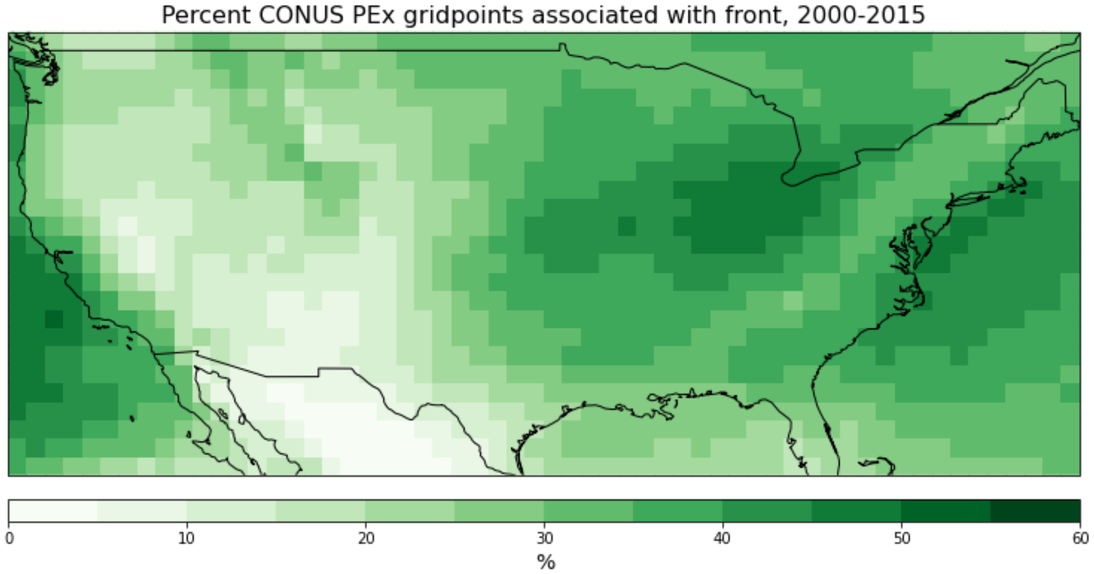


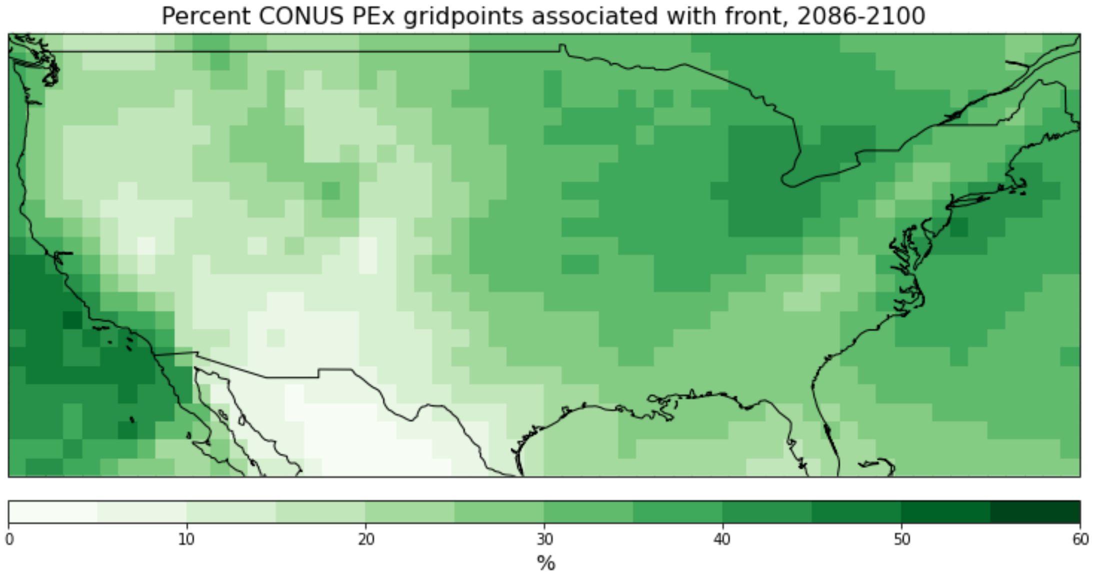
Connecting to Precipitation Extremes

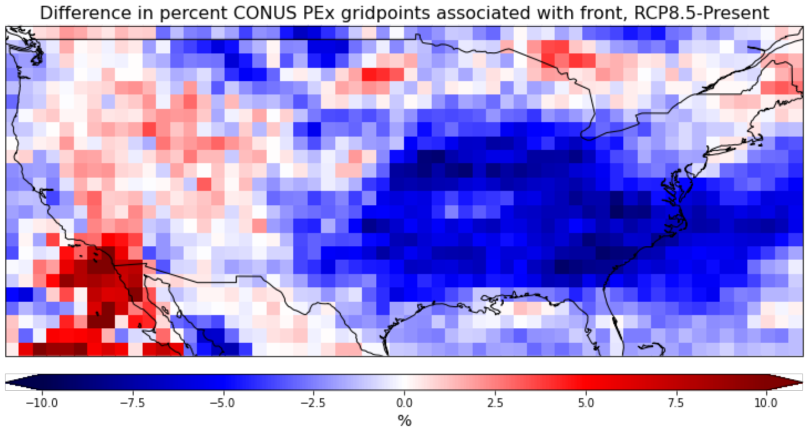


Extreme precipitation (PEx) associated with a detected front

Comparing maps of detected fronts and 90th percentile precipitation, and calculating the percent of PEx gridpoints that coincide with a front by **summing over the time domain**.

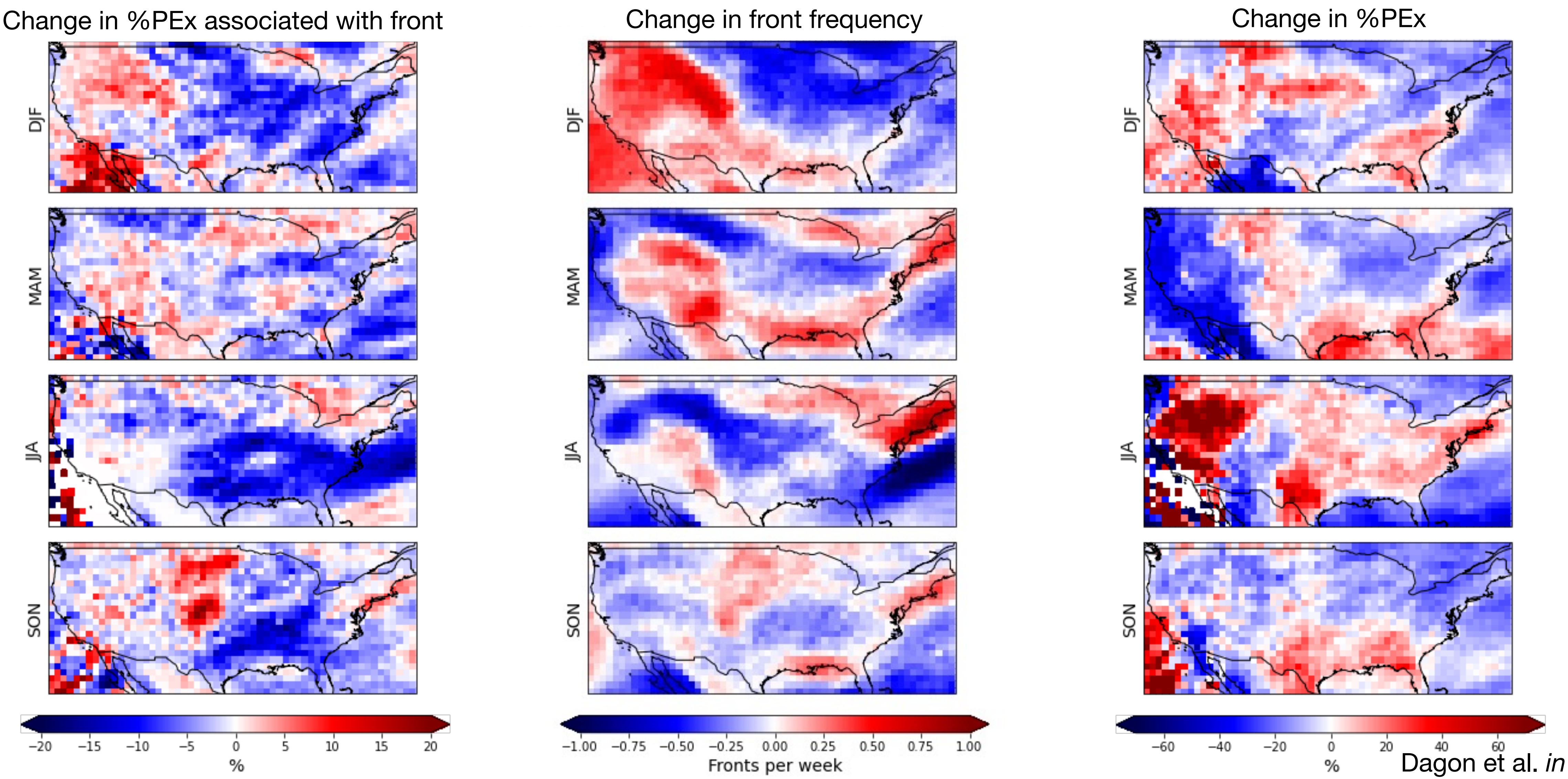






Interesting **dipole feature** in difference plot: (slight) increases in the western US and decreases in the eastern US with climate change.

