NSF | NCAR
OPERATED BY UCAR

CGD Laboratory

FEBRUARY 12, 2026

Emulating Water Isotopes in Coupled Earth System Models

Overview & Preliminary Results of an NSF-CAIG Project

Feng Zhu (fengzhu@ucar.edu)
Scientist III; NSF NCAR

Jiang Zhu (NSF NCAR), Dan Amrhein (NSF NCAR), Yiqun Xie (UMD), Xiaowei Jia (UPitt), Zhili Li (UMD), Ruicheng Wang (UMD), Chonghao Qiu (UPitt)

This material is based upon work supported by the NSF National Center for Atmospheric Research, a major facility sponsored by the U.S. National Science Foundation and managed by the University Corporation for Atmospheric Research. Any opinions, findings and conclusions or recommendations expressed in this material do not necessarily reflect the views of NSF.

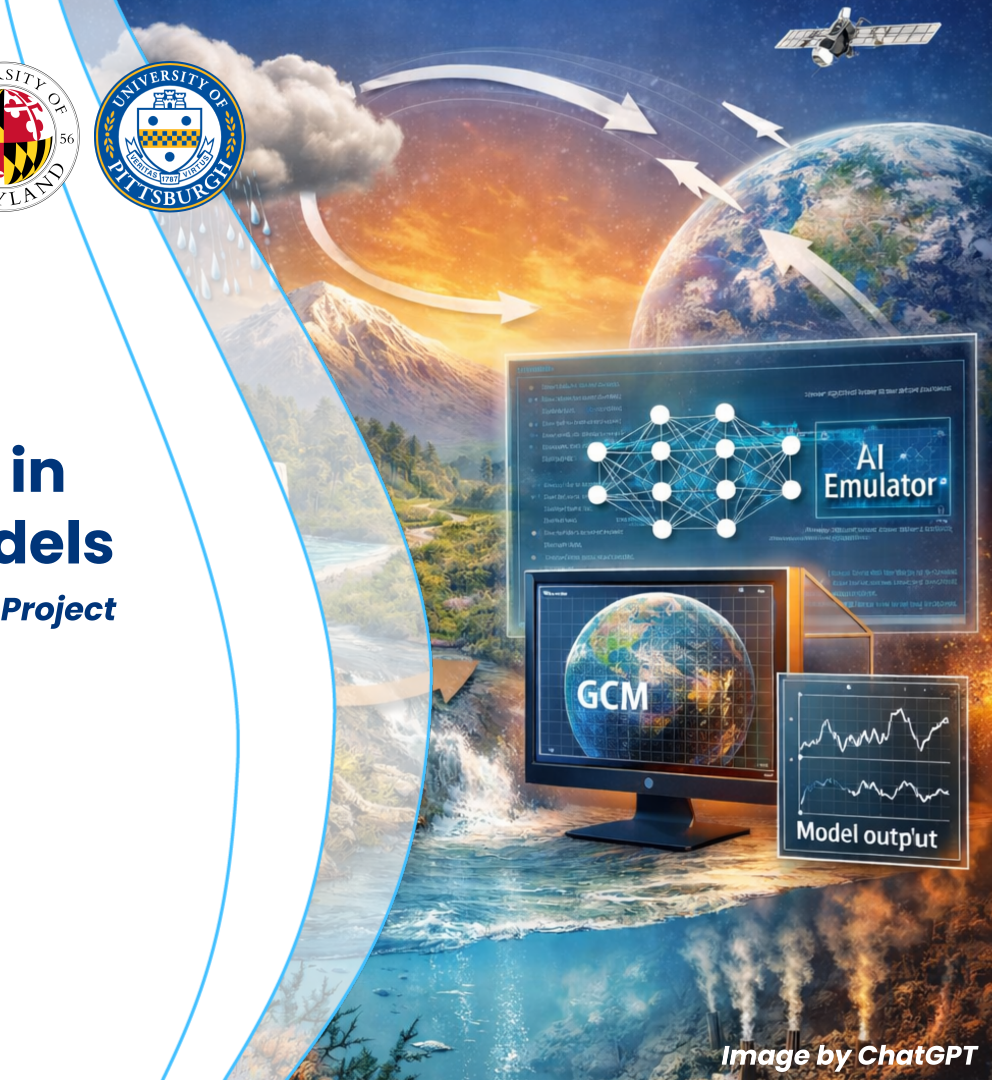


Image by ChatGPT

Motivation

Water isotopes are key tracers of hydrological processes in the Earth system.

