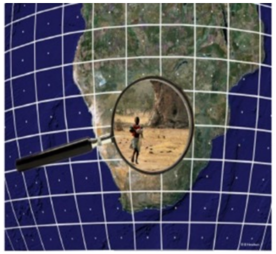
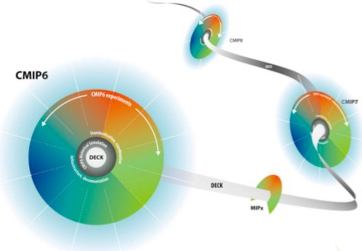
Three climate science research topics that likely require machine-learning for further advancement.

Daniel Feldman[1]
and Many, Many Others

[1] Lawrence Berkeley National Laboratory

UC-Berkeley AI Working Group Presentation
June 15, 2021





Intro: Who I am and What I do

- Staff Scientist at Berkeley Lab, 2021-Present
- Research Scientist at Berkeley Lab 2015-2021
- Project Scientist at Berkeley Lab, 2011-2015
- Postdoc at UC-Berkeley, 2008-2011
- Graduate Student at Caltech, 2002-2008
- Undergraduate at MIT, 1998-2002.

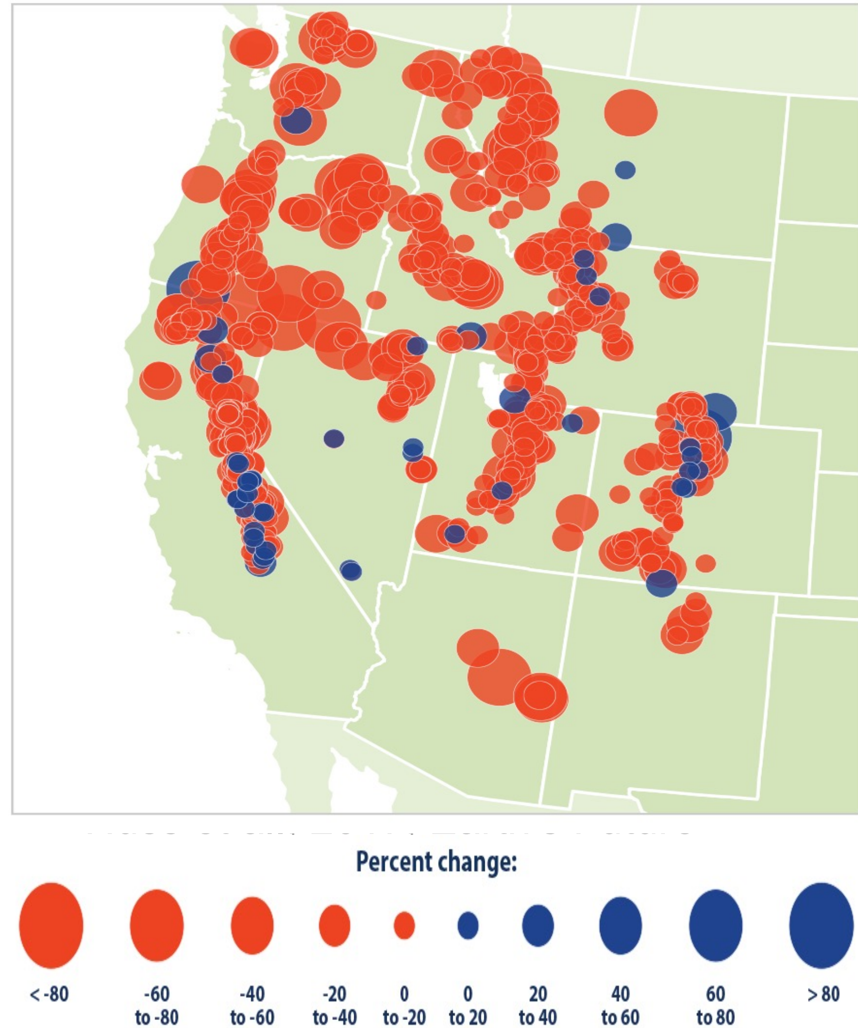
- My personal research interests are in remote sensing and radiative transfer but I work at a National Lab in a highly collaborative environment spanning many disciplines of climate sciences.

Presentation Outline

- Local to Regional Focus: AI for mountainous water resource prediction
- Local to National Focus: AI for climate model downscaling over Conterminous United States
- Global Focus: AI to understand the Earth’s energy balance.
- Discussion of your interests and where there might be overlap.

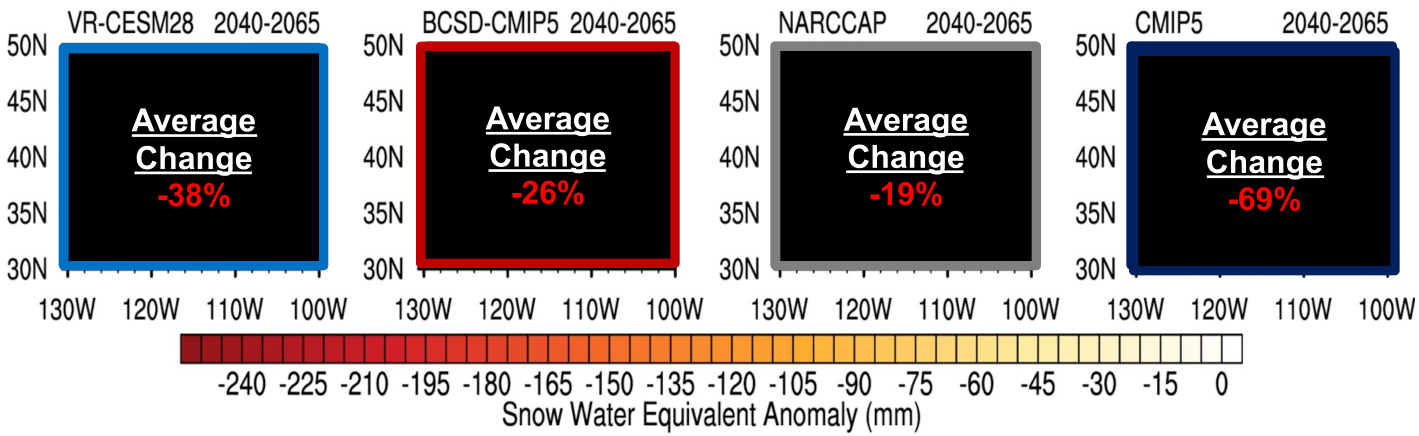
Local to Regional:
Surface Atmosphere Integrated Field Laboratory (SAIL)

- Half of the world depends on water from mountains, but these resources are dwindling.
- Are our predictive tools properly instrumented so that they can predict how these resources will change in the future?

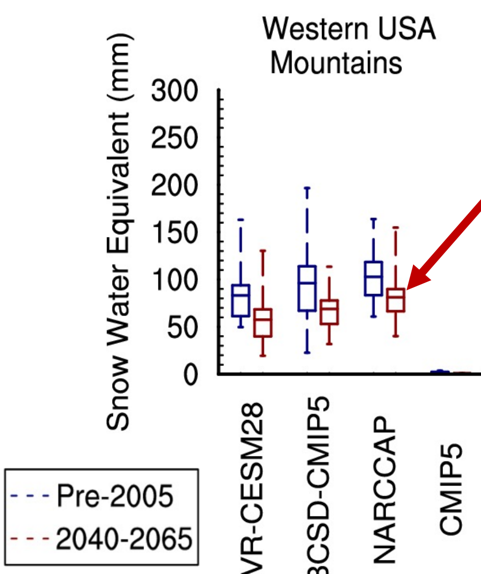


Mote and Sharp, 2016, BAMS

Local to Regional:
Model Development Needed for Water in the West



Regional Downscaling Ensemble Average
-27%



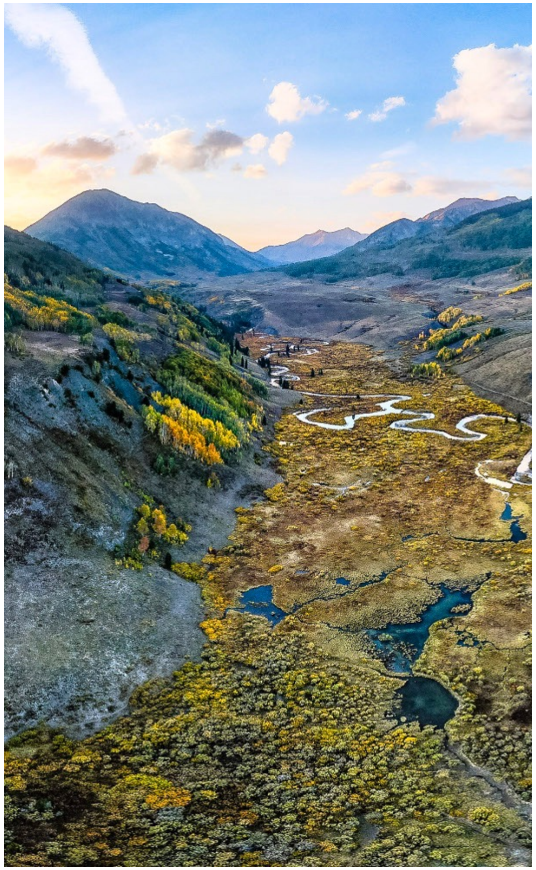
Western USA mountain SWE median values fall at-or-below the 25th percentile of historical by 2040-2065

Rhoades et al, 2018, Clim. Dyn.

Local to Regional: SAIL Campaign Overview

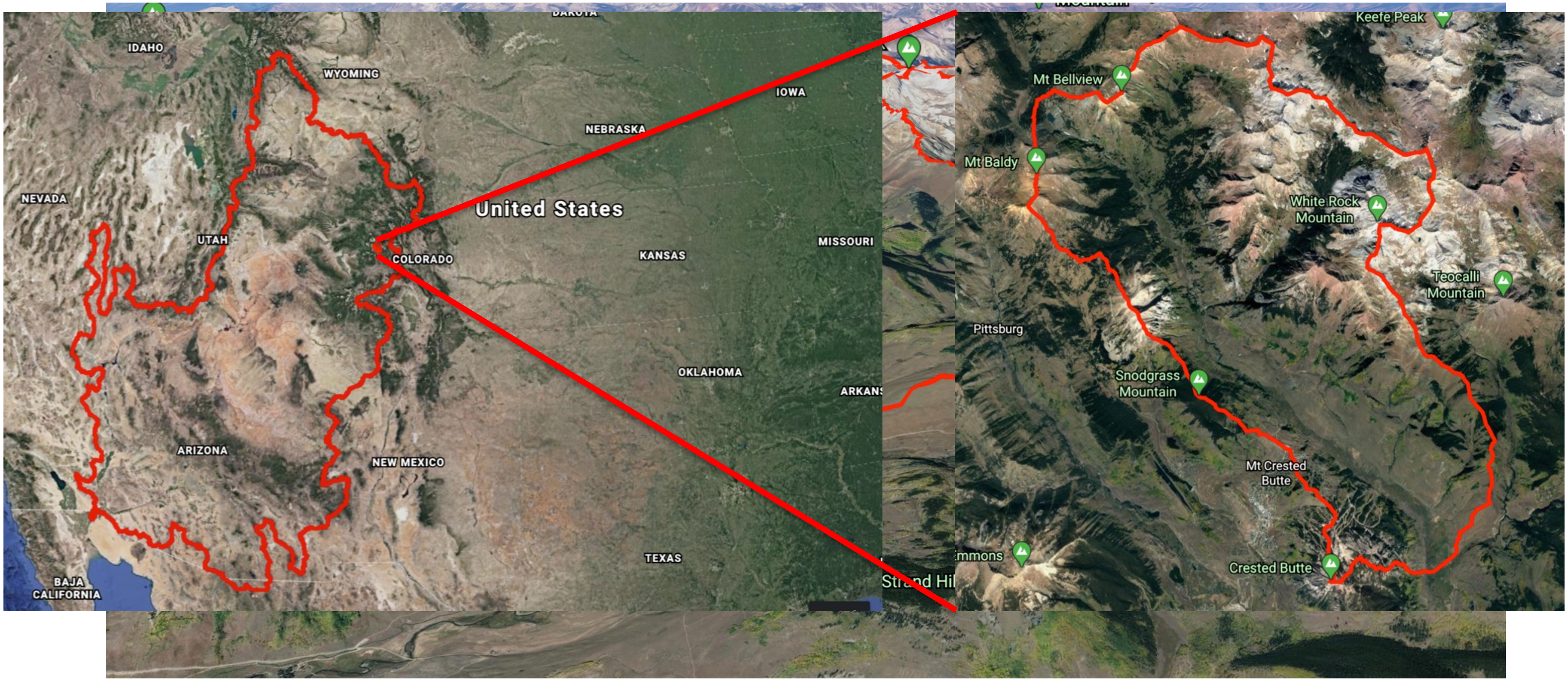
- The Surface Atmosphere Integrated Field Laboratory (SAIL) will deploy an atmospheric observatory to the Colorado Rocky Mountains from 9/21 to 6/23.