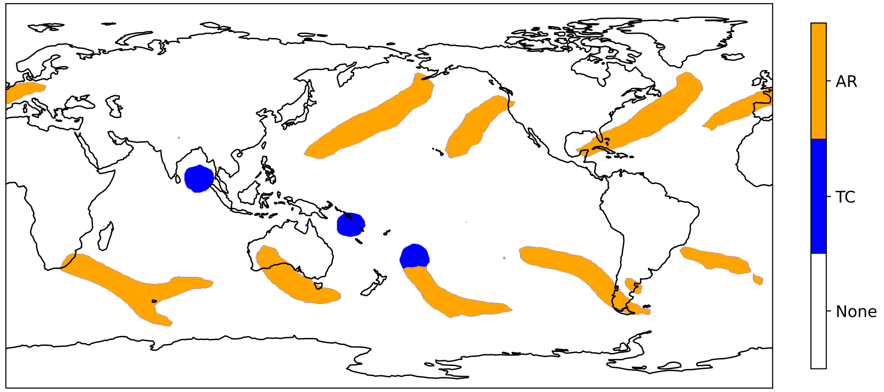
Extreme precipitation (PEx) associated with a detected front

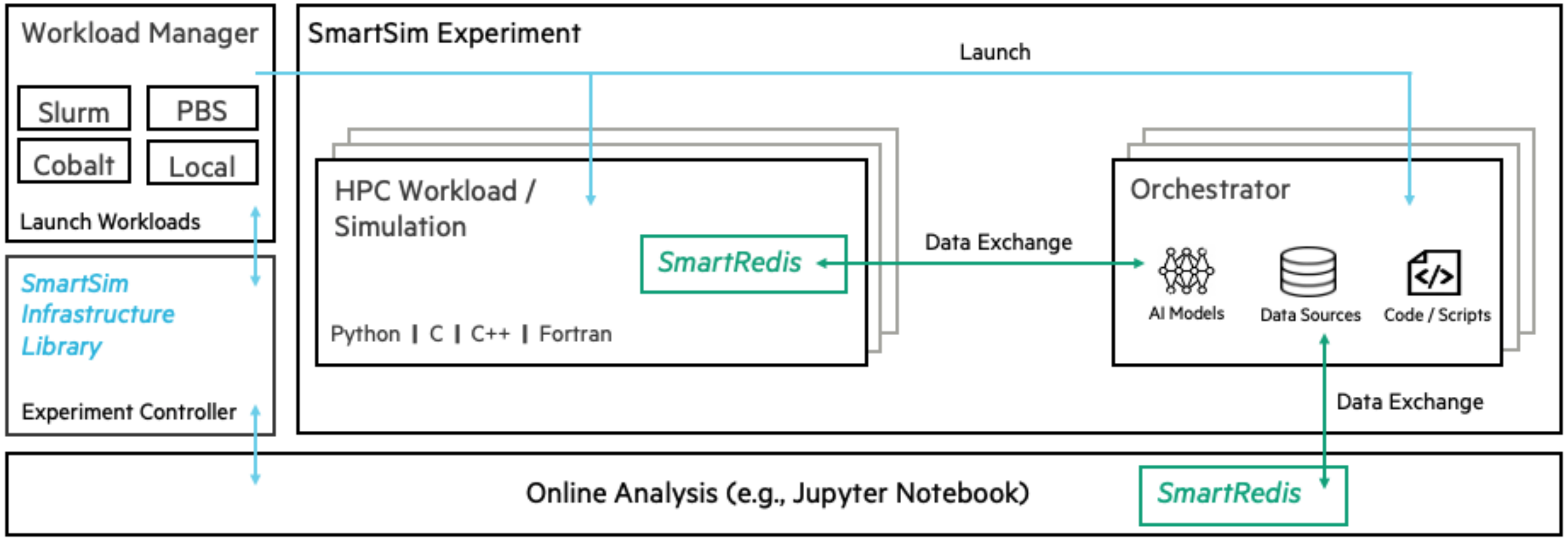


Dagon et al. *in prep*

SmartSim: Online Learning

- Data storage is a persistent issue, especially with high resolution climate model output
- Simulation output not always stored locally and needs to be transferred and extensively post-processed
- Online inference would allow for significant efficiency gains
- *Ongoing work to apply SmartSim to machine learning detection projects with CESM*



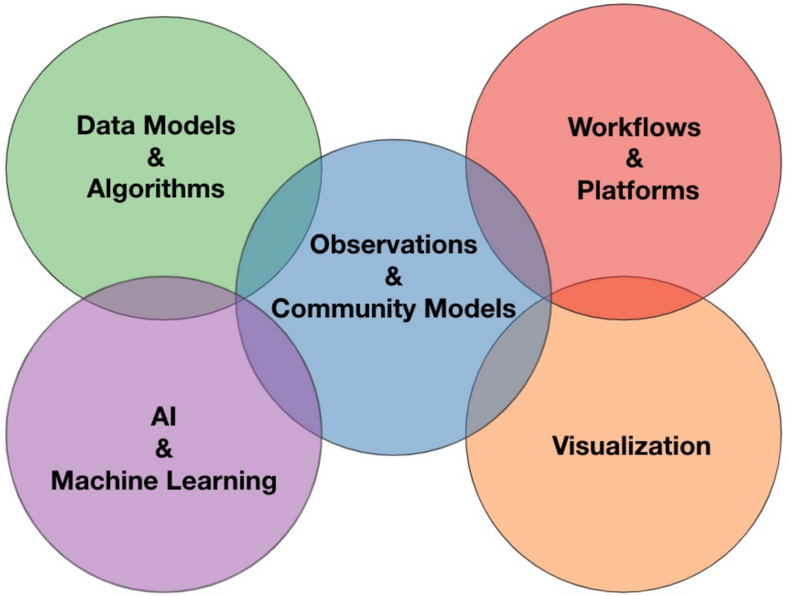


Partee et al. 2021

NCAR Earth System Data Science (ESDS)

Mission statement

The ESDS initiative aims to build an inclusive sociotechnical network to promote effective synthesis and interpretation of data relevant to solving problems in Earth system science and supporting decisions within stakeholder communities.



Vision

An interactive numerical laboratory for Earth system science

Seamless integration of routine model evaluation and cutting-edge science

Community-oriented, community-developed analysis frameworks

Entrain stakeholders in co-design processes

Xdev jupyterhub aws Azure binder GeoCAT PROJECT PYTHIA matplotlib CISL

ESDS Core Team: Deepak Cherian (CGD), Katie Dagon (CGD), Matt Long (CGD), Max Grover (CGD), Kevin Paul (CISL), John Clyne (CISL), Orhan Eroglu (CISL)

Summary

- Machine learning emulators are trained to reproduce land model output with greater computational efficiency; emulator predictions are **optimized to minimize error** between model and observations.

- Machine learning-based detection algorithms are applied to **capture high-impact weather events** in models and observations; detection is connected to extreme precipitation and its response to climate change.

- **Ongoing CESM-related machine learning projects:** Earth system predictability (Molina), model component parameterizations (e.g., CAM6 and MOM6; Gettelman, Gagne, Bachman, Marques), process understanding for sea ice (DuVivier, Holland).

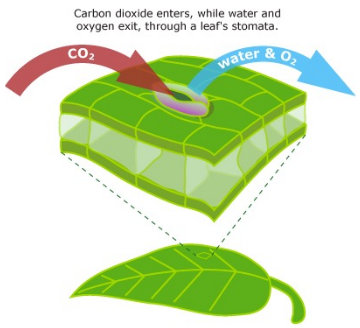
Thanks!
Questions?

kdagon@ucar.edu
@katiedagon

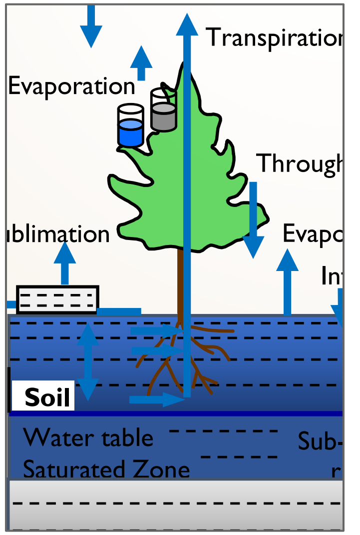
BACKUP

Community Land Model Parameters

- Biophysical features (e.g., surface energy balance, hydrology, carbon uptake)
- Individual parameter uncertainty ranges determined by literature review, updated observations
- Parameter selection based on a series of sensitivity tests with objective metrics



Name	Parameter Description
medlynslope	Slope of stomatal conductance-photosynthesis relationship
dleaf	Leaf boundary layer resistance parameter
kmax	Plant hydraulic stress parameter
fff	Surface runoff parameter
dint	Soil evaporation parameter
baseflow_scalar	Sub-surface runoff parameter



Dagon et al. (2020)

Constructing a Cost Function

- Need to consider first three modes of spatial variability
- Two objectives: gross primary productivity (GPP) and latent heat flux (LHF)
- How to **combine into a single cost function** representing model predictive skill relative to observations?

$$J(p) = \sum_{v=1}^{2} \left[\sum_{m=1}^{3} \lambda_{v,m} \left(\frac{\hat{U}_{v,m}(p) - U_{obs,v,m}}{\sigma(U_{obs*,v,m})} \right)^2 \right]$$