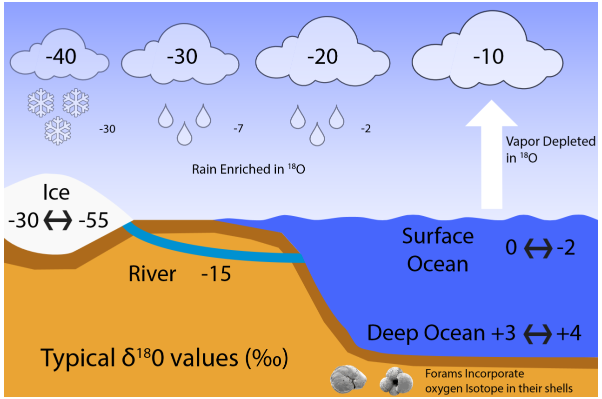


Image Credit: Andreas Schmittner

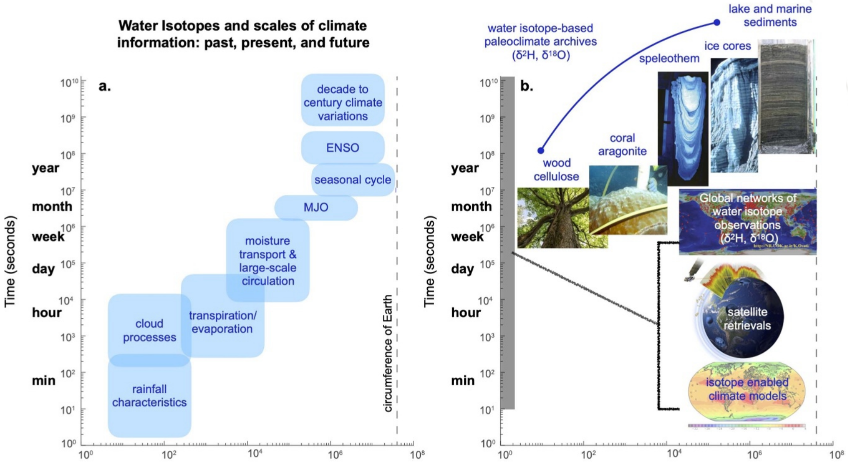


Fig 1. of Dee et al. (2023)

Paleo records of water isotopes can serve as paleo-thermometers and rain gauges, providing real-world constraints for validating Earth System Models (ESMs).

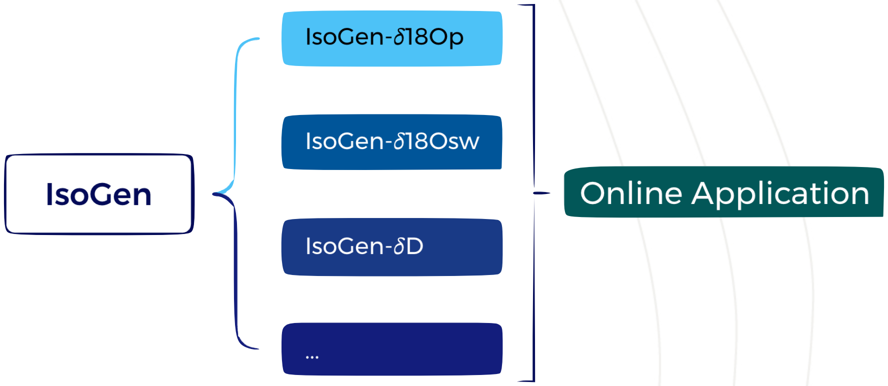
Incorporating water isotopes into ESMs is scientifically and technically challenging.

- It requires modifications to the dynamical core and physical parameterizations.
- It adds ~40% higher runtime computational cost.

Project Objectives

This project aims to:

- develop a machine-learning-based emulator for water isotopes (e.g., $\delta^{18}O$, δD), trained on ESM simulations and observations;
- apply the emulator to non-isotope ESMs to generate their water isotopic fields efficiently and cost-effectively;
- improve **scientific understanding** of the leading drivers of water isotopic variability and support the development of physically based isotope-enabled ESMs;
- contribute to ongoing (paleo)climate data assimilation efforts, where the lack of isotopic prior simulations has been a limiting factor.



Key Scientific Questions

Q1: What are the leading drivers of water isotopic variability in the Earth system?

Q2: Is the underlying climate-isotope mapping relationship stable across different climatologies (i.e., coldhouse, coolhouse, warmhouse, hothouse climates)?

Q3: Is the underlying climate-isotope mapping transferable across different ESMs (i.e., sensitive to specific model physics)?

Preliminary results:

- Single ESM precipitation $\delta^{18}O$ ($\delta^{18}O_p$) emulation [Q1]
- Multiple climatologies [Q2]

State of the Art {$\delta^{18}O_p$ Variability}

NCAR
OPERATED BY UCAR
CGD Laboratory

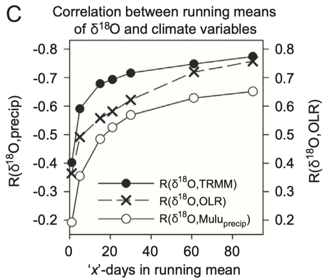
Dansgarrd (1964)

Temperature Effect: the positive $\delta^{18}O_p$–T correlation, dominant in mid-to-high latitudes and high altitude mountains.

Amount Effect: the negative $\delta^{18}O_p$–P correlation, dominant in tropical and monsoon regions.

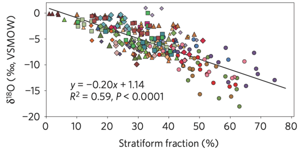
Bony et al. (2008) & **Risi et al. (2008)** suggest that **amount effect** is tied to large-scale atmospheric circulation that organize convective processes, rather than local rainfall amount per se, and temperature changes not associated with circulation changes lead to an anti-amount effect, highlighting the **non-local nature of isotopic controls**, according to model-data comparisons.