- SAIL will work with surface and subsurface researchers to measure all of the relevant physical processes related to the inputs and outputs of a single mountainous watershed.



SAIL
Surface Atmosphere Integrated Field Laboratory

Local to Regional:
SAIL Locations

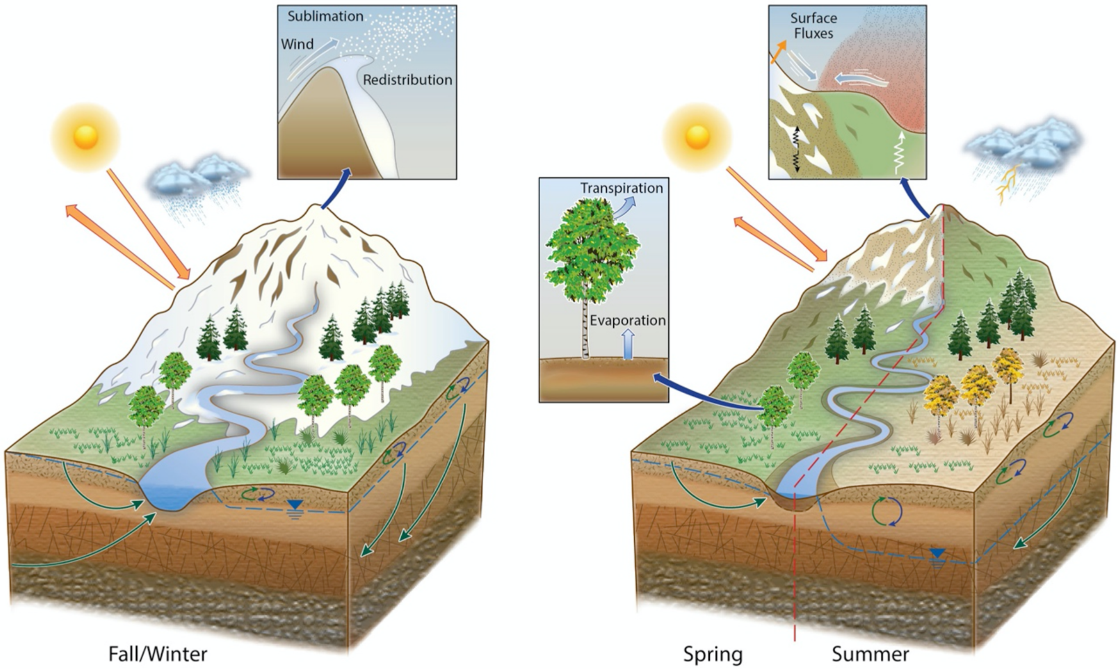


- SAIL will measure in the Upper Colorado River, sited at the 300 km^2 East River Watershed of the Upper Colorado.

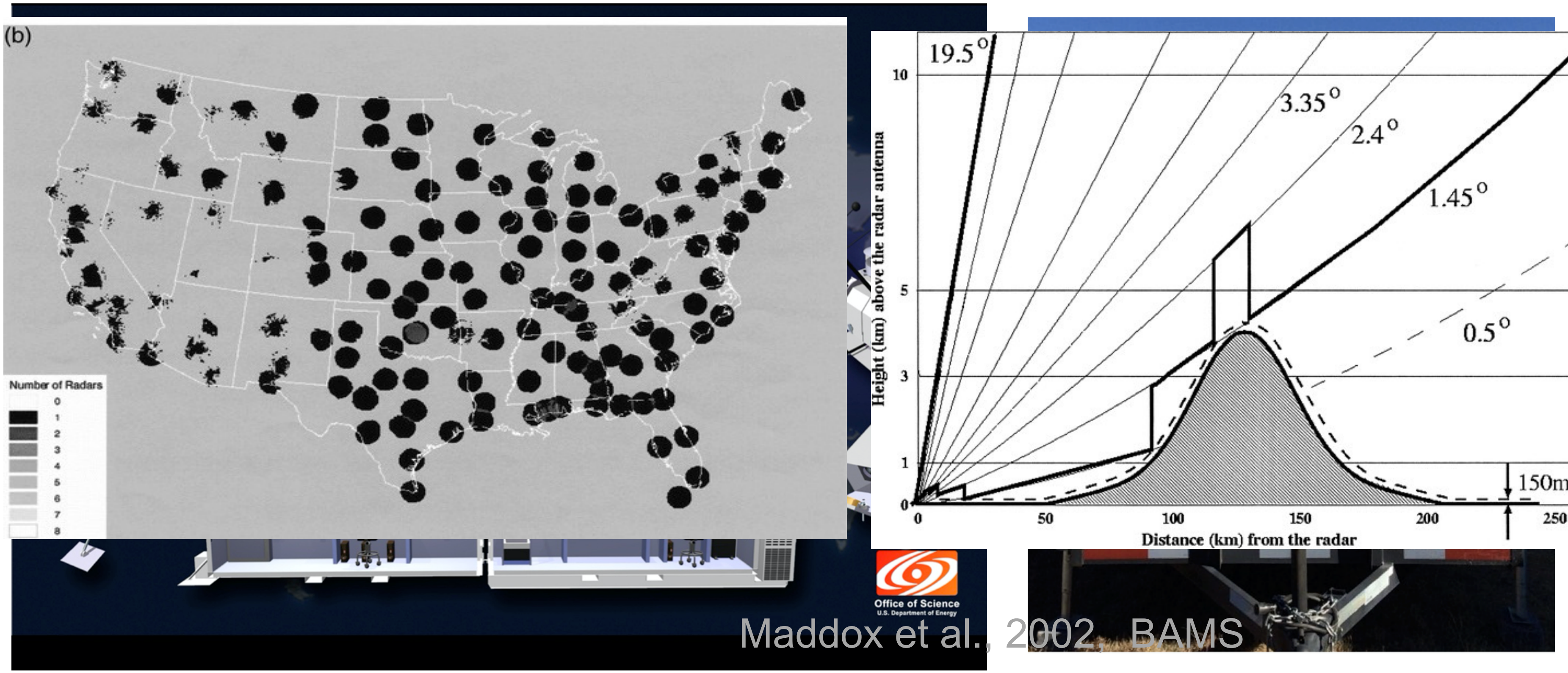
Local to Regional: SAIL Science Objectives

SAIL will focus on the seasonally-varying atmospheric processes and land-atmosphere interactions that impact Upper Colorado hydrology. These include:

- Precipitation amount and phase, and how it's occurring.
- How wind sublimates and redistributes the snowpack.
- Aerosol regimes and radiation.
- Aerosol-precipitation interactions.
- Controls on the surface energy balance.



Local to Regional: SAIL Instruments



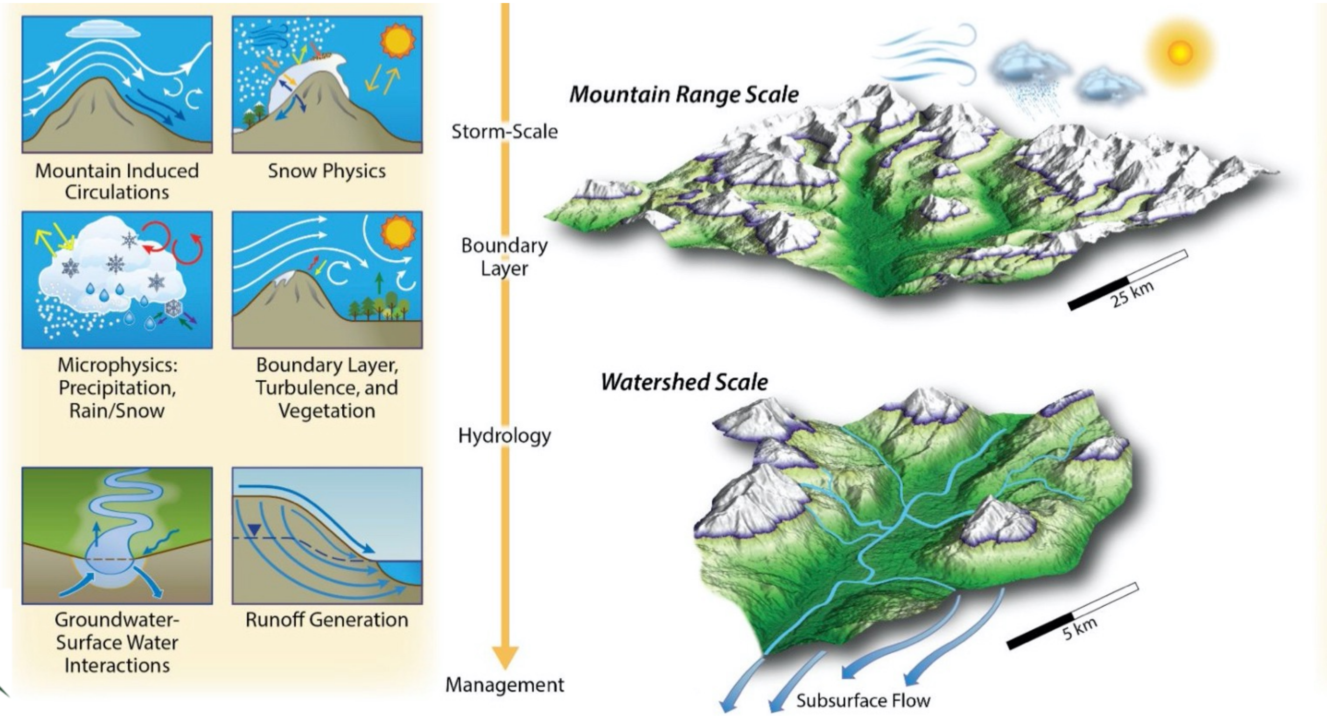
Maddox et al., 2002, BAMS

- SAIL will include ~34 instruments to measure precipitation, clouds, winds, aerosols, temperature, humidity, trace gases, and surface fluxes of water and radiation.