Sum over output variables *v*

Sum over modes *m* for each term, weighting by % variance

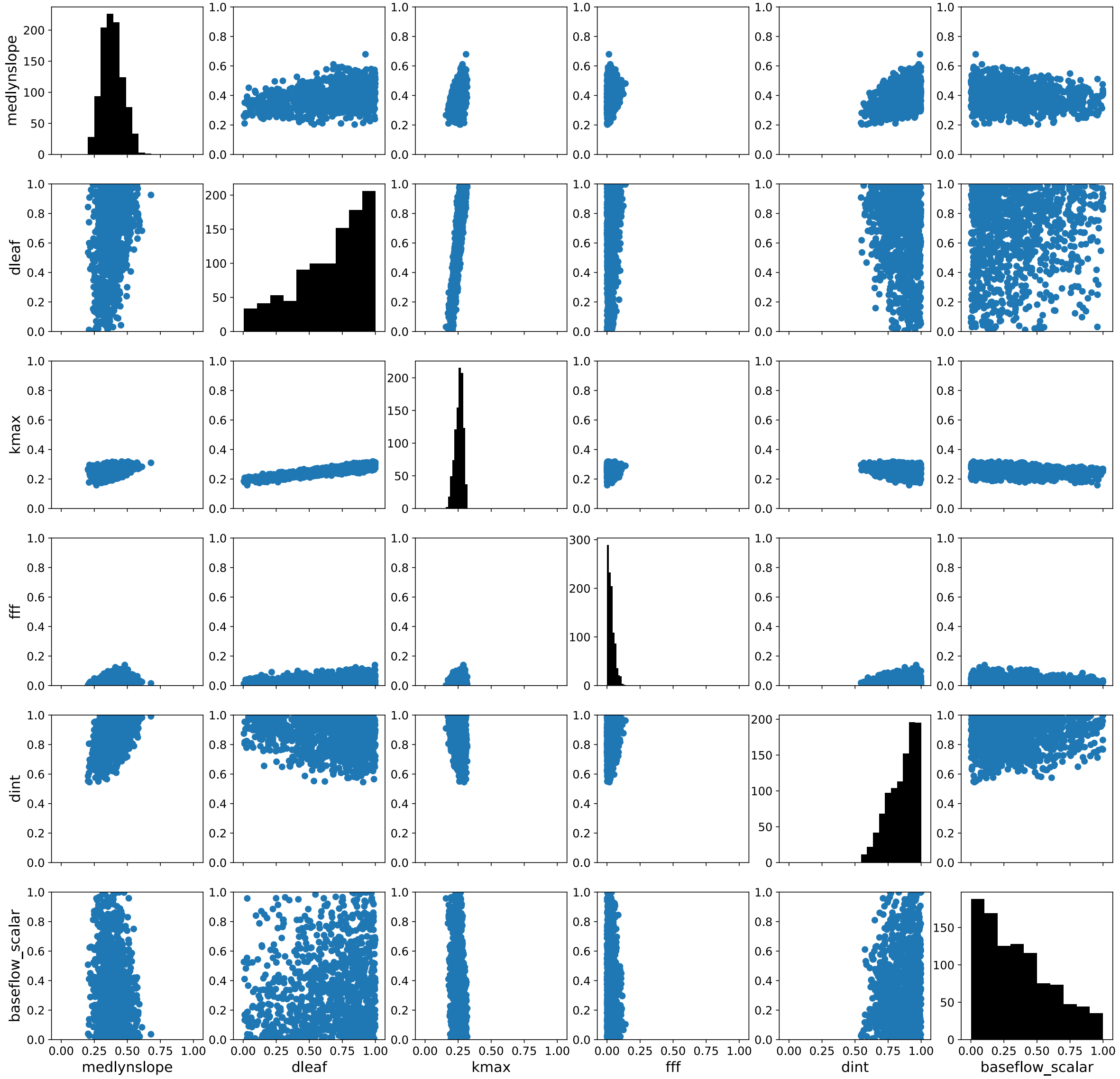
Emulator predictions for parameters *p*

Normalize by standard deviation in observations

Observations

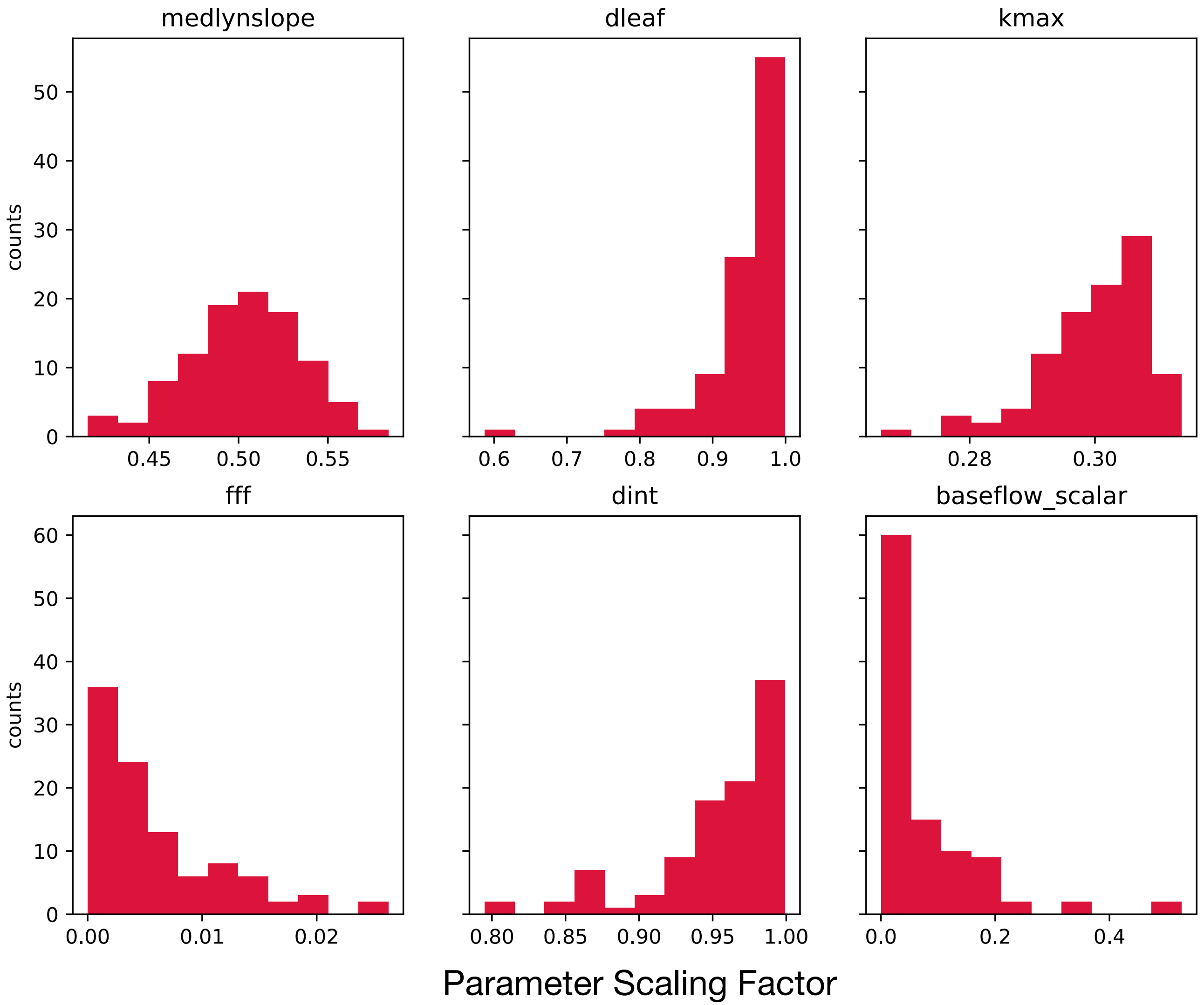
Optimal Parameter Relationships

- Generate an additional large parameter sampling (~10^7 members)
- Subset 1000 members with the smallest predicted normalized error
- Explore parameter relationships and resulting distributions
- Also generating posterior parameter distributions via Markov Chain Monte Carlo (MCMC)