Moerman et al. (2013) studies a δ18Op record (daily, 5-yr-long) from site "Mulu" and suggests that the δ18Op-P correlation increases with increased **temporal and spatial averaging**.



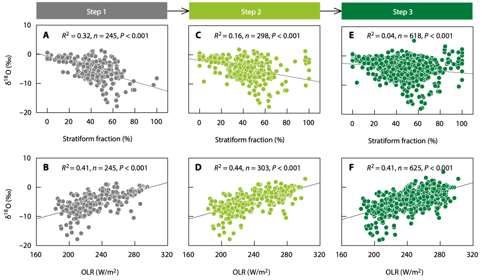
Konecky et al. (2019) suggests that "cloud type is leading influence where stratiform rain is abundant, and moisture transport plays key role along tropical rain belt", and that "$\delta^{18}O_p$ is a more reliable proxy for **large-scale** hydrological processes than precipitation", based on a conceptual framework and statistical model: $\delta^{18}O_p = \beta_1 \mathrm{RE}_{frac} + \beta_2 \mathrm{MF} + \beta_3 \mathrm{MTD} + \beta_4 \mathrm{SRF}$

Aggarwal et al. (2016, Nat. Geosci.) proposes a **Stratiform-Fraction (SF) theory** based on obs.

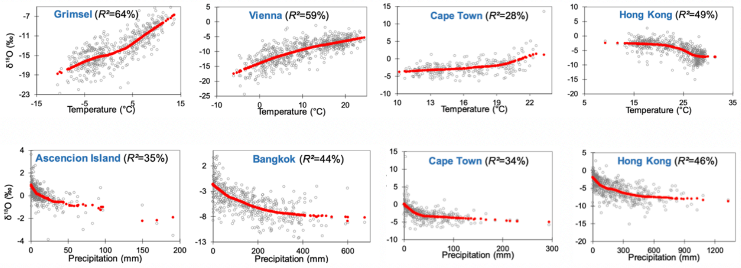


Leading Drivers [Q1]
- **Nonlocal**
- **Nonlinear**
- **Nontrivial**

Yu et al. (2024, Sci. Adv.) denies the **SF theory** based on more obs and suggests the importance of convection intensity (OLR).



Vystavna et al. (2021) studies 20 GNIP stations (monthly, 60-yr-long) and suggests **nonlinear** climate-isotope relationships.



Experimental Design

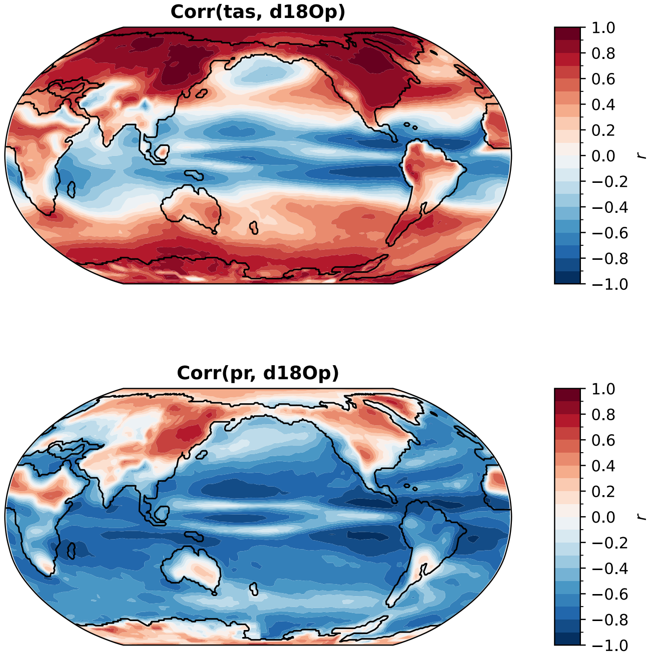
- **Goal: learning the climate-isotope mapping $\delta^{18}O_p = f(climate)$ and gain scientific insights**
- **Strategy: fitting $\delta^{18}O_p = f(climate)$ using different input variables**
- **Neural network: Fourier Neural Operators (FNOs) -> nonlocal & nonlinear problems**
  (FNOs learn global interactions in Fourier space, where expensive convolution becomes cheap multiplication: Li et al., 2021)
  (A benchmark of multiple deep learning methods for water isotope emulation: Li et al., 2025)
- **Dataset: iCESM1.3 simulations of the 1.5xCO2 & 3xCO2 MCO cases**
  (Long Simulations of the Miocene Climatic Optimum: Zhu & Zhu, 2025)
  (iCAM5 is the only one that can simulate the observed SF-$\delta^{18}O_p$ correlation among other iGCMs: Hu et al., 2018)
- **Data splitting**
  - Total: 200 yrs x 12 months = 2400 months
  - Train / Valid / Test: 70% / 10% / 20%
- **Experiments**
  - In-distribution (ID) Exps. (Train: 1.5xCO2, Test: 1.5xCO2)
  - Out-of-distribution (OOD) Exps. (Train: 1.5xCO2, Test: 3xCO2)