- Will fill major observational gaps in the Colorado Rockies

SAIL and Artificial Intelligence Algorithms

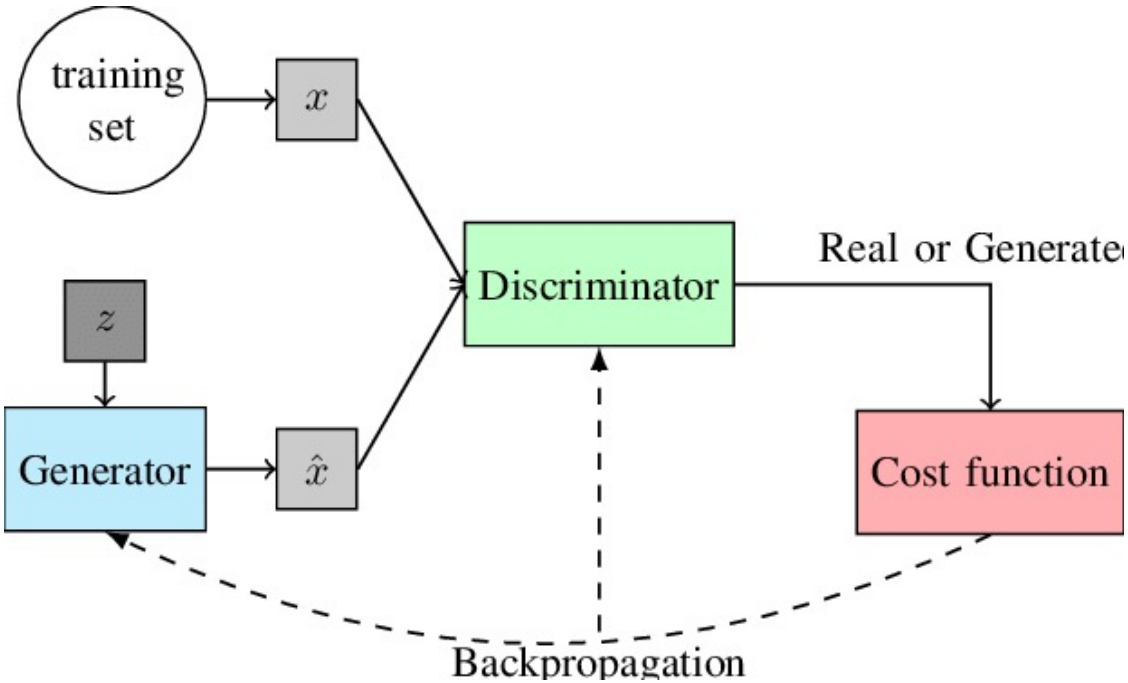
- Earth sciences is adopting AI for many applications because we understand physical processes qualitatively but it's hard to put them together in a coherent model.
- There may be opportunities to use SAIL data to test AI methods and/or to use it to advance physical modeling to advance SAIL science. Currently, there is not a good path forward for atmospheric process physical model development in the mountains due to obs gaps and multiple scales of interaction. AI can help through emulation and surrogate modeling.



Woodburn et al, In Review

AI Model Emulation

- For immature physical models, AI emulation has some useful features:
  - Extremely computationally efficient.
  - Gradients are inexpensive and easily calculated.
- We may can use AI emulation to understand our physical models and their errors.
- We will focus here on Generative Adversarial Networks (GANs) since they generally prevent overtraining and can be physics-constrained.

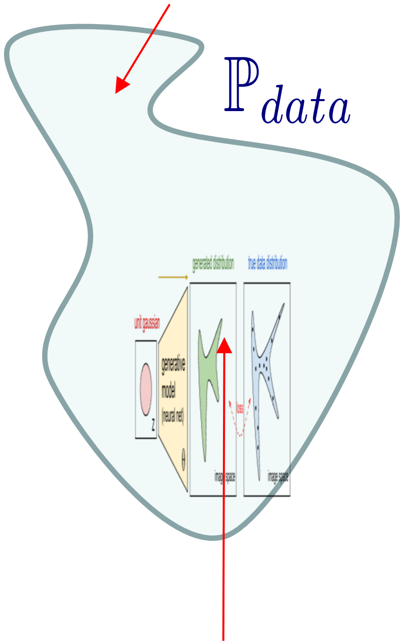


Ponti et al, 2017, 10.1109/SIBGRAPI-T.2017.12

Physics-Constrained GANs

- GANs can also include physics constraints (e.g., non-negative precipitation).
- Physics constraints are achieved via a simple regularization of the optimization loss function.

data distribution



physically-consistent region

Standard GAN:

Loss function: $L(D,G) = \mathbb{E}_{x \sim p_{\text{data}}}[\log D(x)] + \mathbb{E}_z[\log(1 - D(G(z)))]$

Optimization: $\min\limits_{G} \max\limits_{D} L(D,G)$

Physics-informed GAN:

Loss function: $L_{\text{PI}}(D,G) = L(D,G) + \alpha C_{\text{phys}} + \beta C_{\text{stats}}$

Physical constraint: $C_{\text{phys}} = \mathcal{F}(G)$

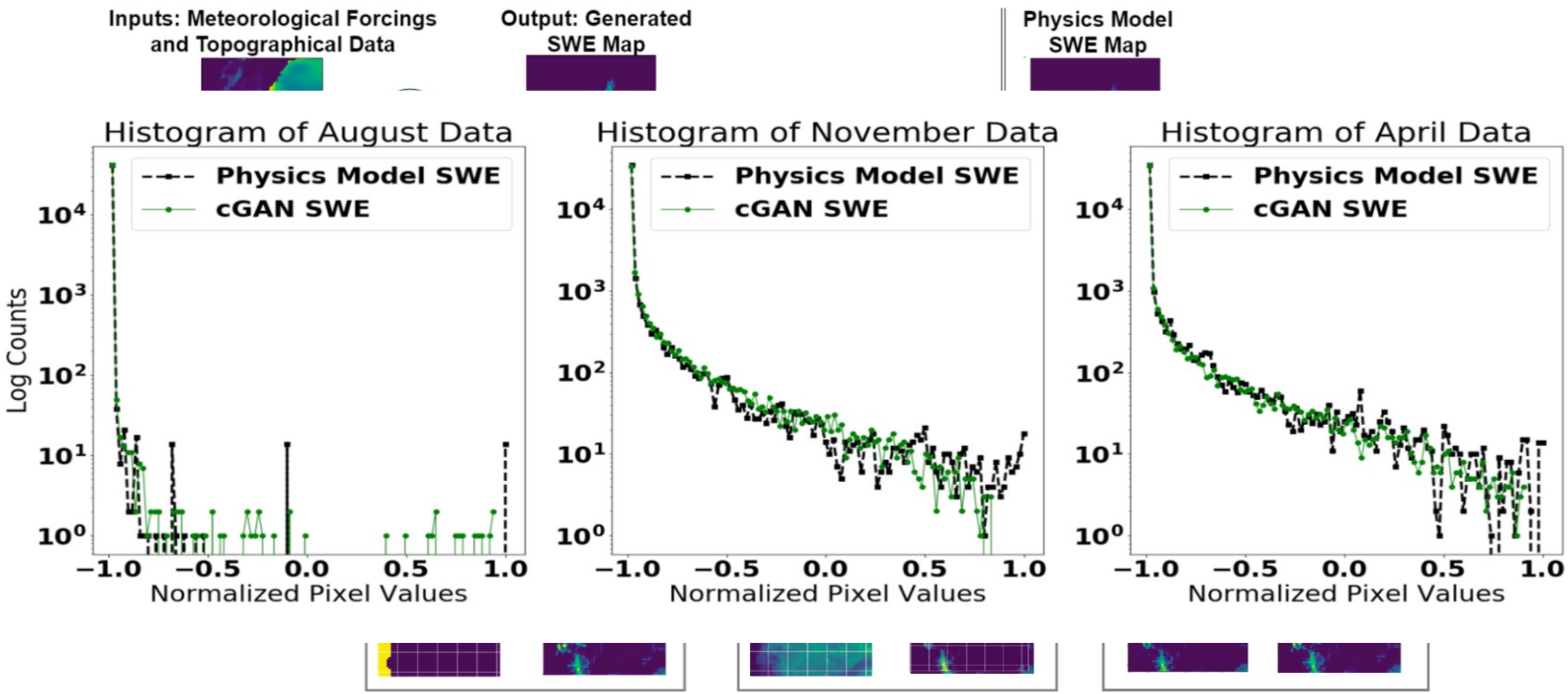
Statistical constraint: $C_{\text{stats}} = d(\boldsymbol{\Sigma}(p_{\text{data}}), \boldsymbol{\Sigma}(p_{G(z)}))$

Optimization: $\min\limits_{G} \max\limits_{D} L_{\text{PI}}(D,G)$

HydroClimate GAN

- We train a GAN based on historical reanalysis products over California including precipitation, temperature, radiation, winds to emulate the most important hydrological variable in the west: snowpack snow-water equivalent.

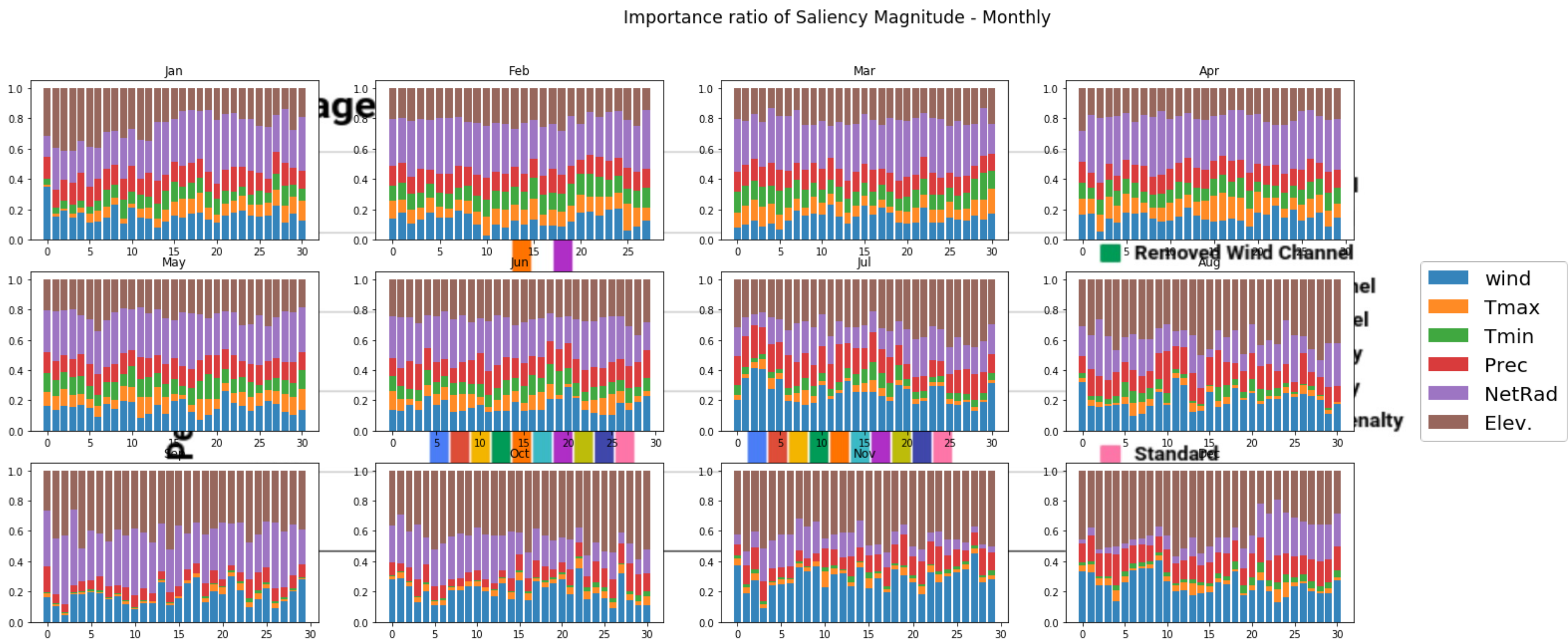
- The emulation can capture SWE behavior across multiple time and space scales (including 0's!).