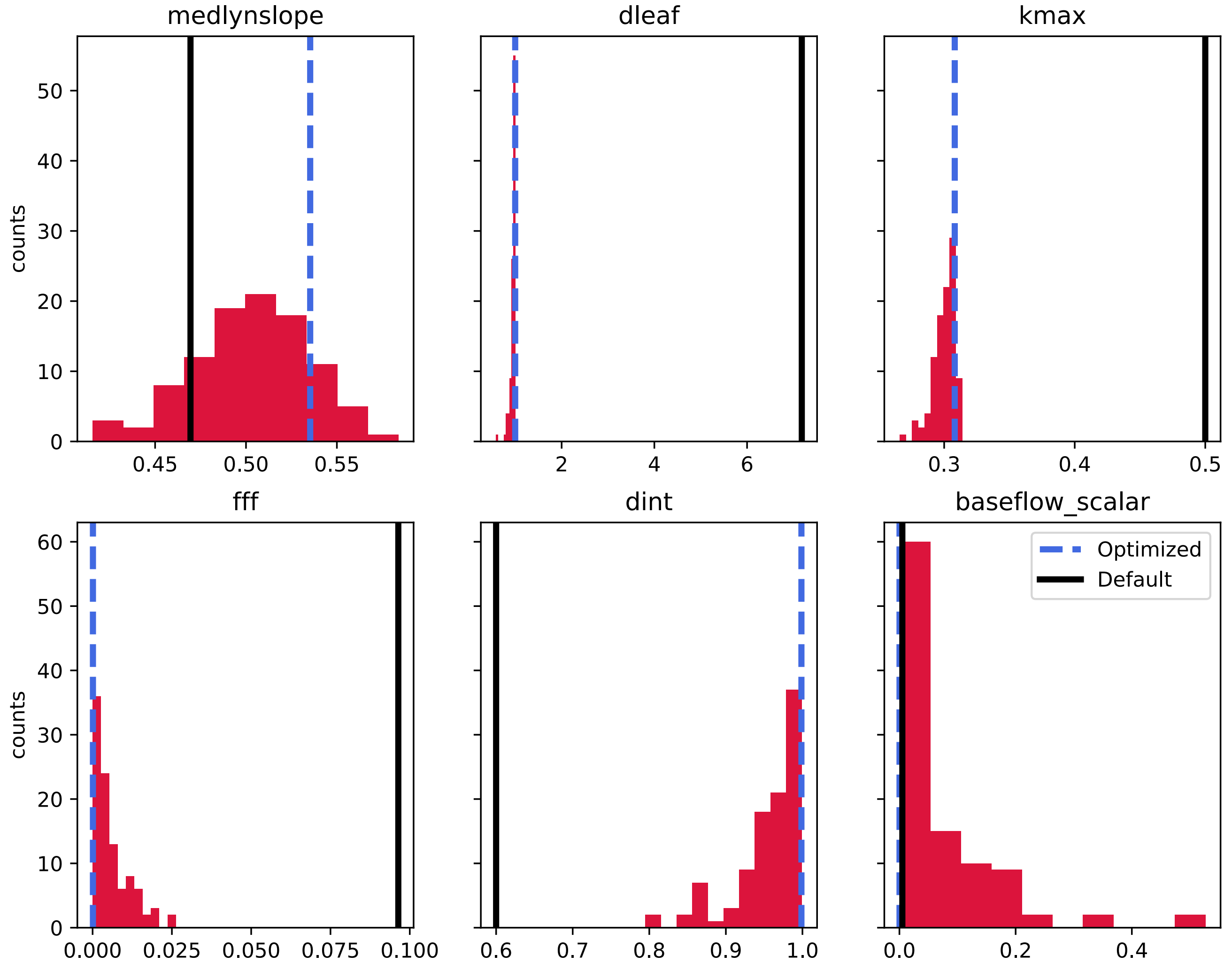
Bayesian Calibration

- Similarity to optimal parameter relationships exercise
- Constraining **medlynslope, kmax** parameters
- Somewhat constraining **fff, dint**, but favoring distribution edges
- **dleaf, baseflow_scalar** not well constrained



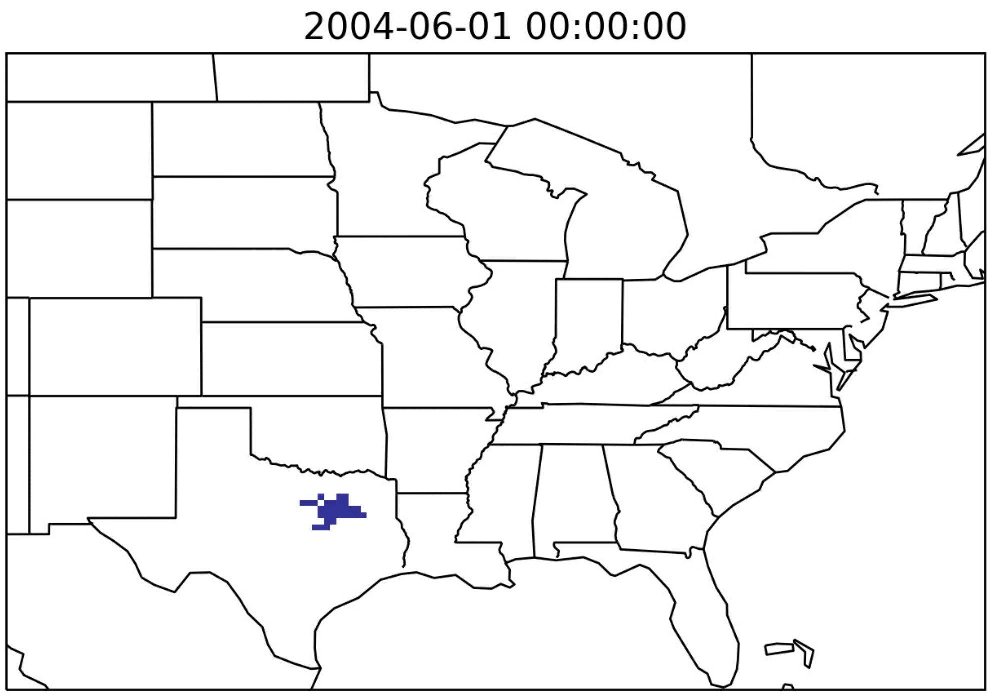
Bayesian Calibration

- How do the optimized and default parameters compare?
- **Optimized** values mostly sit in the median of the parameter distributions
- **Default** values vary and can be far outside distributions

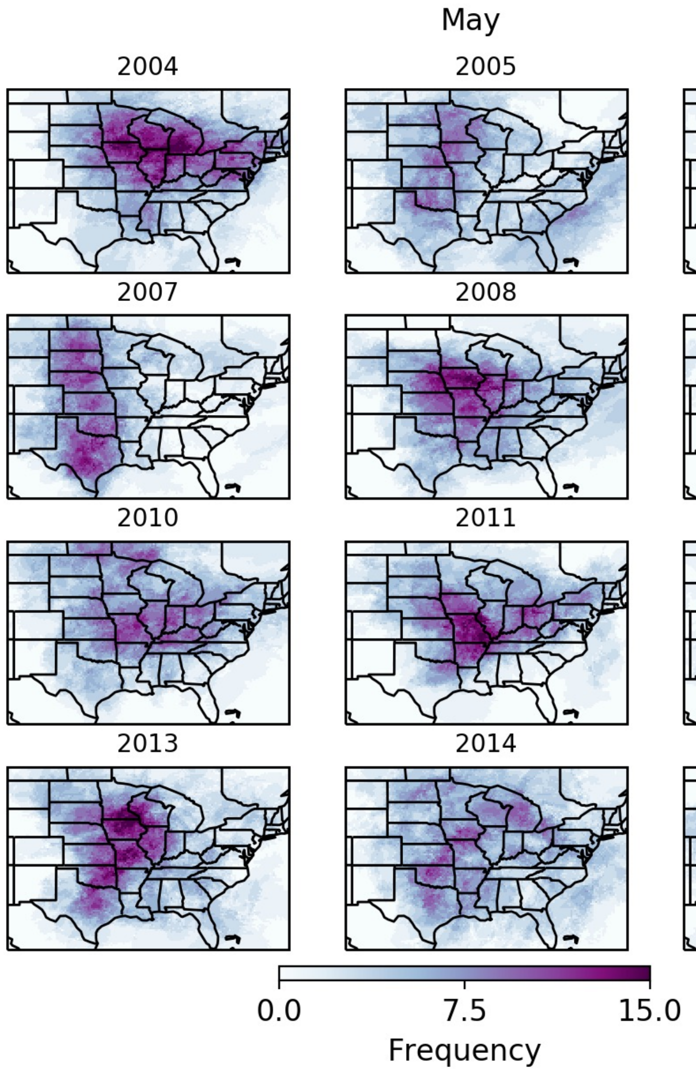


Detection of Mesoscale Convective Systems

Goal: Train a deep learning model to detect mesoscale convective systems (MCSs).
Led by Maria Molina, NCAR



MCS labels using FLEXTRKR (Feng et al. 2018)

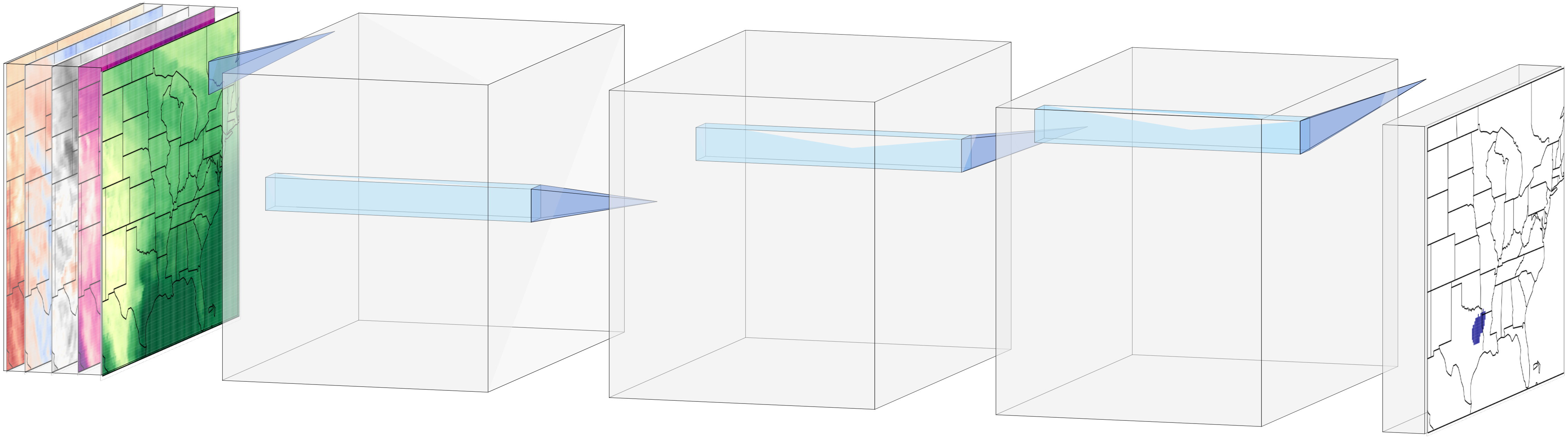


Collaborators: Zhe Feng and Fengfei Song (PNNL)

Deep Learning Infrastructure for MCS Detector

Input: meteorological fields from reanalysis (ERA5)

Output: MCS mask (FLEXTRKR)



Input fields consistent with similar feature detection algorithms: surface temperature, surface specific humidity, sea level pressure, surface u/v winds.