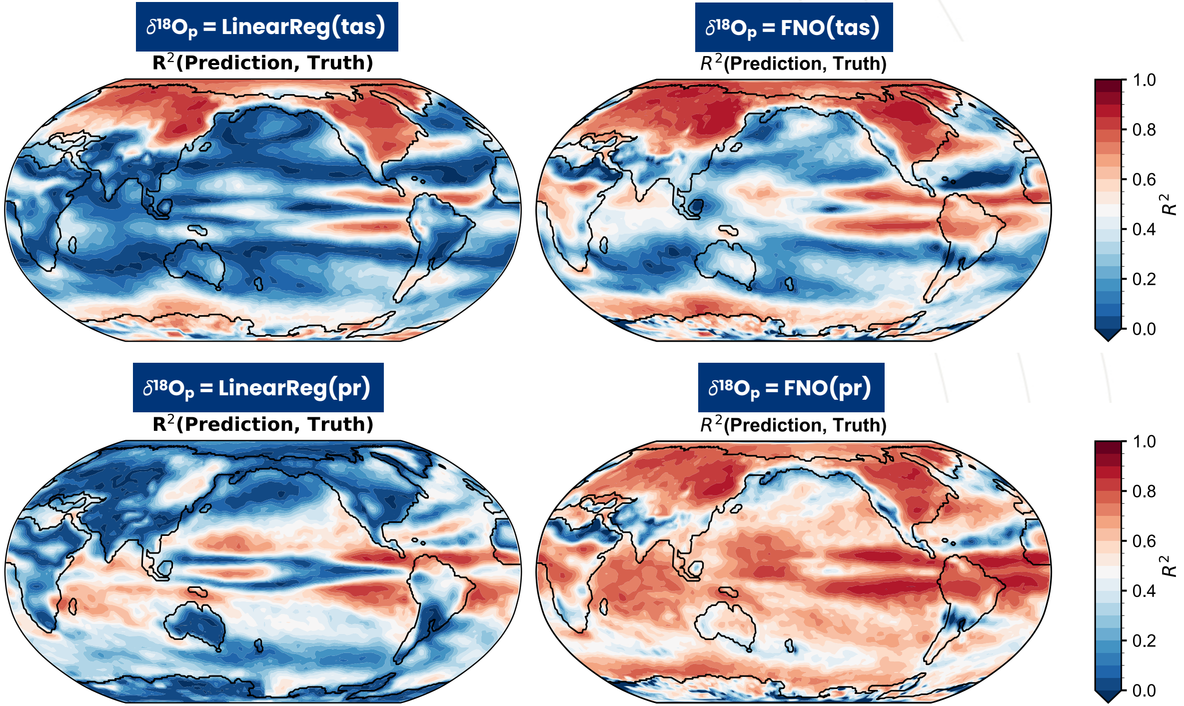
Preliminary Results

ID Exps.
Train: 1.5xCO_2; Test: 1.5xCO_2

CGD Laboratory

Diagnostics: local correlations





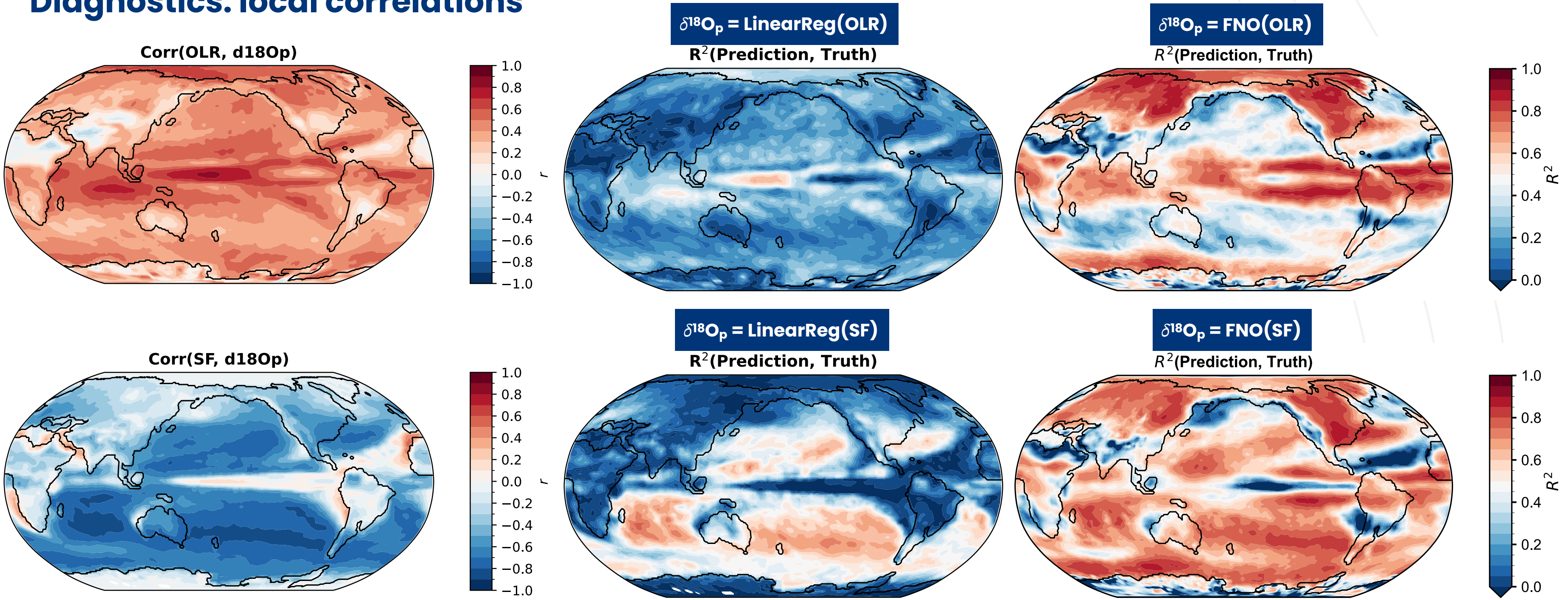
Taking nonlinearity and nonlocality into account (FNO fitting) appears to be effective, confirming the previous studies.