Manepalli et al, 2019, Climate Informatics

Hydroclimate GAN Emulation Utility

- Using gradients, saliency mapping we evaluate the relative importance of atmospheric forcings to the skill of the output model for projecting SWE.
- We uncover the relative importance of input variables to GAN output across seasons.
  - Suggests different processes that shape SWE.
  - Helps prioritize process studies.



Manepalli et al, 2019, Climate Informatics

Summary of Local SAIL+AI

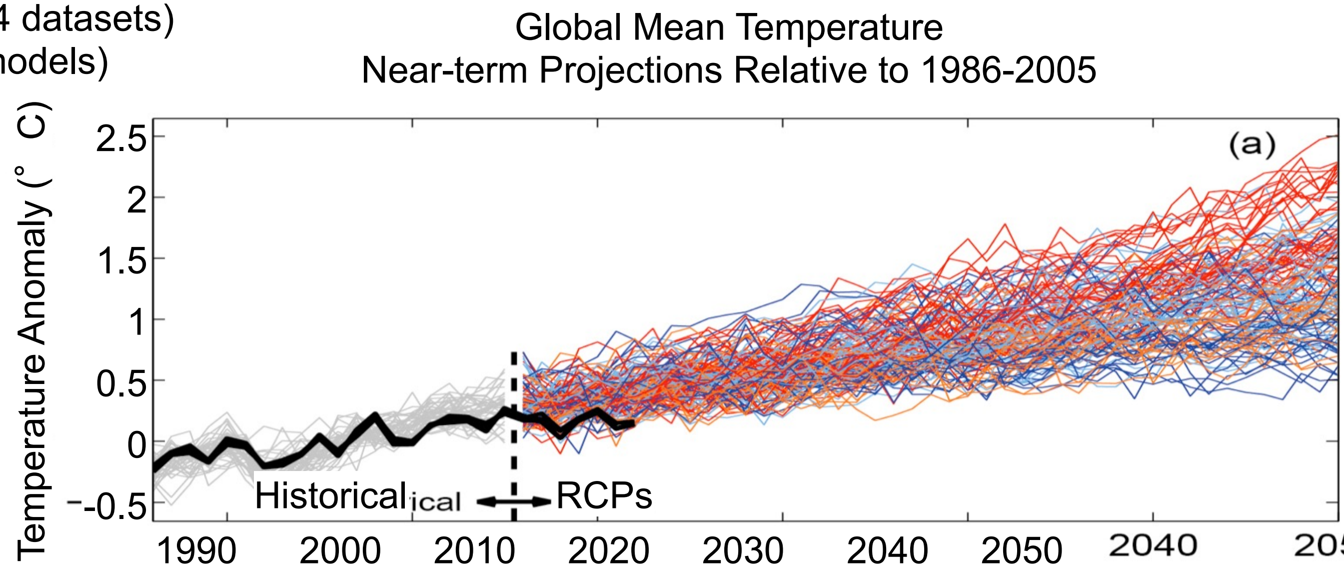
- **The SAIL campaign will be collecting many disparate datasets related to mountainous hydrology.**

- **Fundamentally, many processes that drive hydrology are under-resolved by observations and physics models.**
  - **AI methods can serve as a tool and a guide for SAIL science.**
  - **Caution must always be exercised: the burden of proof is on the AI user!**

- **SAIL can test AI methods and AI methods can advance SAIL science.**
  - **Rapid process-model emulation to prioritize process studies.**
  - **Atmospheric process model challenges suggest surrogate models may be appropriate.**

- **Learn more at https://sail.lbl.gov or let's chat (drfeldman@lbl.gov)!**

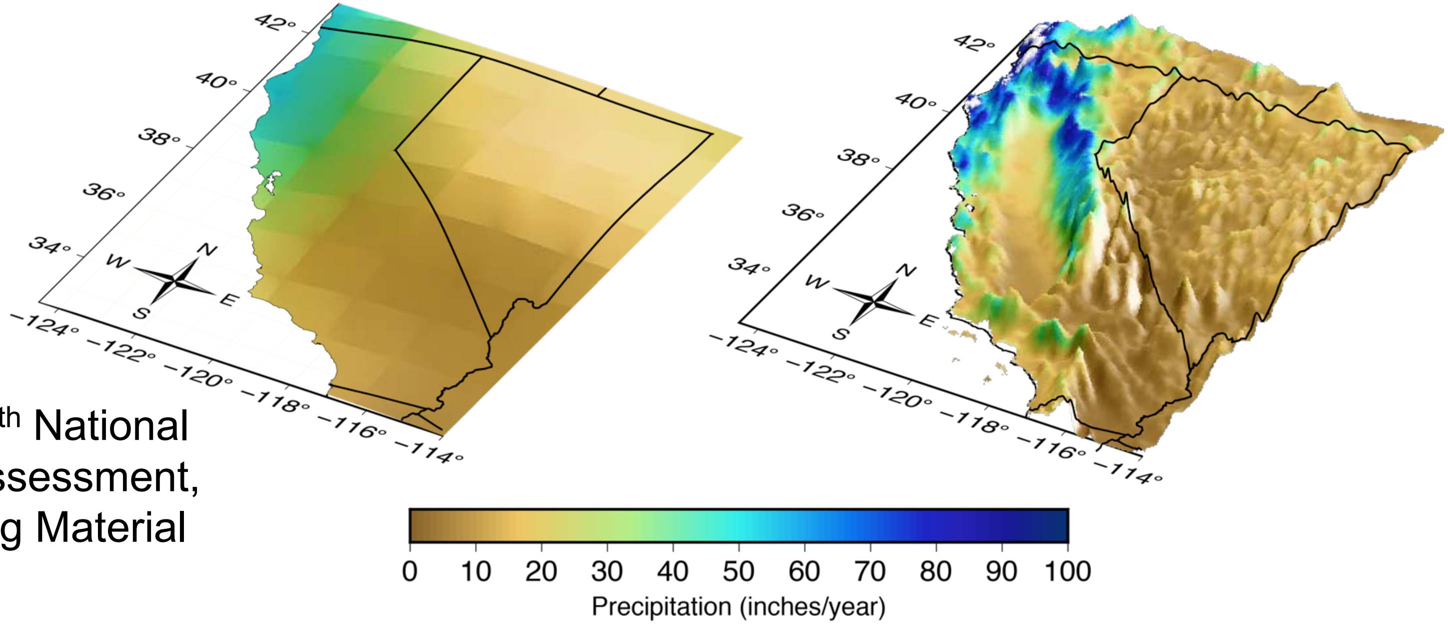
Local to National: Translating Climate Models Projections



Source: IPCC Fifth Assessment Report, WG1, Figure 11.25a
Note: RCPs = Representative Concentration Pathways

- **Climate models are parameterized, physics-based tools for projecting change.**
- **The Coupled Model Intercomparison Project (CMIP) is an international effort to examine climate model spread.**
  - **Model projections can differ significantly from each other.**

Local to National: Need for Downscaling

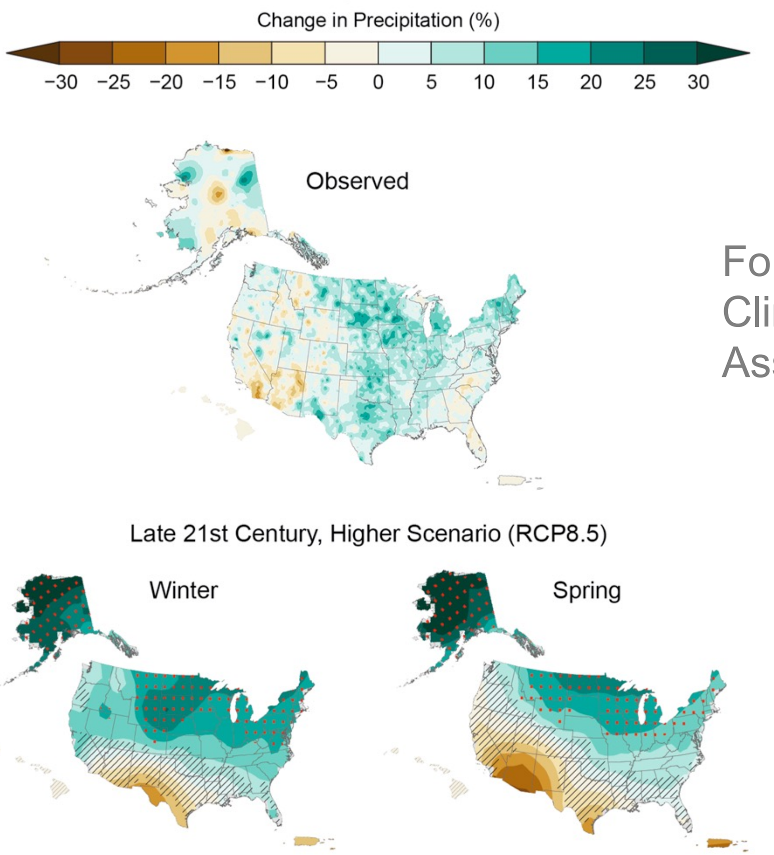


Source: 4th National Climate Assessment, Supporting Material

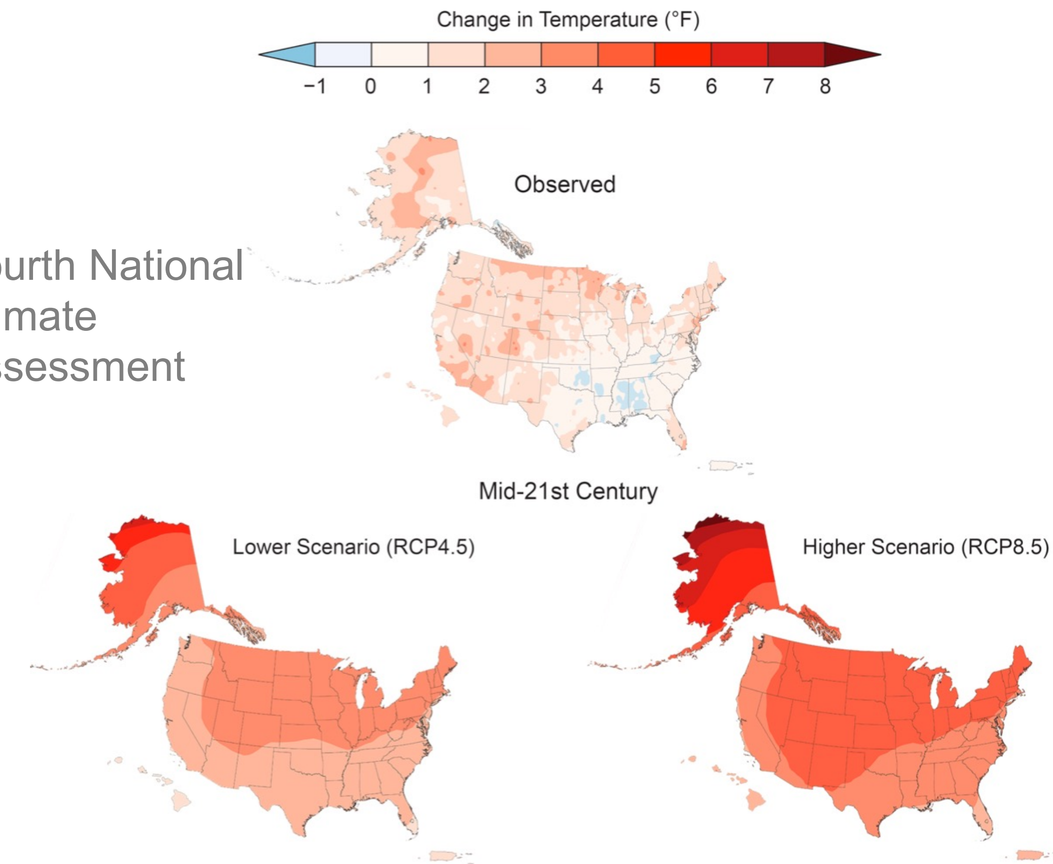
- **Climate models capture large-scale effects but are blunt instruments for developing local projections.**
- **They are too coarse (~100 km) for regional and local-level infrastructure and operations planning, so downscaling techniques are needed.**
- **Statistical methods are based on historical patterns between coarse and fine scale.**
- **Dynamical methods are based on running a high-res model forced by a climate model.**

Local Projections Needed!

