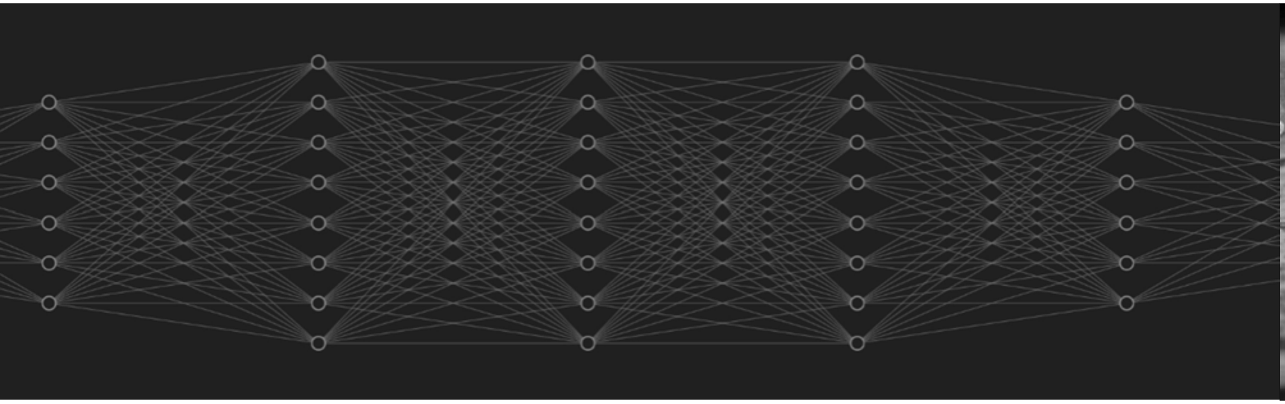
COLLEGE OF
COMPUTER, MATHEMATICAL,
& NATURAL SCIENCES
DEPARTMENT OF ATMOSPHERIC & OCEANIC SCIENCE

# Uses and Applications of Machine Learning in

## Subseasonal Forecasting, Extreme Weather Prediction, and Climate Variability



Maria J. Molina, Assistant Professor, University of Maryland, College Park, MD

Subseasonal Prediction

AI/ML

Climate Variability

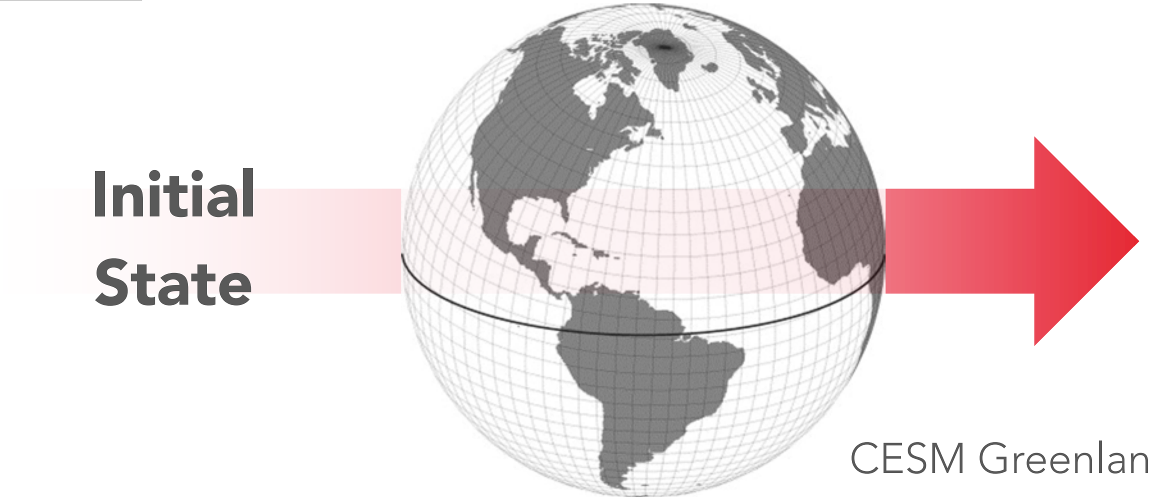
Extreme Weather Prediction

# "Traditional" numerical weather prediction / climate modeling

**Input**
Observations or Representation of the Initial State

**Run Model**
Parameterizations
High Performance Computing

**Output**
Predictions with Certain Lead Time or Future Projections




CESM Greenland Pole Grid.

Molina, M. J., T. A. O'Brien, G. Anderson, M. Ashfaq, K. E. Bennett, W. D. Collins, K. Dagon, J. M. Restrepo, and P. A. Ullrich (2023). A Review of Recent and Emerging Machine Learning Applications for Climate Variability and Weather Phenomena. Artificial Intelligence for the Earth Systems.