Preliminary Results

ID Exps.
Train: 1.5xCO2; Test: 1.5xCO2

NCAR
OPERATED BY UCAR
CGD Laboratory

Diagnostics: local correlations



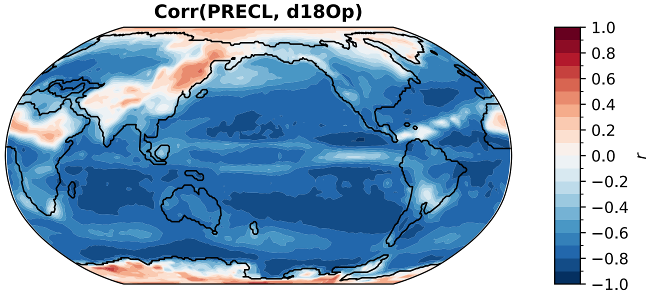
SF (stratiform fraction) appears to be more informative than OLR (representing convective intensity) over ocean.

Preliminary Results

ID Exps.
Train: 1.5xCO2; Test: 1.5xCO2

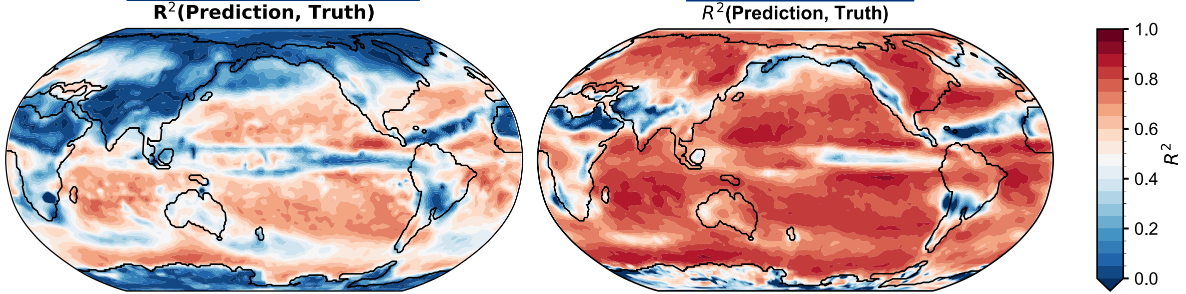
NCAR
OPERATED BY UCAR
CGD Laboratory

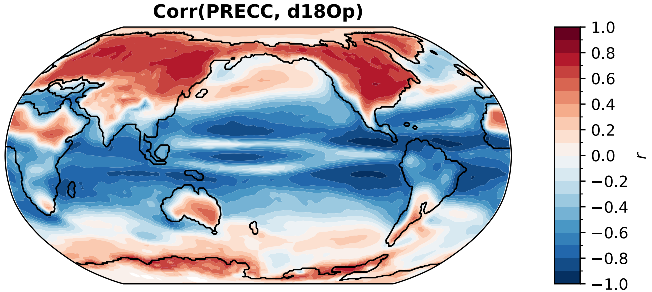
Diagnostics: local correlations



$\delta^{18}O_p$ = LinearReg(PRECL)

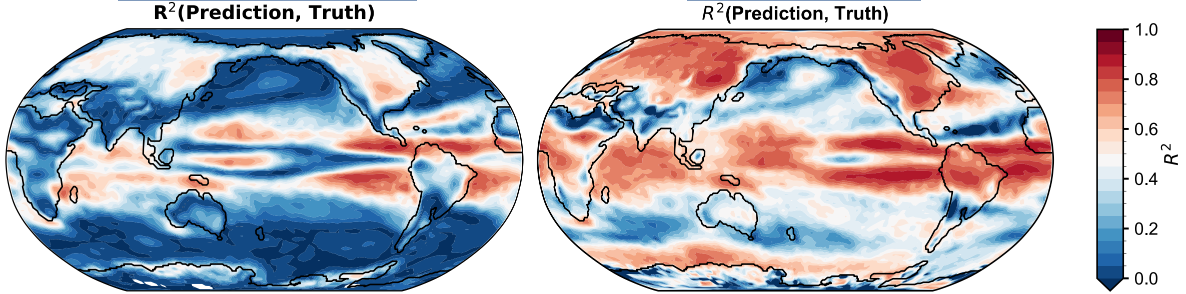
$\delta^{18}O_p$ = FNO(PRECL)