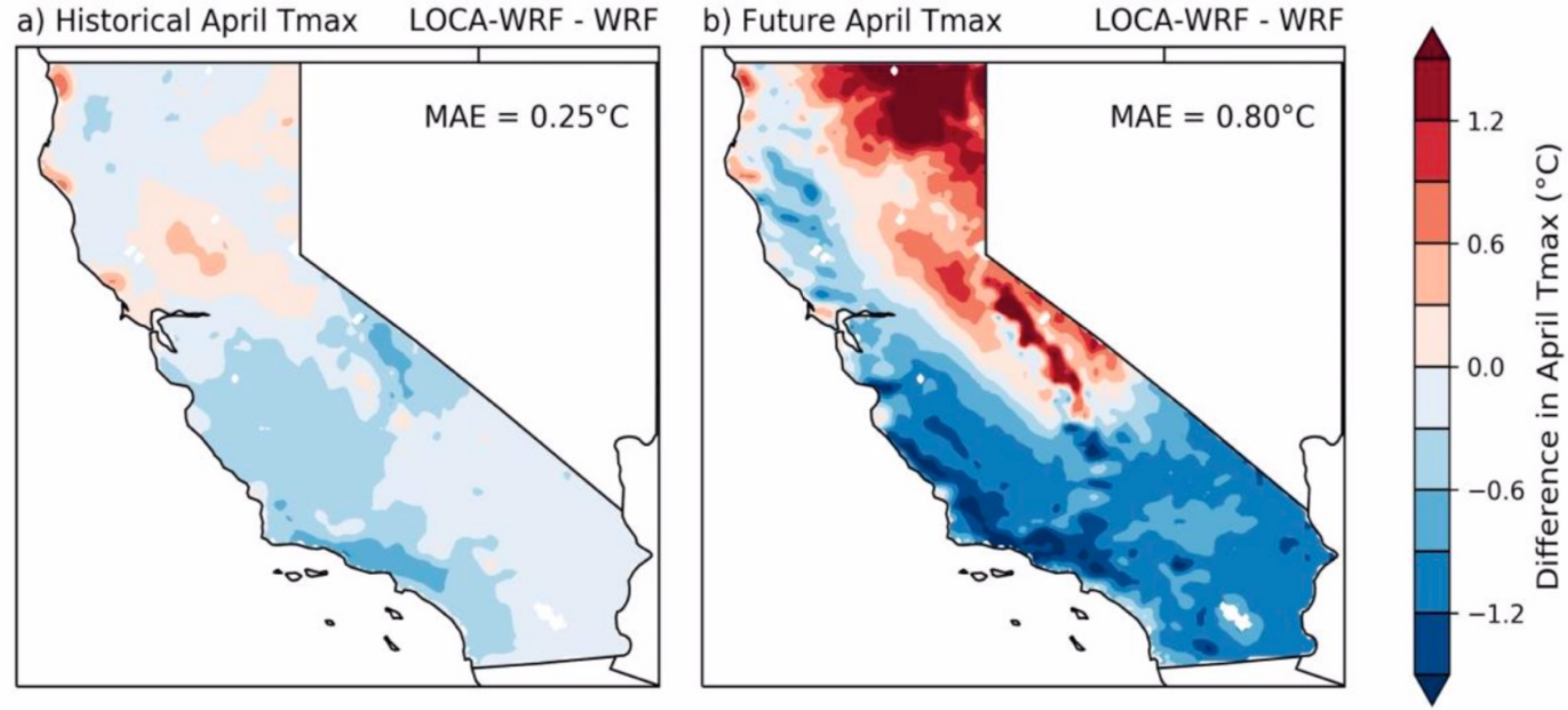
CMIP6 is producing results. Local, state, and national agencies need numbers! National Climate Assessments used downscaled solutions for recommendations.



Fourth National Climate Assessment



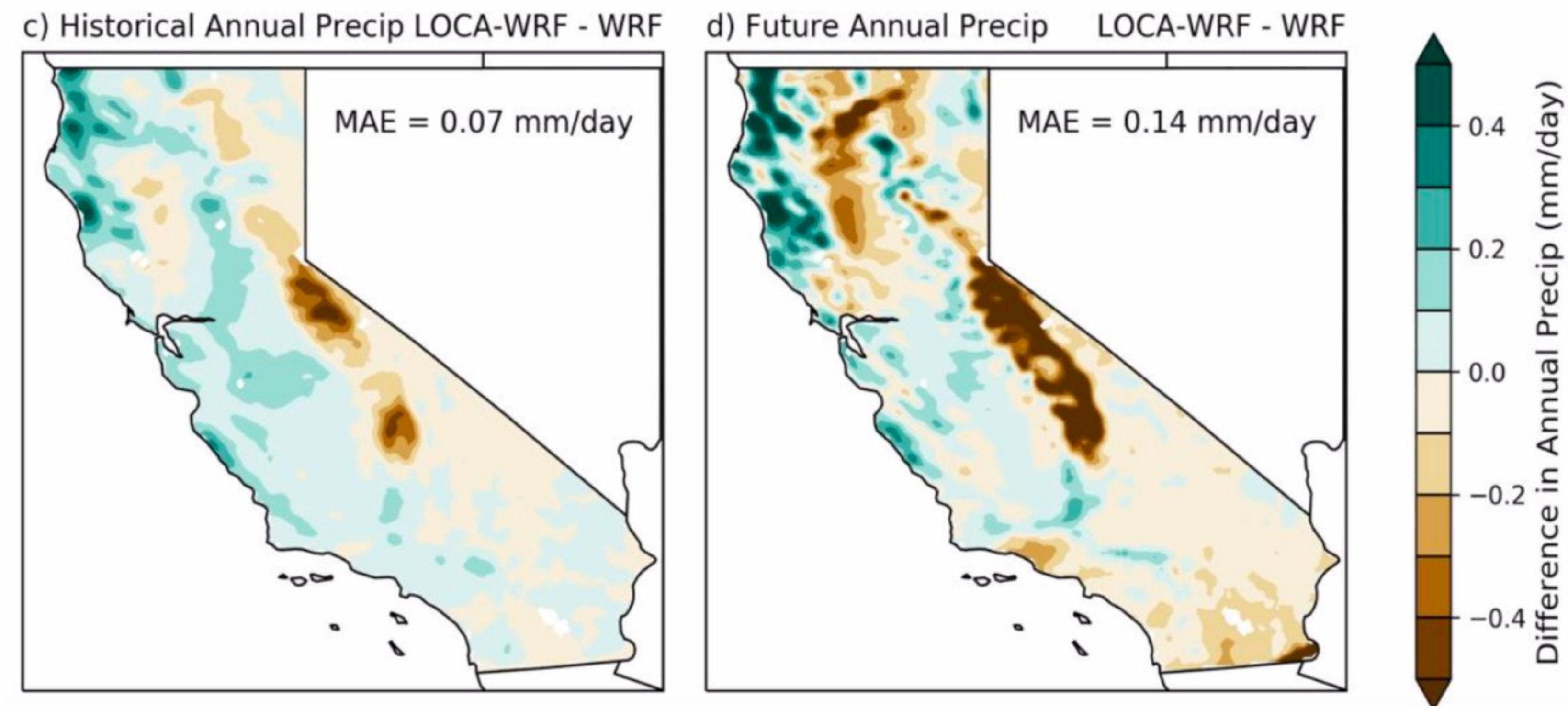
Non-Stationarity in T Downscaling Solutions



Fourth National Climate Assessment

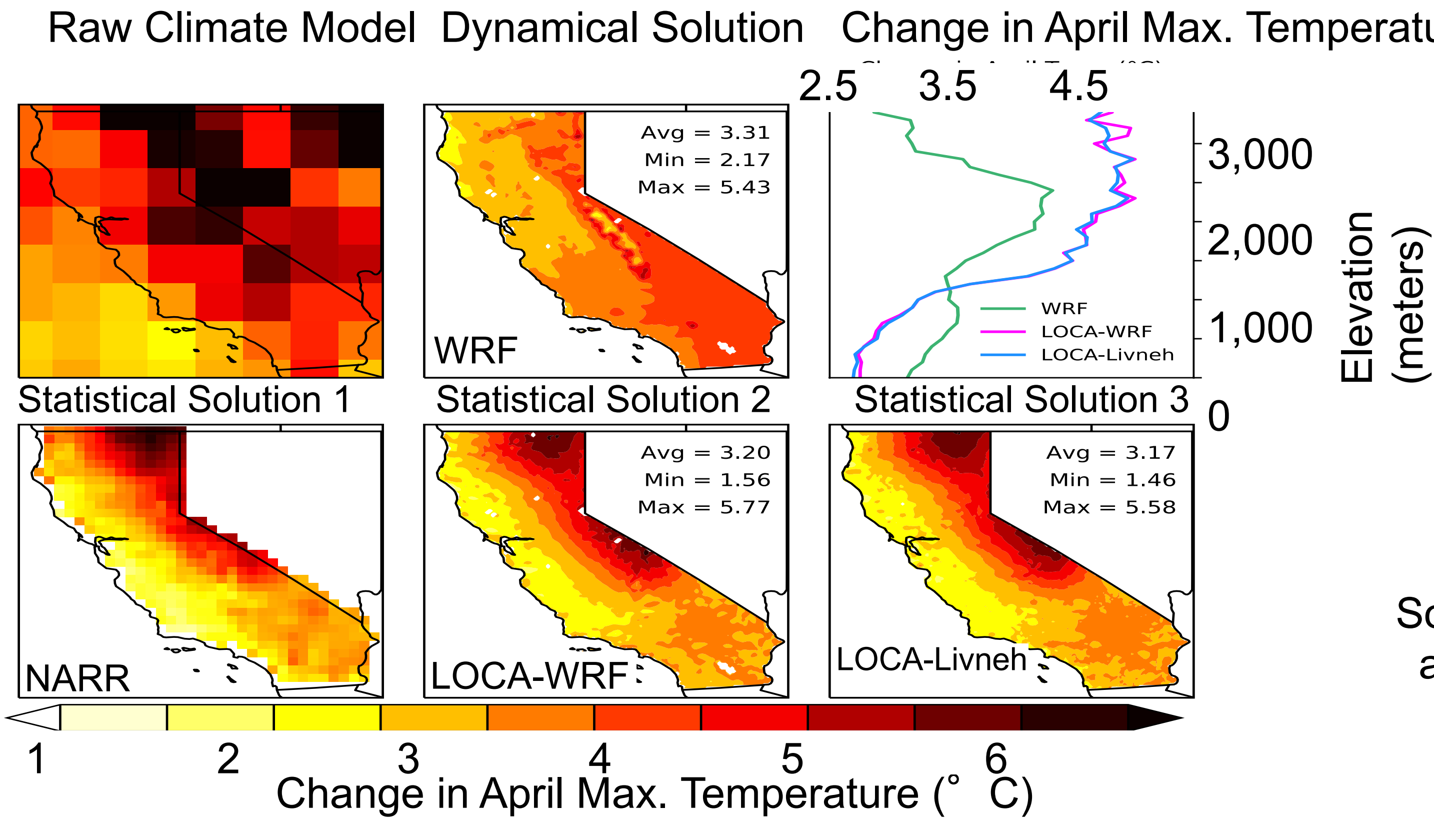
- **But what is/are the best approaches to downscaling? The divergence in modeled downscaling solutions between historical and future scenarios is a red-flag.**
- **Past performance can be a poor predictor of the future because processes leading to nonstationarity may be arise in the future and just not be significant to date..**
- **Temperature projection errors triple over CA from historical to end-of-century.**