Series of 2D convolutional layers with filtering and dropout, also inspired by existing feature detection algorithms.

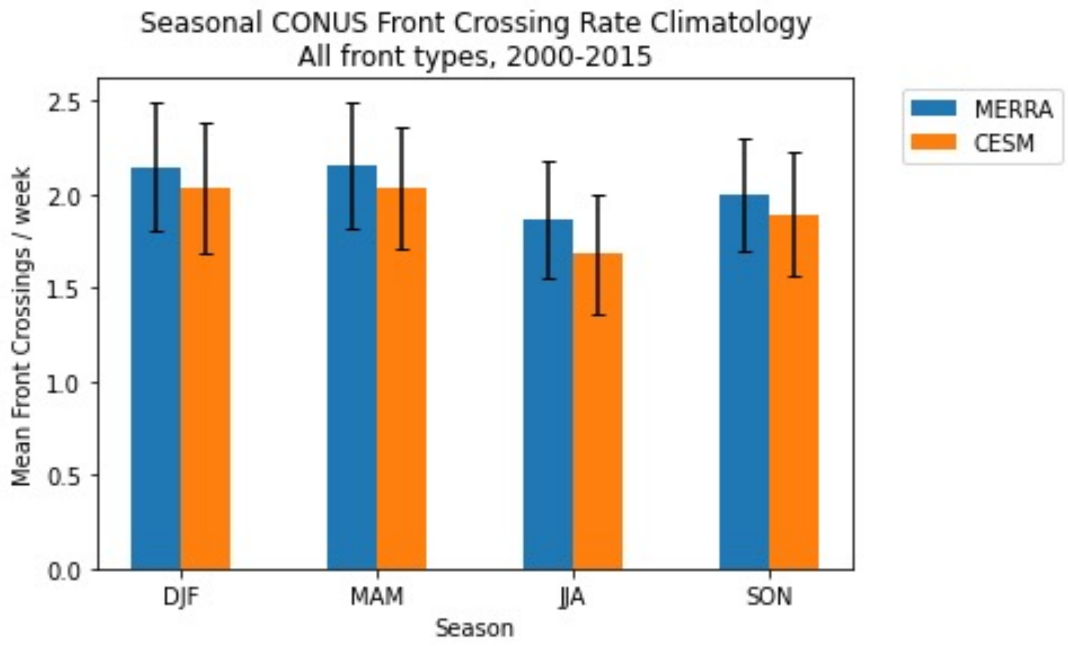
Labeled MCS dataset using FLEXTRKR and ERA5 observations.

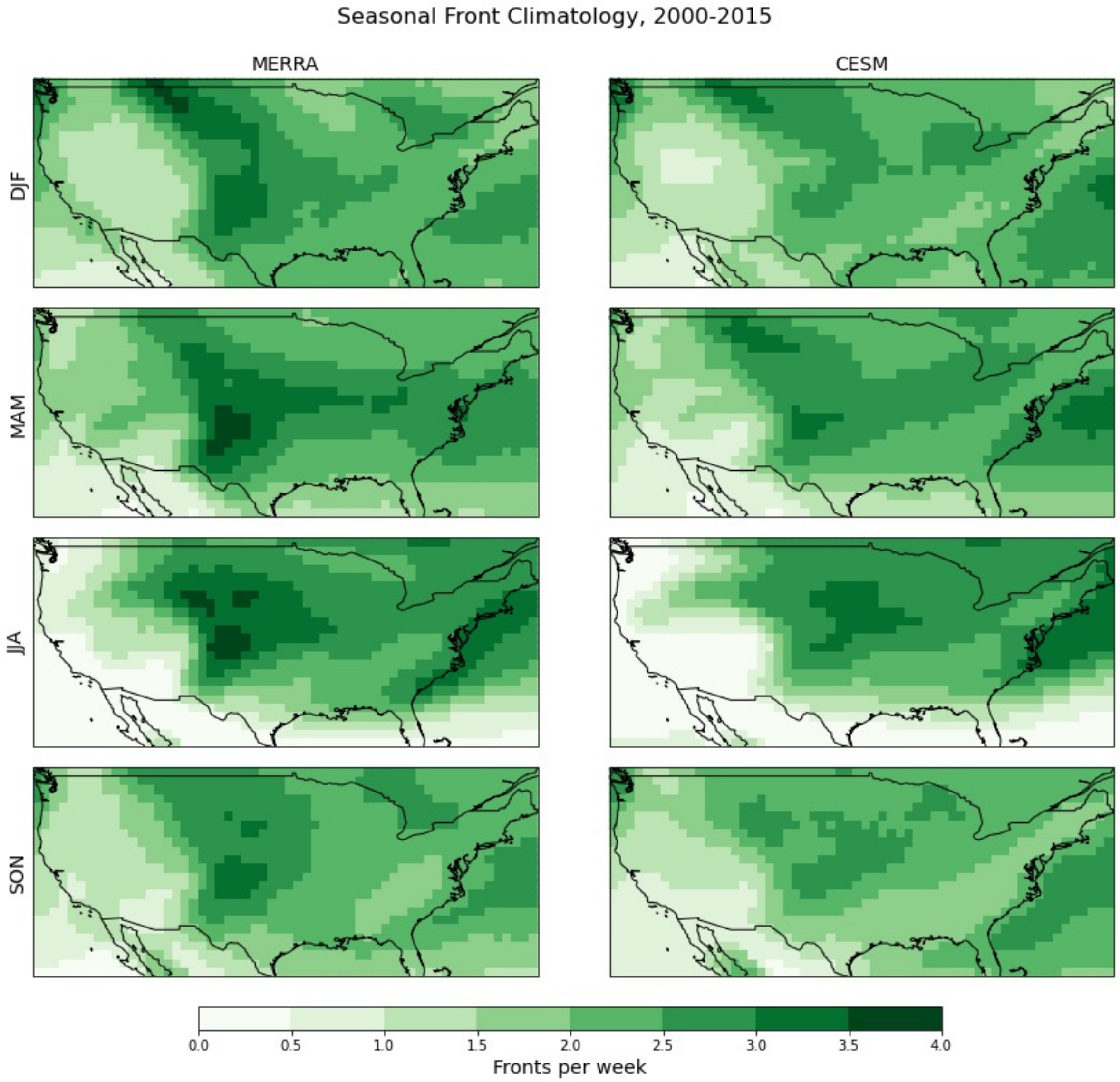
Images from Maria Molina

Validating Frontal Detection

Validation using **seasonal front crossing rate climatologies** (fronts/week) at each grid point.

*Comparing **climate model results (CESM)** with validation data from **MERRA-2 reanalysis**.*