$\delta^{18}O_p$ = LinearReg(PRECC)

$\delta^{18}O_p$ = FNO(PRECC)



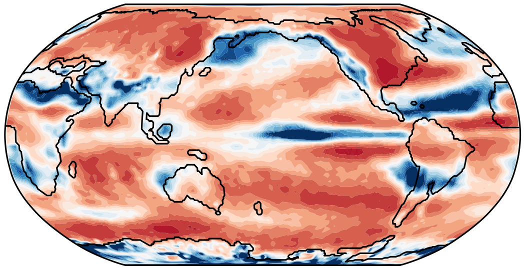
PRECL (stratiform precipitation) appears to be informative using FNO -- "Stratiform Amount Effect".

Preliminary Results

ID Exps.
Train: 1.5xCO2; Test: 1.5xCO2

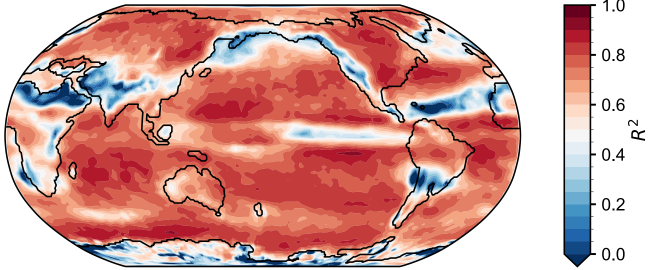
$\delta^{18}O_p$ = FNO(SF) **GM: 0.56**

R^2(Prediction, Truth)



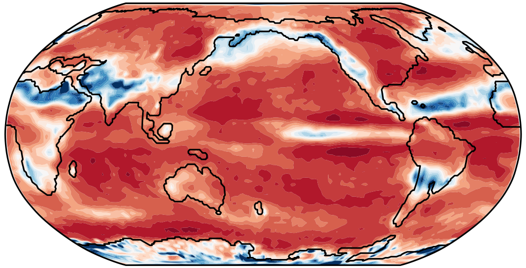
$\delta^{18}O_p$ = FNO(PRECL) **GM: 0.66**

R^2(Prediction, Truth)



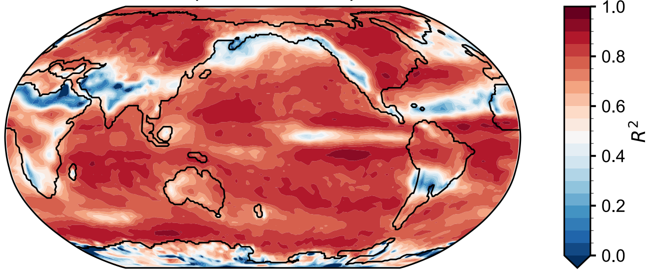
$\delta^{18}O_p$ = FNO(pr, PRECL) **GM: 0.71**

R^2(Prediction, Truth)



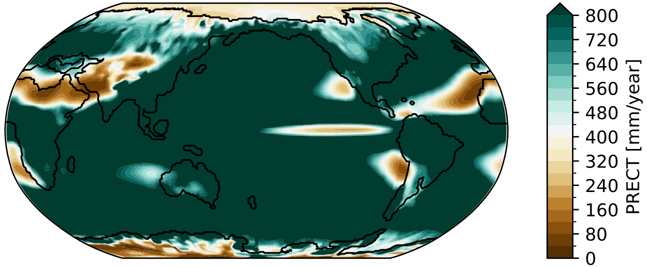
$\delta^{18}O_p$ = FNO(tas, pr, PRECL) **GM: 0.72**

R^2(Prediction, Truth)



A plausible cause of the weaker performance in specific regions: persistent drought conditions.

Annual Mean Total Precipitation

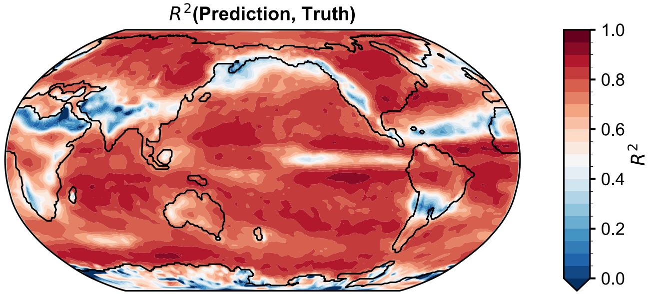


A mixture of the Temperature Effect, Amount Effect, and SF theory yields the best skill so far.