Non-Stationarity in Pr Downscaling Solutions



- **But what is/are the best approaches to downscaling? The divergence in modeled downscaling solutions between historical and future scenarios is a red-flag.**
- **Past performance can be a poor predictor of the future because processes leading to nonstationarity may be important.**
- **Precipitation errors double over CA from historical to end-of-century.**

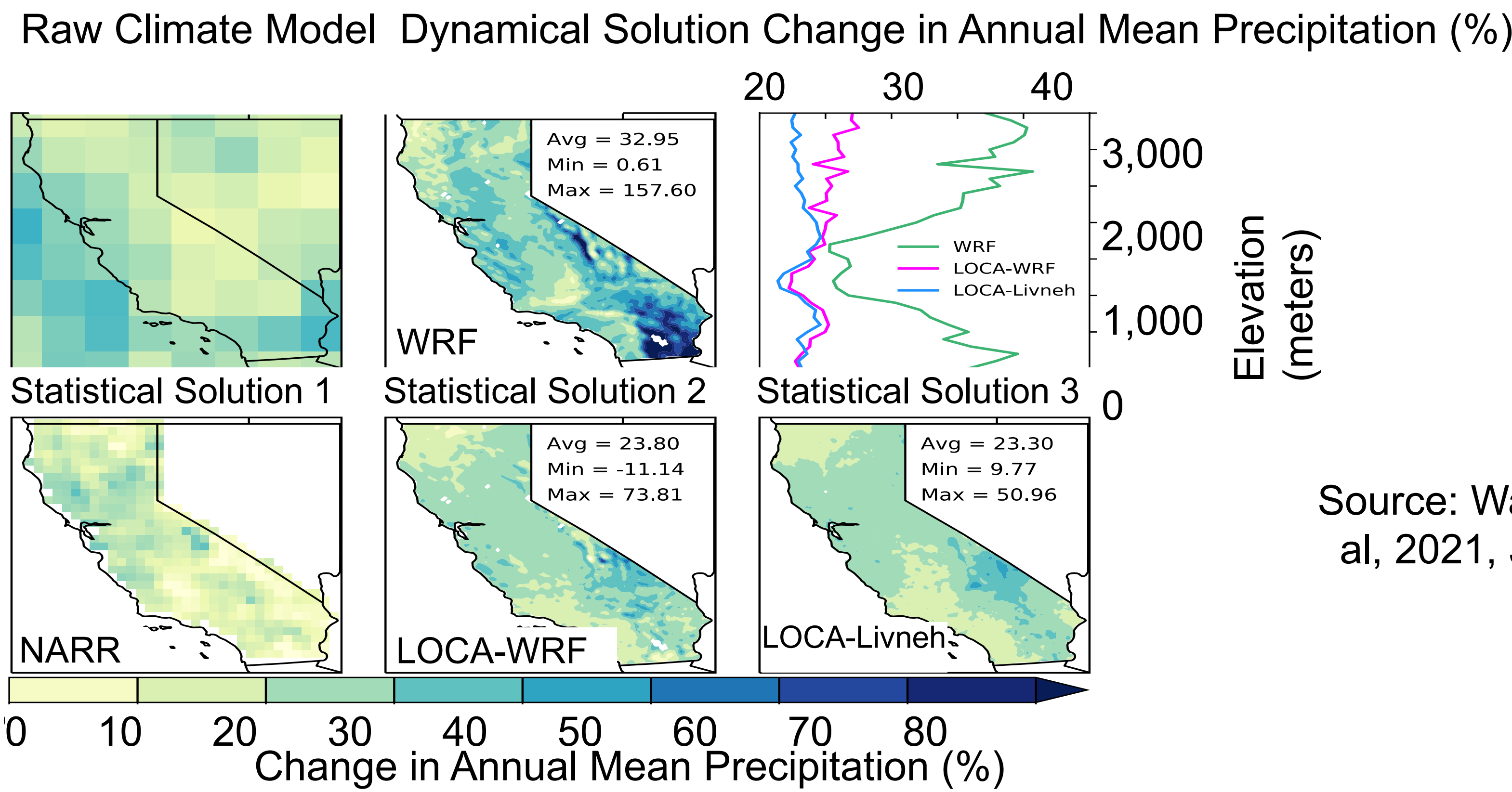
Why do we see this divergence? Cause(s) of T Nonstationarity.



Source: Walton et al, 2021, JAMC

- **A closer look reveals systematic differences between dynamical downscaling and various statistical downscaling solutions.**
- **In this case, only the dynamical solution (WRF) captures key changes that are without historical analog (for T, the disappearance of snow leads to much warmer mountains that historical patterns do not capture) and lead to nonstationarity.**

Why do we see this divergence? Cause(s) of Pr Nonstationarity.



Source: Walton et al, 2021, JAMC

- **A closer look reveals systematic differences between dynamical downscaling and various statistical downscaling solutions.**
- **In this case, only the dynamical solution (WRF) captures key changes that are without historical analog (for Pr, possible changes in atmospheric rivers and gulf moisture surges are not contained in the historical record) and lead to nonstationarity.**

Dynamical Solution Challenges

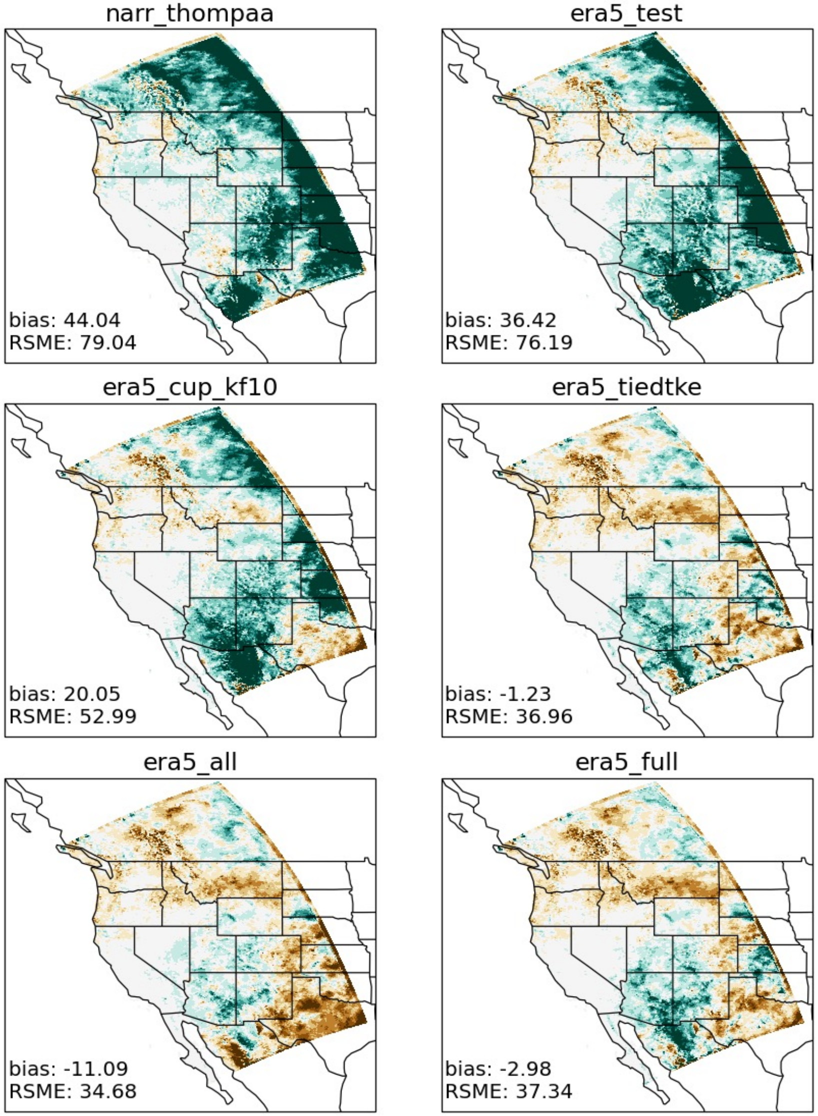
WRF model downscaling is highly sensitive to model configuration!

NARR vs ERA5 forcing

Cumulus parameterizations and nudging

Rain/snow partitioning and radiative transfer in LSM

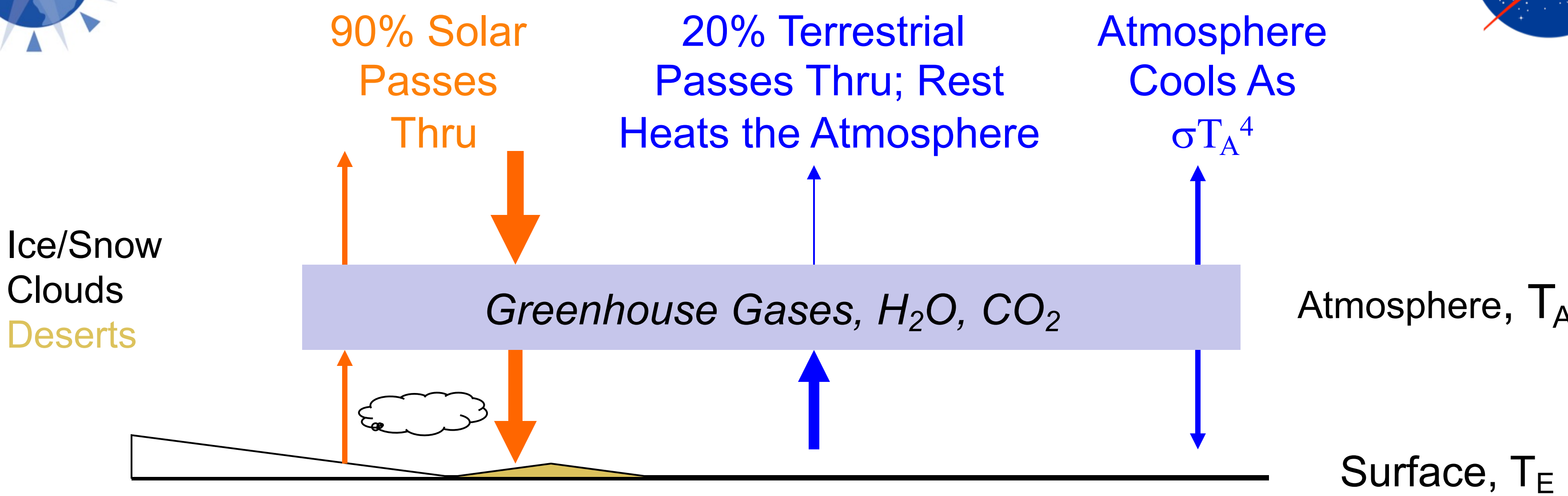
June-July-August Precipitation



Summary of Downscaling Project and Needs

- **Climate models are blunt instruments. Decision-makers and scientists need pinpointed projections.**
- **Downscaling provides numbers for these groups.**
- **AI methods are likely needed to accelerate dynamical downscaling and identify model sensitivities and explore when/where statistical methods fall down.**
  - **Rapid process-model emulation to prioritize process studies.**
- **Learn more at https://downscaling.lbl.gov or let's chat (drfeldman@lbl.gov)!**