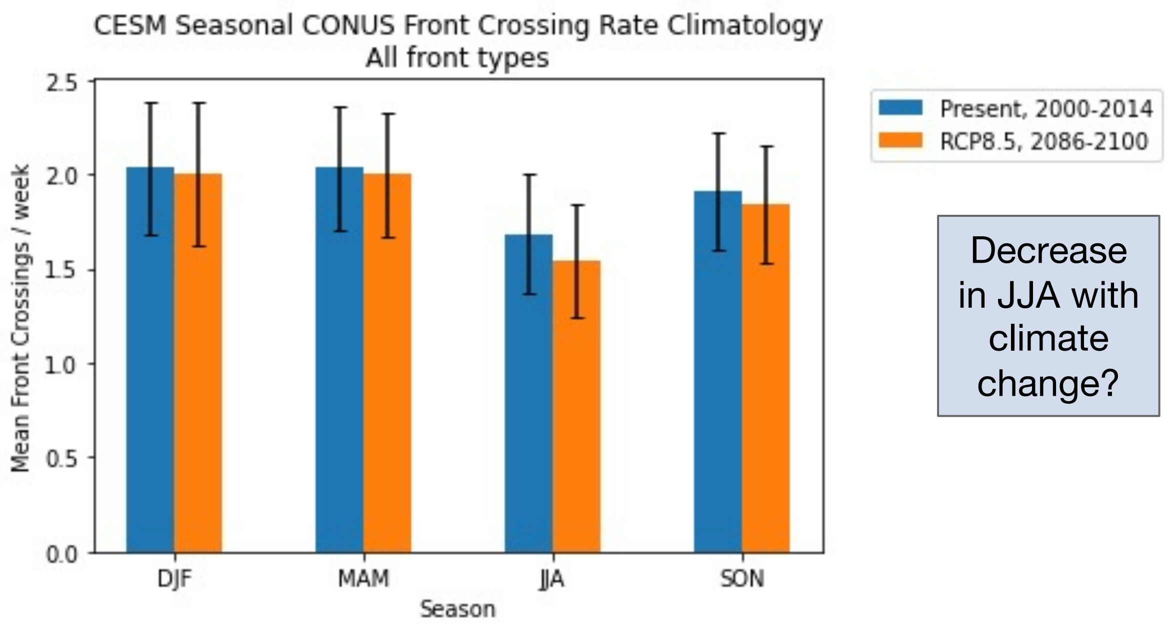




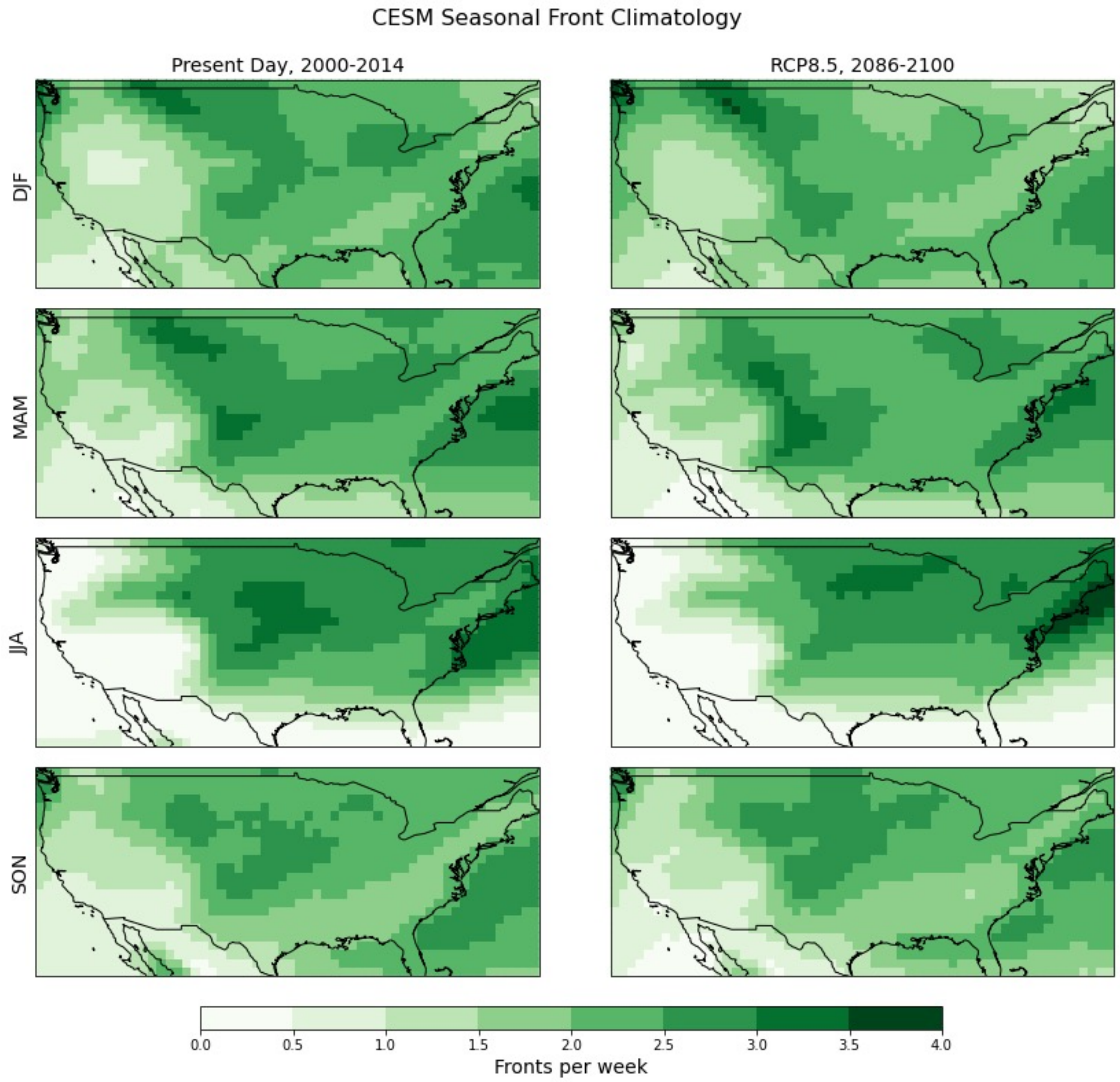
Front Detection Response to Climate Change

Analysis using **seasonal front crossing rate climatologies** (fronts/week) at each grid point.

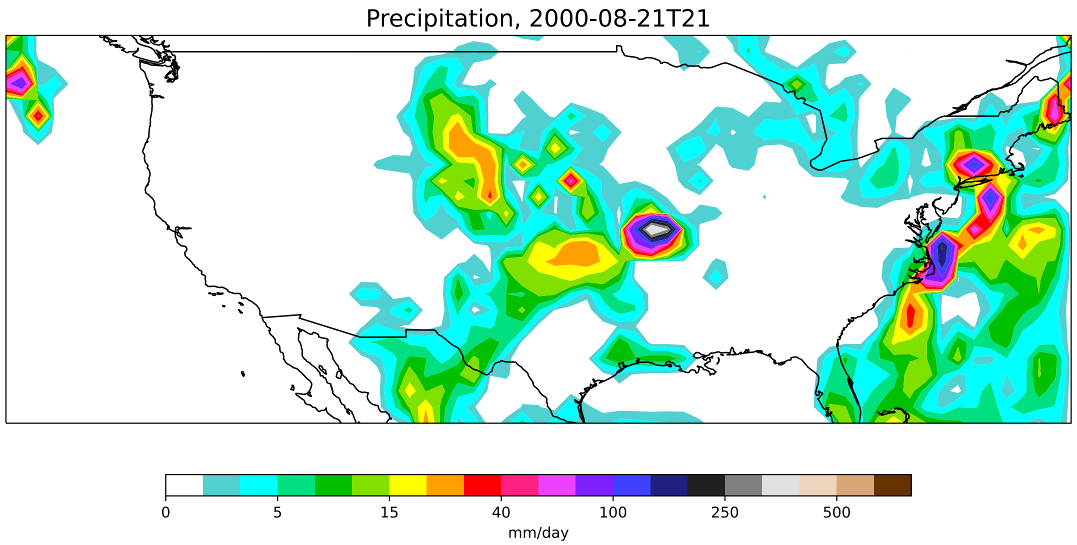
Comparing climate model results (CESM) for ***present-day*** *and* ***future climate*** *simulations.*

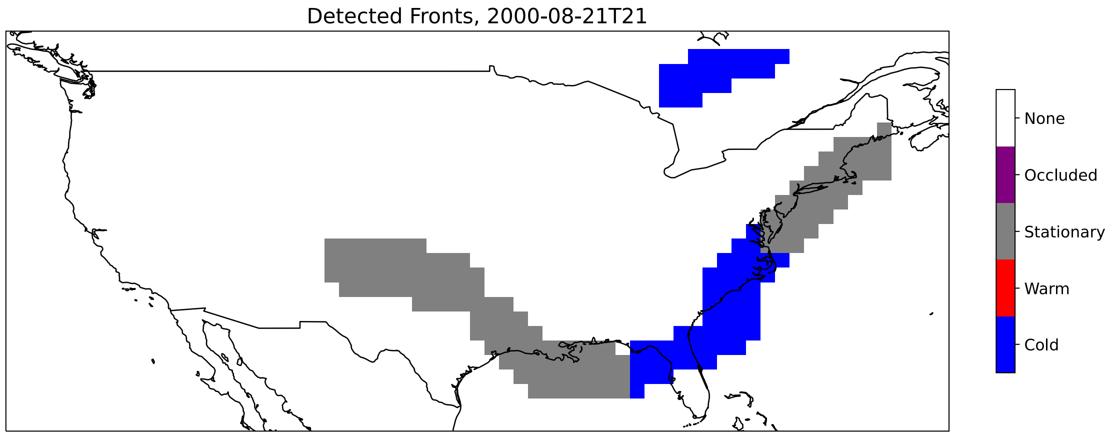


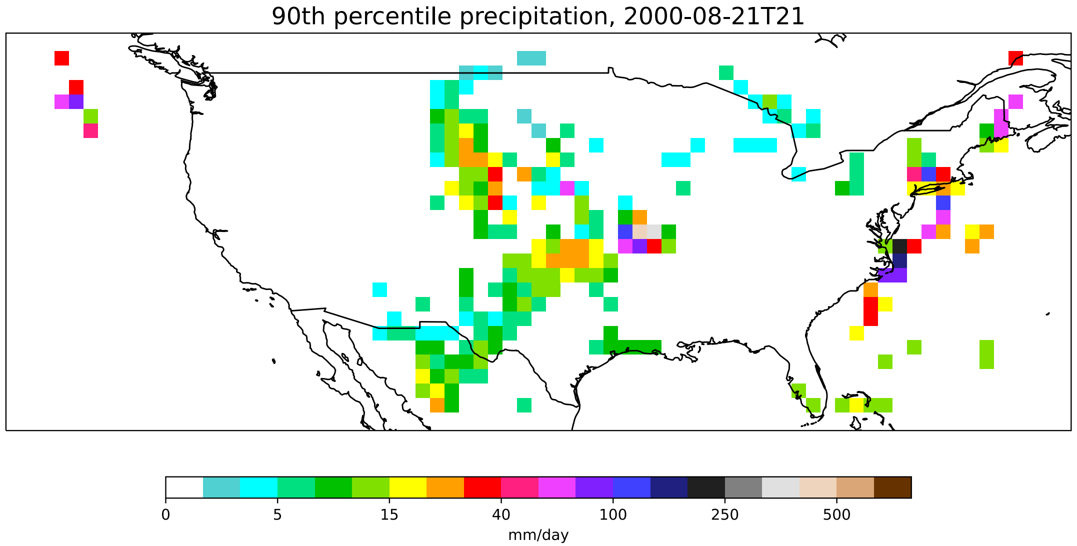
Decrease in JJA with climate change?