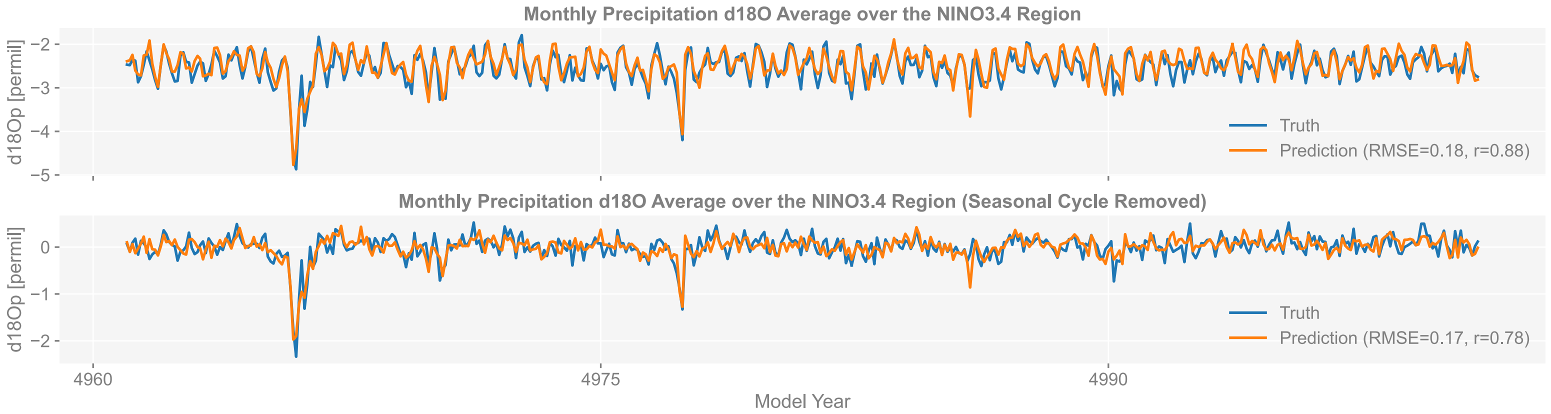
Preliminary Results

ID Exps.
Train: 1.5xCO2; Test: 1.5xCO2

$\delta^{18}O_p$ = FNO(tas, pr, PRECL)



Good performance in internal variability predictions over the NINO3.4 region.

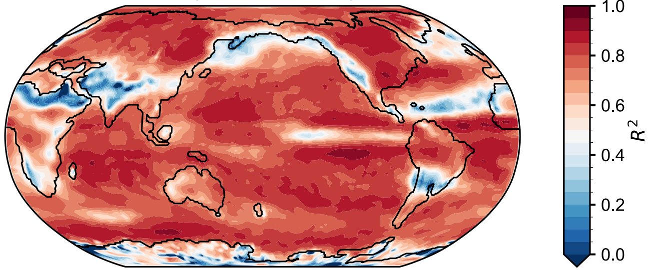


Preliminary Results

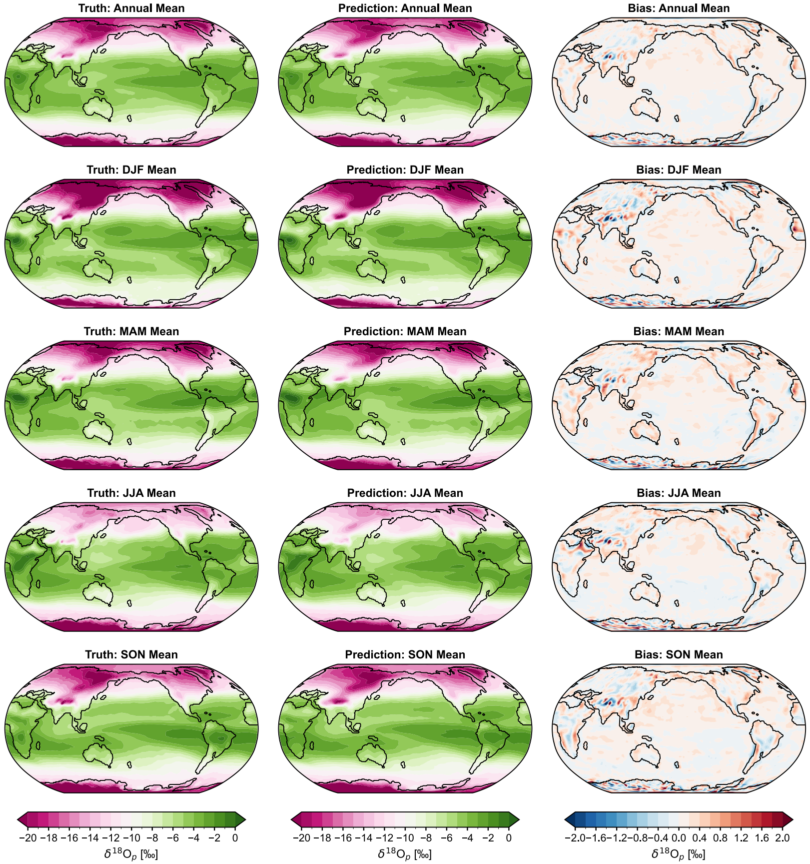
ID Exps.
Train: 1.5xCO2; Test: 1.5xCO2

$\delta^{18}O_p$ = FNO(tas, pr, PRECL)

R^2(Prediction, Truth)



Good performance in both annual and seasonal mean climate predictions.