AI for Earth's Energy Balance: 1-D Model

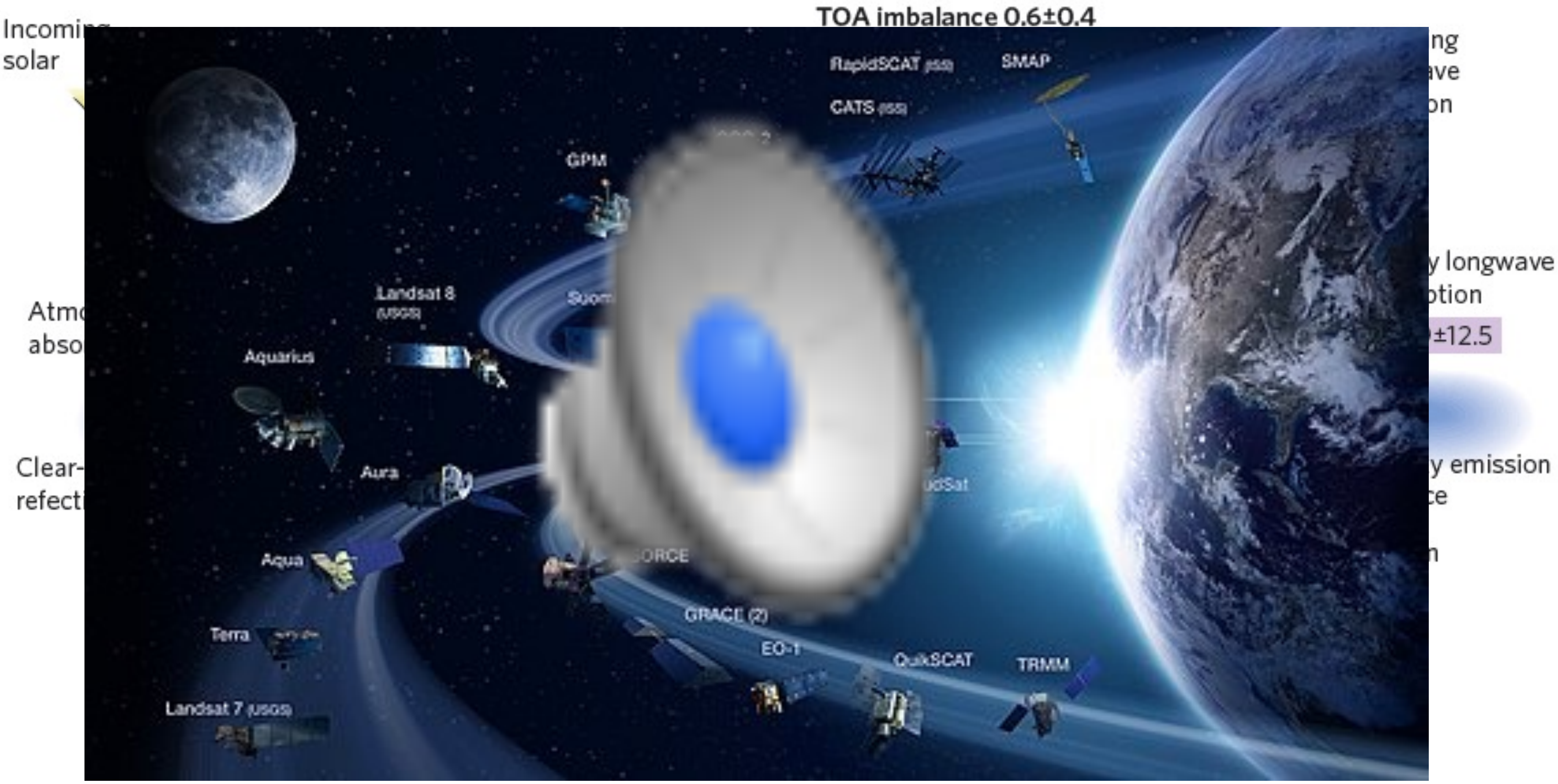


Now, We Balance Energy (i.e. ↑ & ↓)
at the Top of the Atmosphere and at the
Surface - *2 Equations & 2 Unknowns*.
Lets Spare the Details…..

Now Solve For T => 286 K = 13 C ~ 55 F
This is pretty close! Actual Tavg ~ 288 K

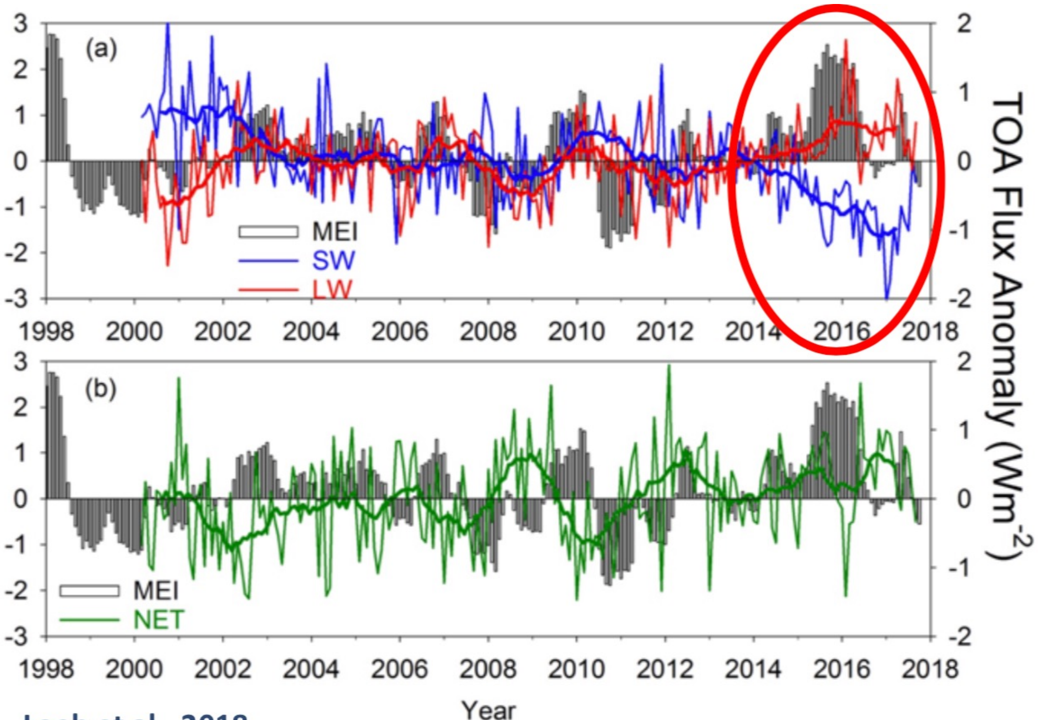
Unfortunately, some of the numbers that go into this model are poorly understood

AI for Earth's Energy Balance: Actual Shortwave and Longwave Energy Flows

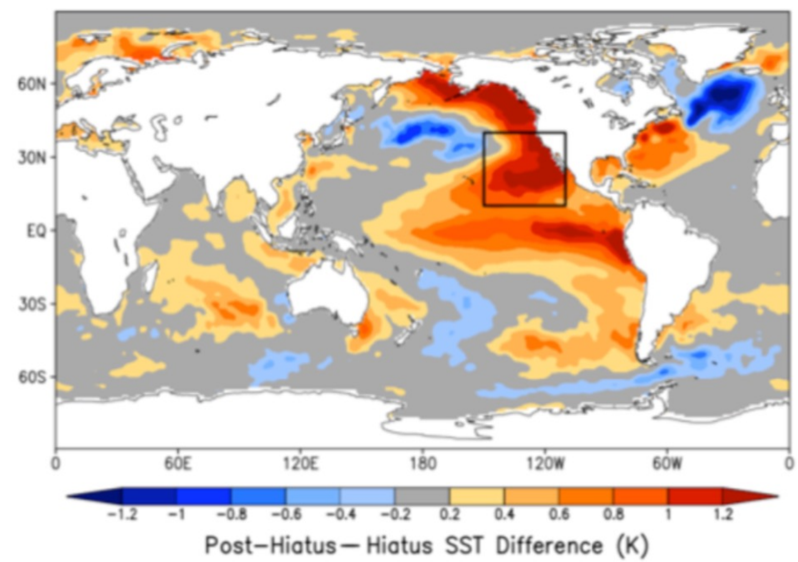


We use remote sensing to measure the components of the Earth's energy budget. They show large inflows and outflows that nearly perfectly balance each other out.