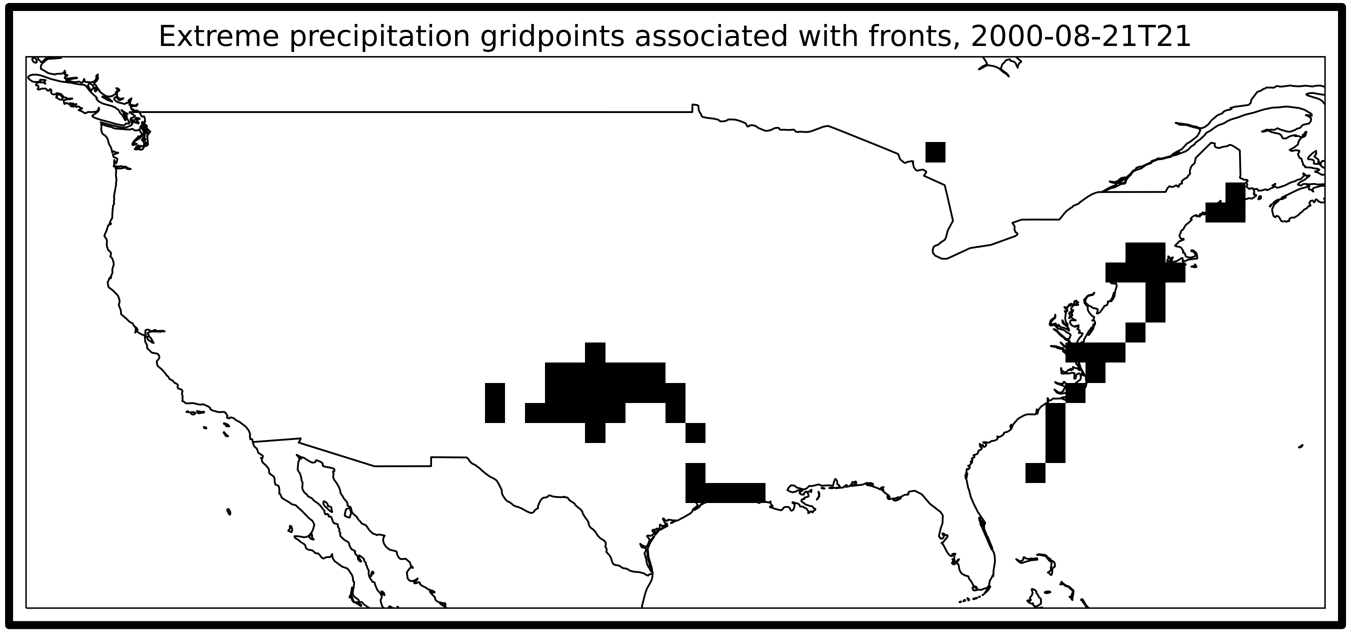


Extreme precipitation associated with a detected front





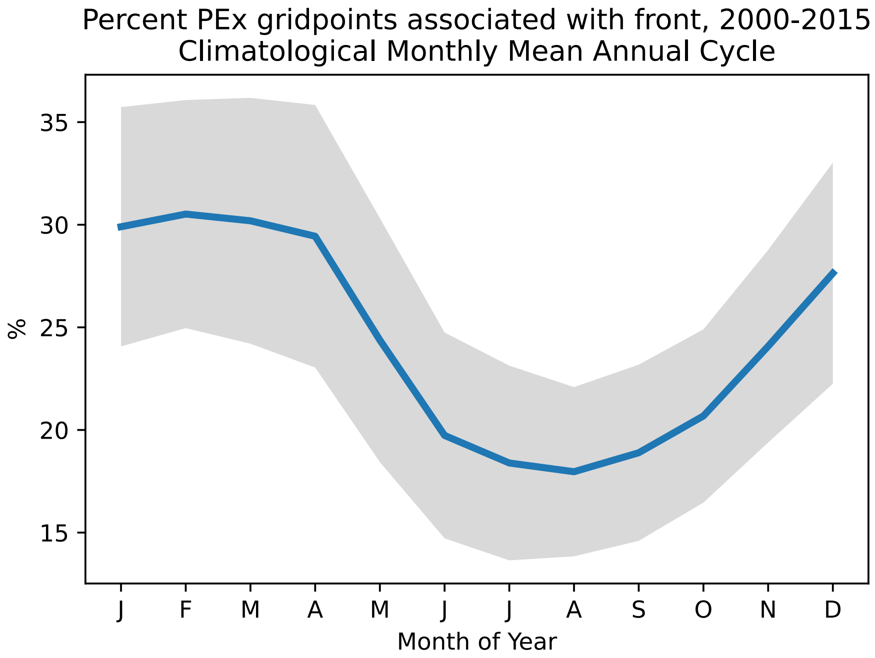




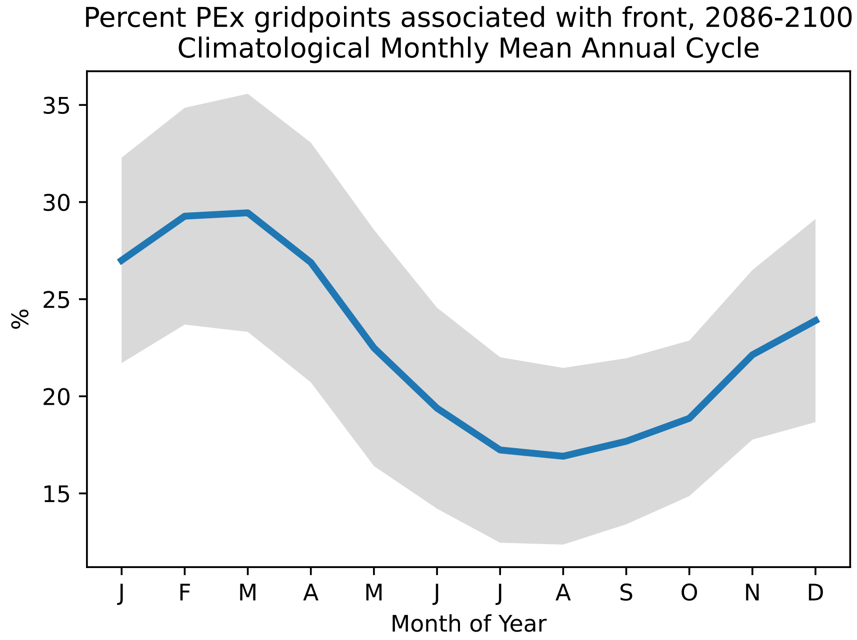
Extreme precipitation (PEx) associated with a detected front

Comparing maps of detected fronts and 90th percentile precipitation, and calculating the percent of PEx gridpoints that coincide with a front by **summing over the spatial domain**.

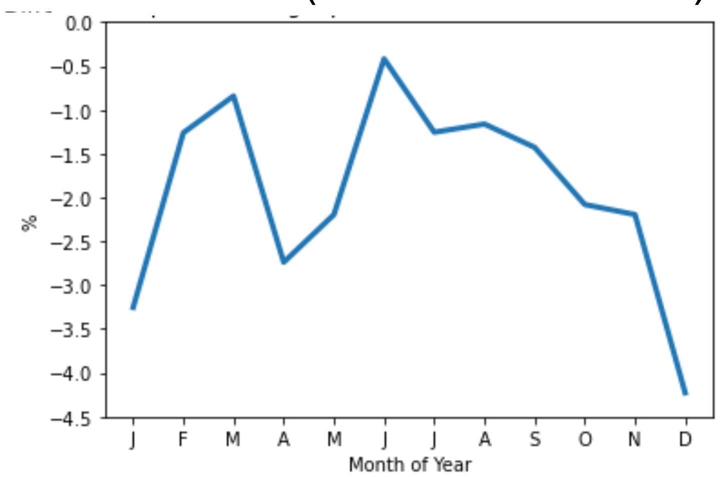
CESM Present Day (2000-2015)



CESM RCP8.5 (2086-2100)



Difference (RCP8.5 – Present)



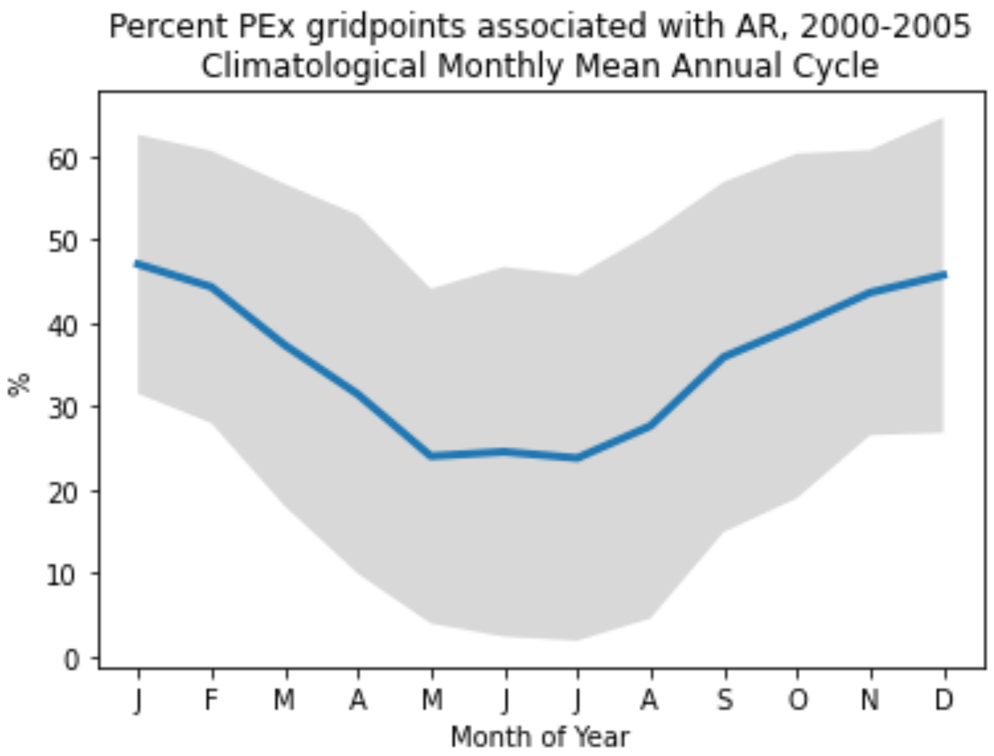
Decreases in every month, more so in fall/winter.