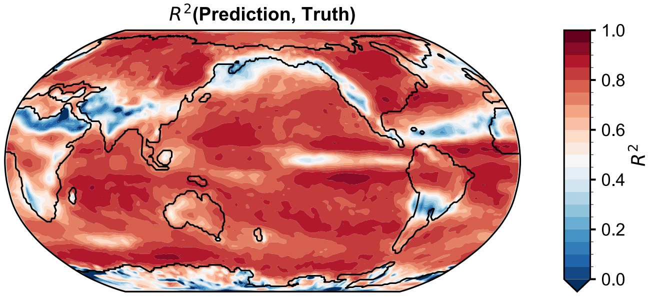


Preliminary Results

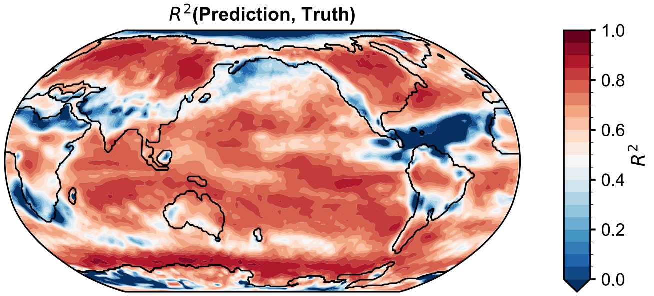
OOD Exps.
Train: 1.5xCO_2; Test: 3xCO_2

CGD Laboratory

$\delta^{18}O_p$ = FNO(tas, pr, PRECL) **ID Test**



$\delta^{18}O_p$ = FNO(tas, pr, PRECL) **OOD Test**



The essential challenge of an OOD test:

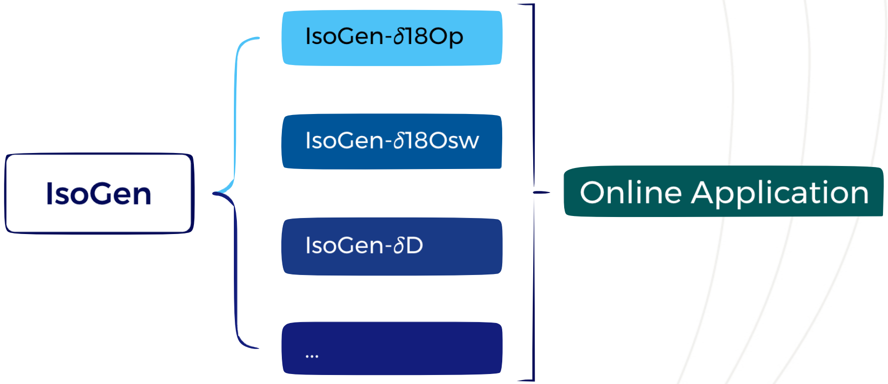
- **given the different distributions of the variables across climate regimes,**
- **normalizing the Test set using statistics from the Train set could be problematic.**

Conclusions

- It is **feasible** to predict d18Op variability using **a machine learning based emulator** of the climate-isotope mapping and **apply it to different climatologies**.
- By testing different combinations of input variables, we gain **scientific insights** into the **leading drivers of $\delta^{18}O_p$ variability**.
- **Taking nonlinearity and nonlocality into account appears to be effective**, confirming the previous studies.
- The emulator **$\delta^{18}O_p$ = FNO(tas, pr, PRECL)** mixing the **Temperature Effect**, **Amount Effect**, and **Stratiform-Fraction theory** yields the best skill so far.
- The weaker performance in specific regions (e.g., over the tropical Atlantic) is likely due to **persistent drought conditions**, leading to ill-defined $\delta^{18}O_p$ variability.

Future Research

- **Scientific interpretations [Q1]** via modeling, obs, and ML techniques on
  - the **nonlinearity** and **nonlocality** nature of the isotopic controls
  - the "**Stratiform Amount Effect**"
- **Improvements** on the OOD tests **across different climatologies [Q2]**
- **OOD tests across different ESMs [Q3]**
  - WisoMIP (Bong et al., 2026): iCAM5, iCAM6, ECHAM6-wiso, GISS-E2.1, IsoGSM3, LDMZ6, MIROC5-iso, NICAM-WISO
  - iHadCM3 (Tindall et al., 2009)
- Emulating **other water isotopic variables**



NSF NCAR
OPERATED BY UCAR

CGD Laboratory

Thank You!

Questions and comments?

Feng Zhu (fengzhu@ucar.edu)

Scientist III; NSF NCAR

Jiang Zhu (NSF NCAR), Dan Amrhein (NSF NCAR), Yiqun Xie (UMD), Xiaowei Jia (UPitt), Zhili Li (UMD), Ruicheng Wang (UMD), Chonghao Qiu (UPitt)

This material is based upon work supported by the NSF National Center for Atmospheric Research, a major facility sponsored by the U.S. National Science Foundation and managed by the University Corporation for Atmospheric Research. Any opinions, findings and conclusions or recommendations expressed in this material do not necessarily reflect the views of NSF.

Image by ChatGPT