AI for Earth's Energy Balance: A Mysterious Balancing Act



Loeb et al., 2018

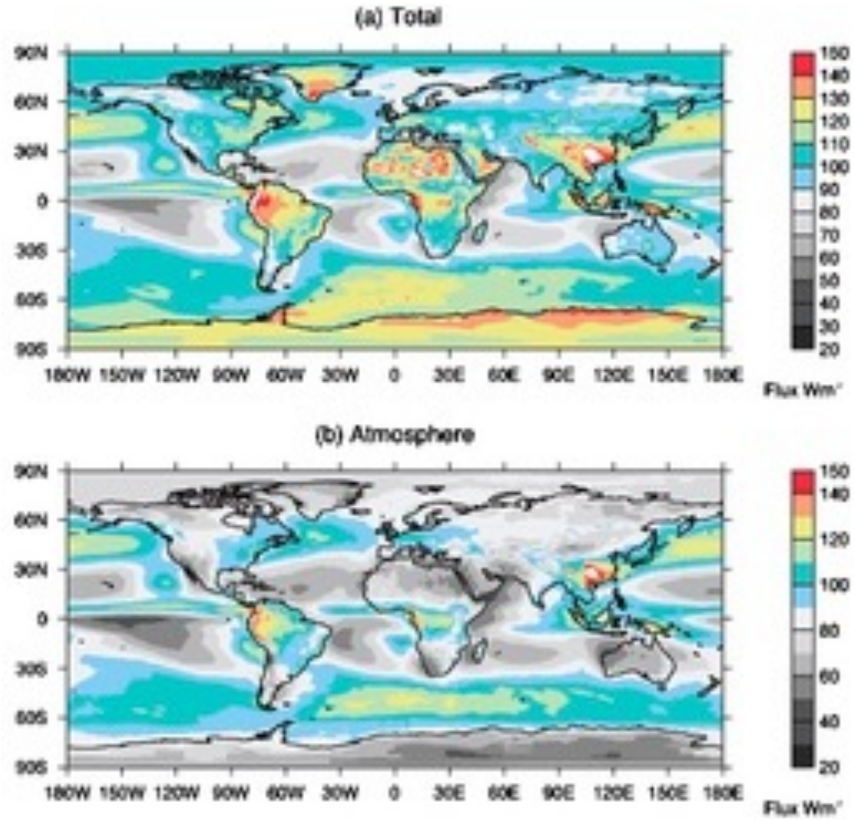


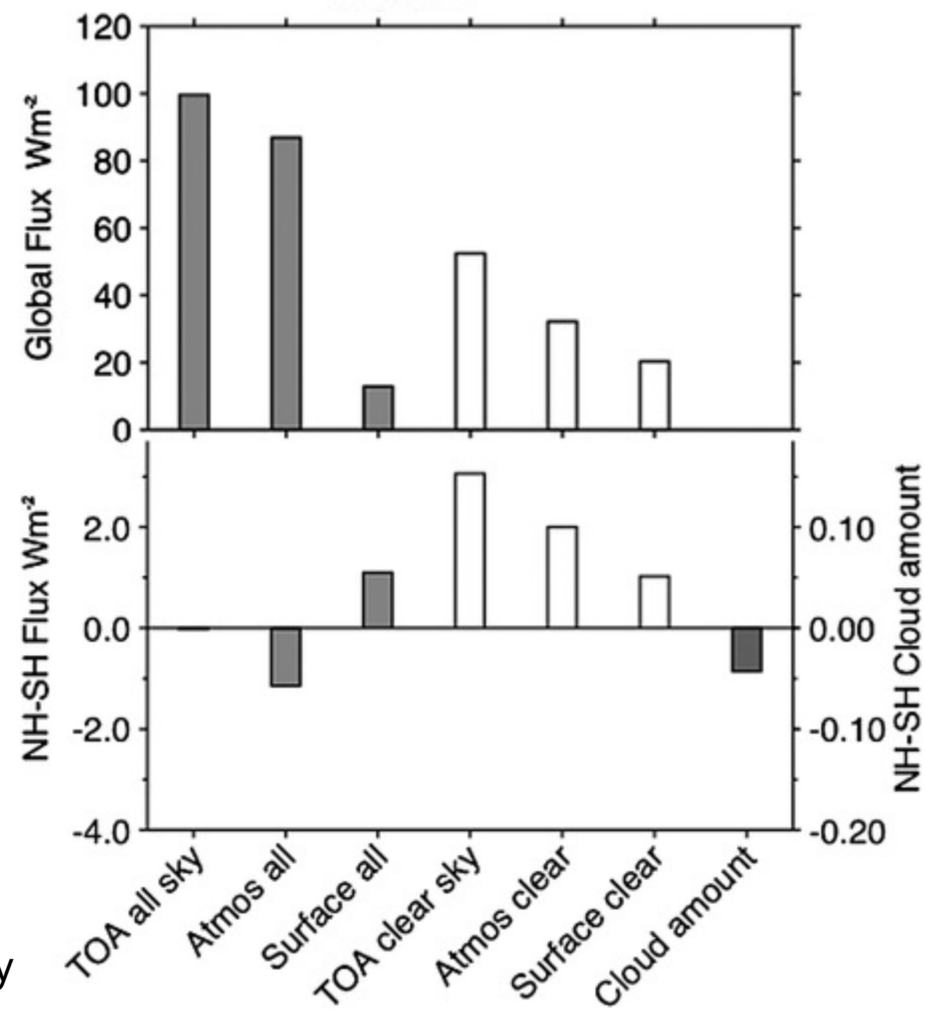
Loeb et al., 2020

Over the annual time-scales, observations show that SW and LW balance each other out even though there is large spatial and temporal variability in each term.

Clouds dominate the variability and losses in one area appear to be compensated by other areas.

AI for Earth's Energy Balance: A Mysterious Balancing Act, Part 2



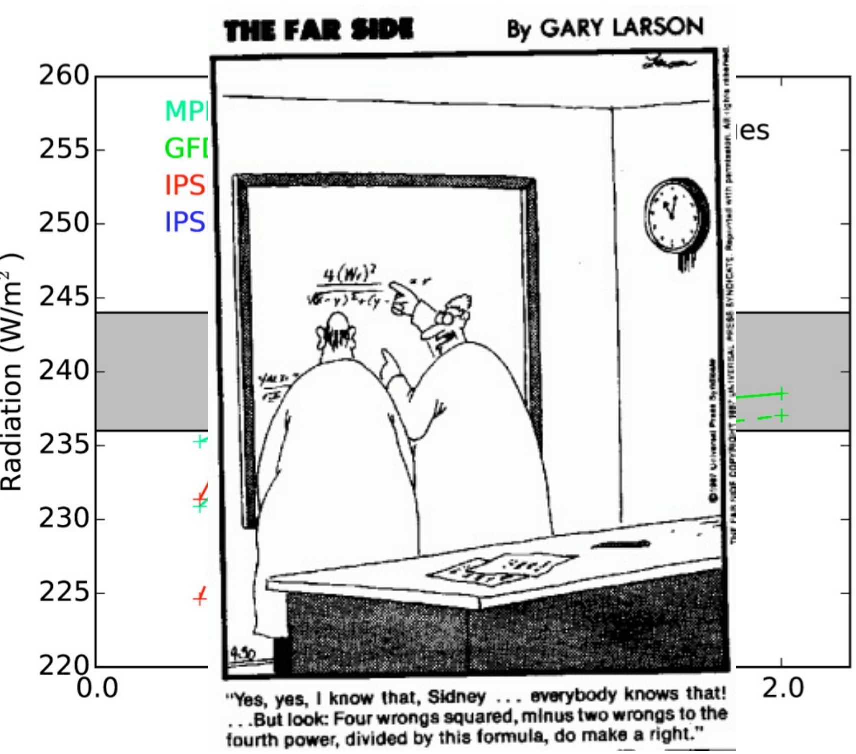


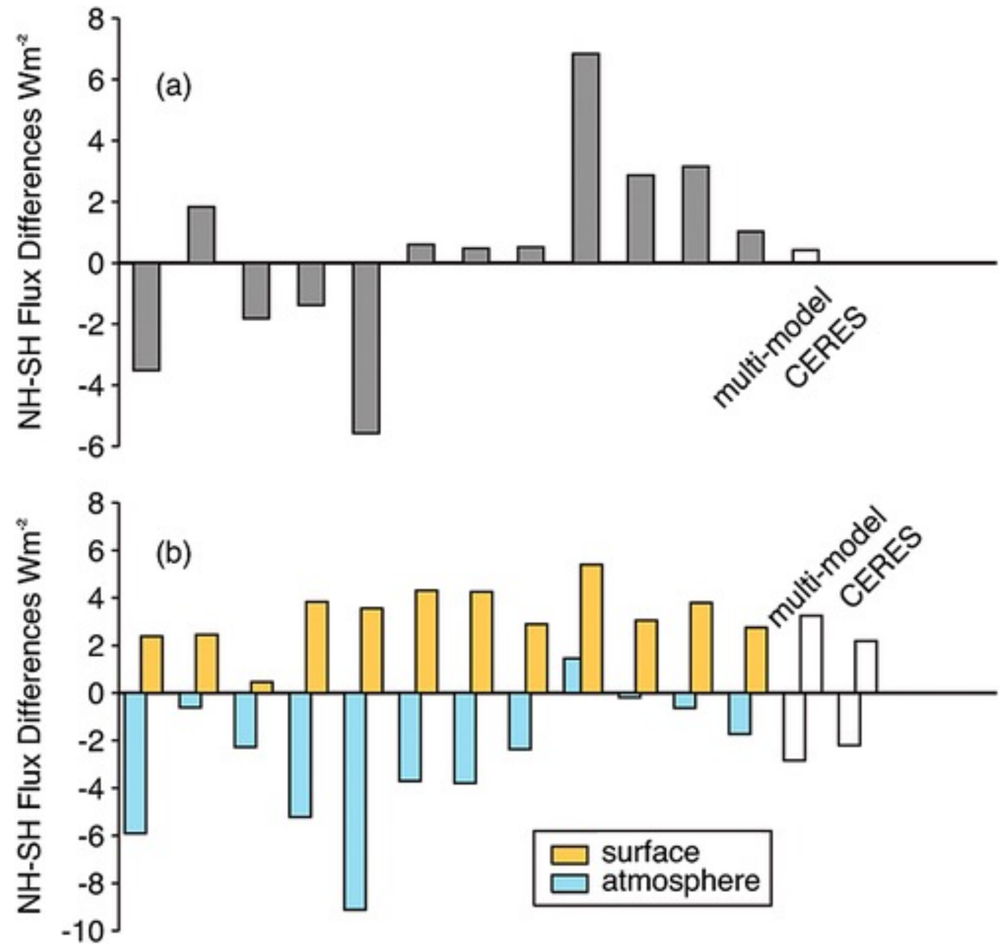
- A closer look leads to even more mysterious phenomena.
- SW atmospheric reflection is almost perfectly balanced between NH and SH.

AI for Earth's Energy Balance: Climate Models are Not Appropriate Tools

Climate models contain many different components that fit together awkwardly.

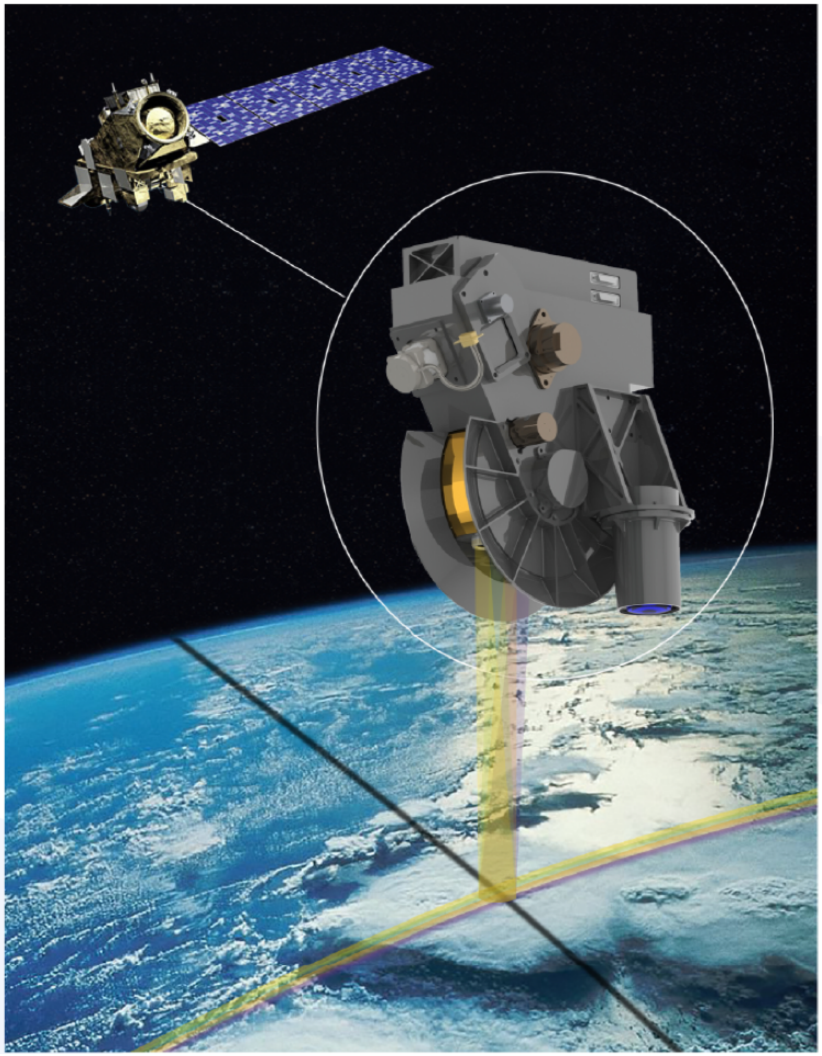
Tuning/calibration is used to fit the components together. SW and LW energy budgets are a constraint for tuning.





How can AI be used for Earth's Energy Balance

- We have terabytes of data on the Earth's radiation budget and the specific contributions of the surface and atmosphere to albedo stability.
- We do not have a theory to make sense of all of those measurements … the problem is just too big!
- Perhaps AI can help guide theory development.
- AI may uncover both the obvious and subtle relationships, particularly teleconnections, that have lead to the large-scale organization of cloud systems to stabilize Earth's albedo.
- AI can also explore if there are changes in those relationships that would portend a destabilization of albedo.
- NASA Libera can test these models! See https://lasp.colorado.edu/home/libera/



Presentation Wrap-Up

- I've presented three projects that I'm working on where AI could be extraordinarily helpful.
  - Understanding/predicting water resources in the Upper Colorado River with the SAIL field campaign.
  - Uncovering the source(s) of error in downscaling approaches to produce localized climate forecasts across the Conterminous United States.
  - Exploring the mysteries of why/how our Earth balance's its energy budget and whether that will change in the future.

- I'm a traditional observationalist and modeler who recognizes that the traditional approaches that have not borne scientific fruit after decades of sustained study are stuck, and am hopeful that the ability to rapidly evaluate data relationships that AI enables can unstick them.

Reach me at:
drfeldman@lbl.gov

Also, you can schedule a meeting with Sara Hefty:
shefty@lbl.gov