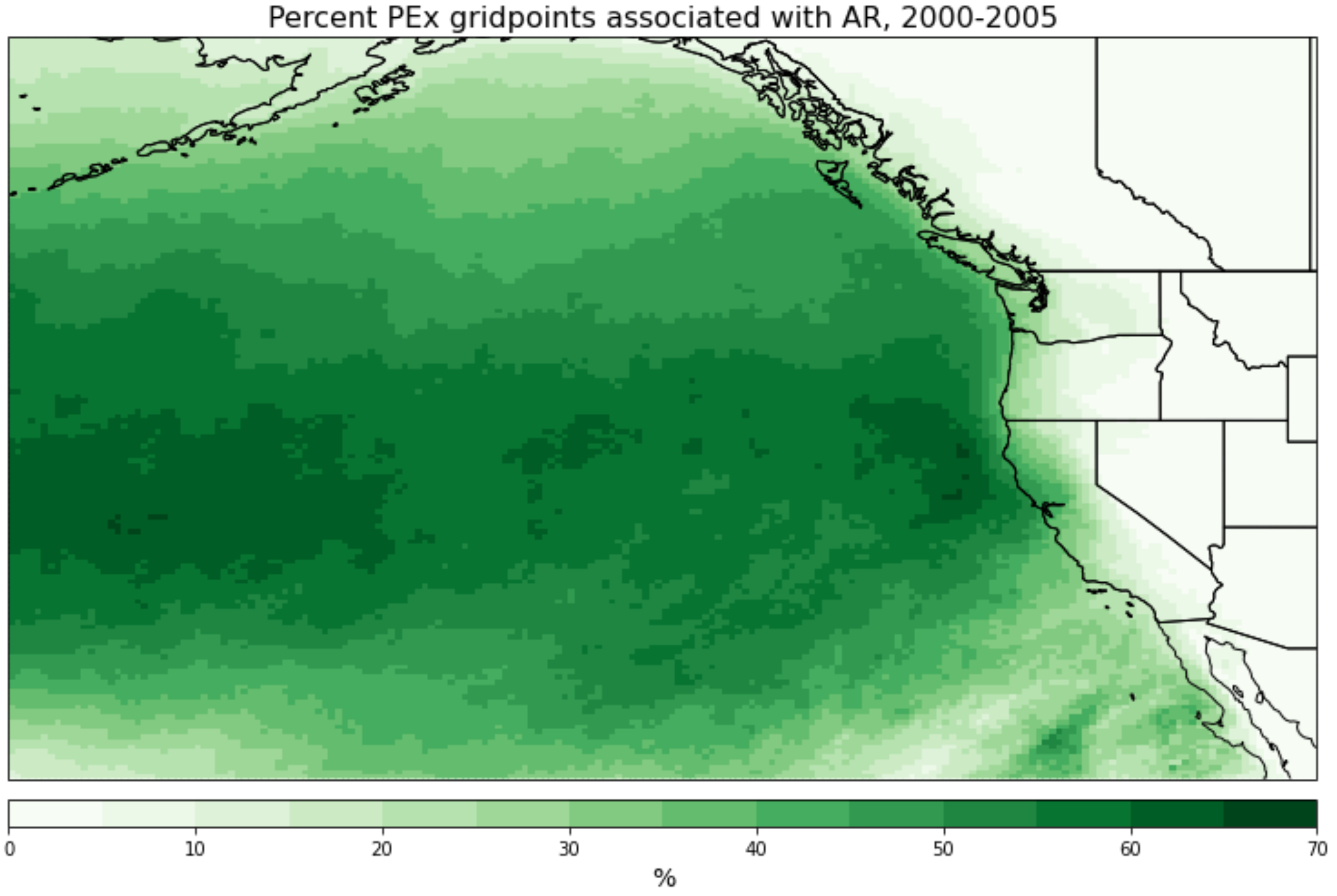
Percentages are **very seasonal** (high in winter, low in summer).

Extreme precipitation (PEx) associated with detected ARs

PEx = 90th percentile

Spatial region inspired by Payne & Magnusdottir (2015)

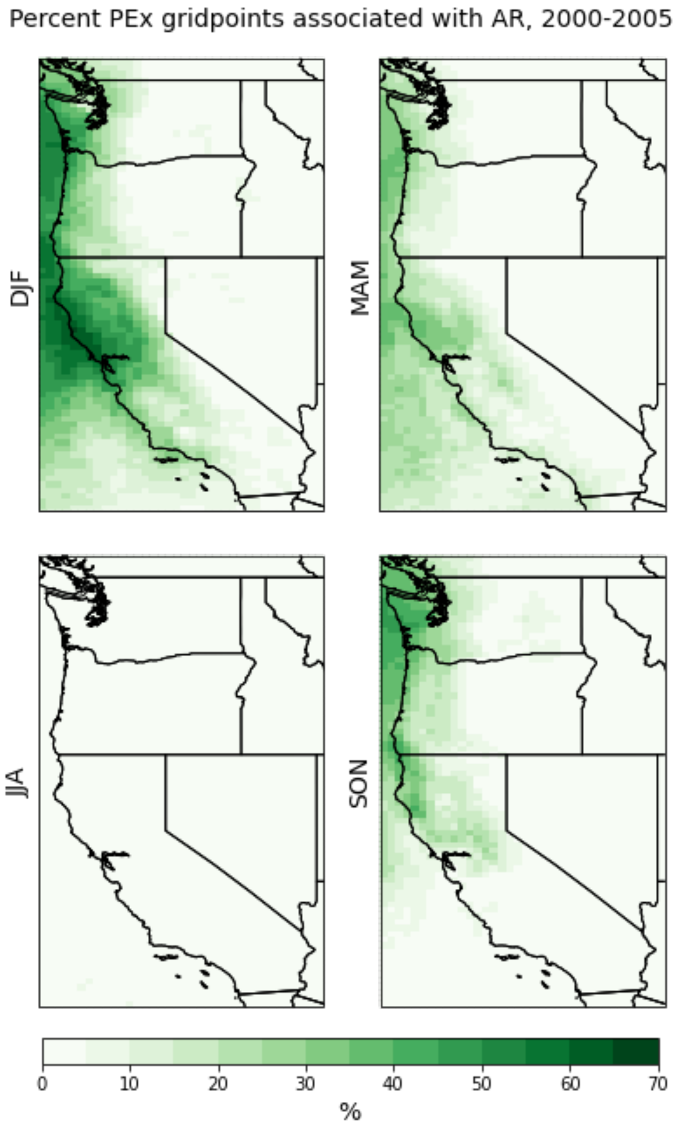




Extreme precipitation (PEx) associated with detected ARs

PEx = 95th percentile

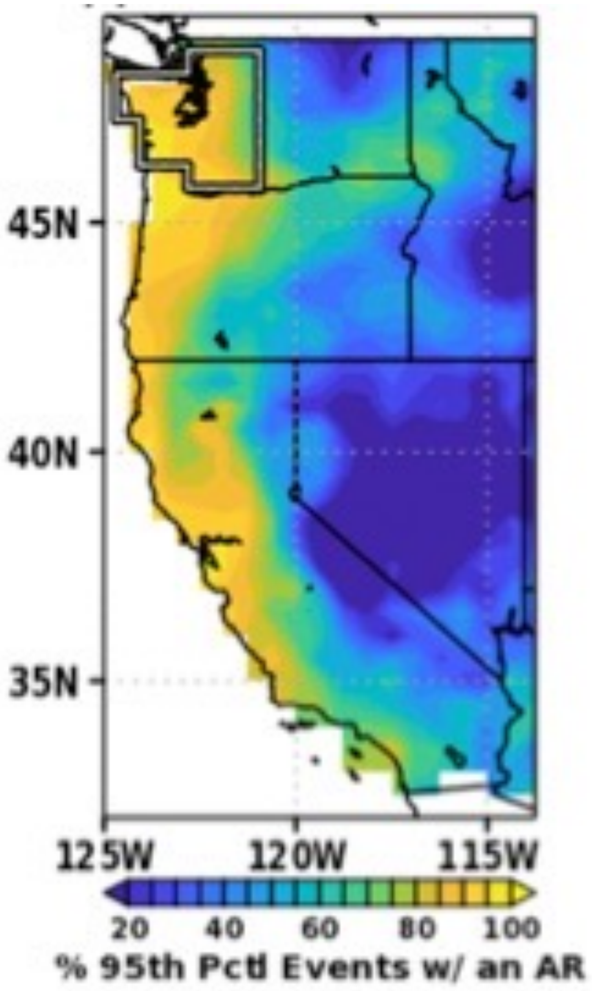
Spatial region inspired by Collow et al. (2020)



Dagon et al. *in prep*

PEx associated with AR in observations

Nov-Jan only, 1980-2019



Collow et al. (2020)

Next Steps

ML for Emulation and Parameter Estimation

- ❖ Currently extending this work to a **large CLM (and CAM) perturbed parameter ensemble (PPE) experiments** with the goal of emulation and global parameter estimation.

ML for Feature Detection

- ❖ Working towards **combining detection algorithms** for multiple features (e.g., fronts and mesoscale convective systems).
- ❖ Investigating the **responses of detection and extreme precipitation** to climate change in other models.