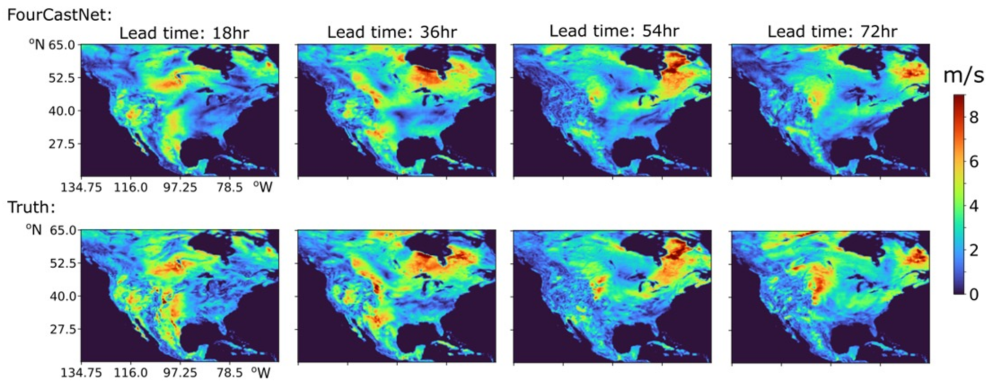
# **ML-based** numerical weather prediction / climate modeling

**Input**
Observations or
Representation of
the Initial State

**Run Model**
Parameterizations
High Performance
Computing

**Output**
Predictions with
Certain Lead Time
or Future Projections

Pathak, J., et al., 2022. **Fourcastnet: A global data-driven high-resolution weather model using adaptive fourier neural operators.** arXiv:2202.11214.

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## …and regardless of your approach, there will be **errors.**

| **Input** | **Run Model** | **Output** |
|---|---|---|
| Observations or Representation of the Initial State | Parameterizations<br>High Performance Computing | Predictions with Certain Lead Time or Future Projections |

Molina, M. J., T. A. O'Brien, G. Anderson, M. Ashfaq, K. E. Bennett, W. D. Collins, K. Dagon, J. M. Restrepo, and P. A. Ullrich (2023). A Review of Recent and Emerging Machine Learning Applications for Climate Variability and Weather Phenomena. Artificial Intelligence for the Earth Systems.

## …and regardless of your approach, there will be errors.

| Input | Run Model | Output |
|---|---|---|
| Observations or Representation of the Initial State | Parameterizations High Performance Computing | Predictions with Certain Lead Time or Future Projections |

1. Can we reduce the errors with ML/AI?
2. Can we learn something new about the Earth system and/or our numerical models?

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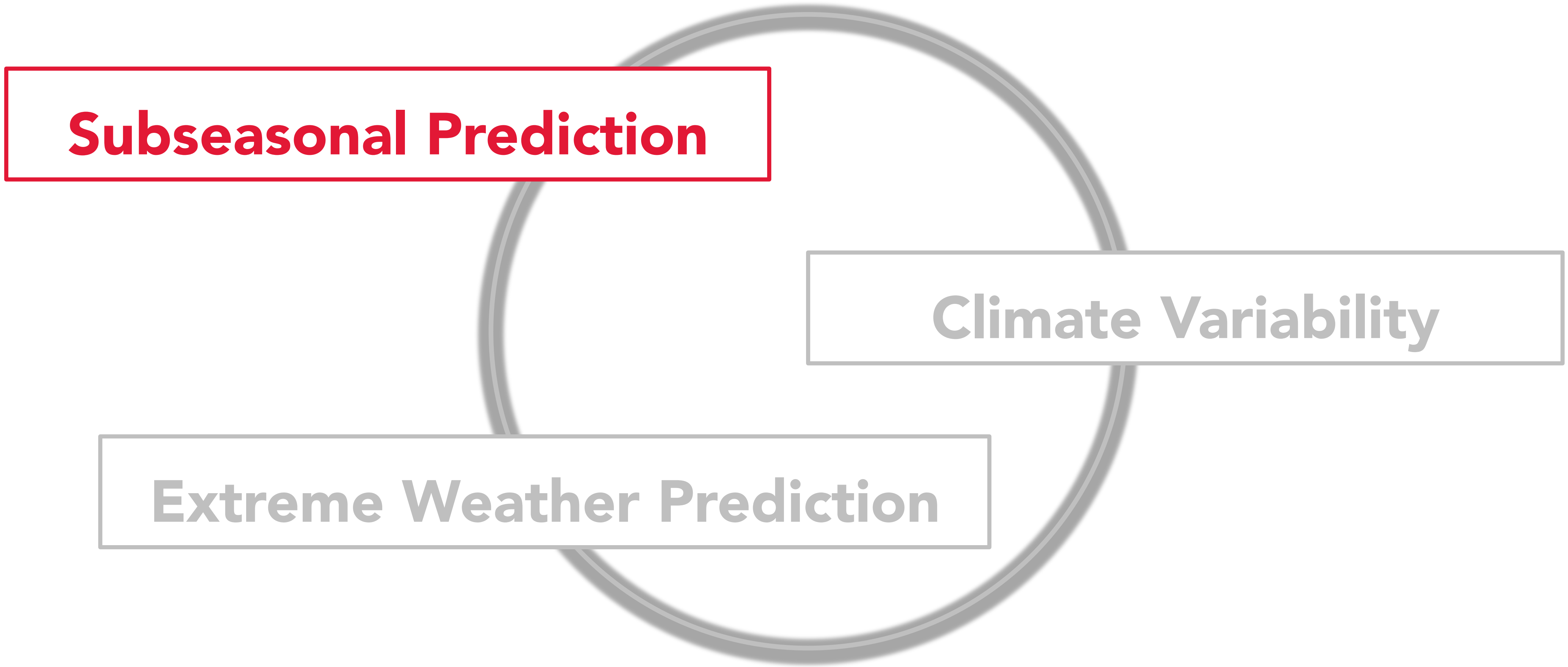
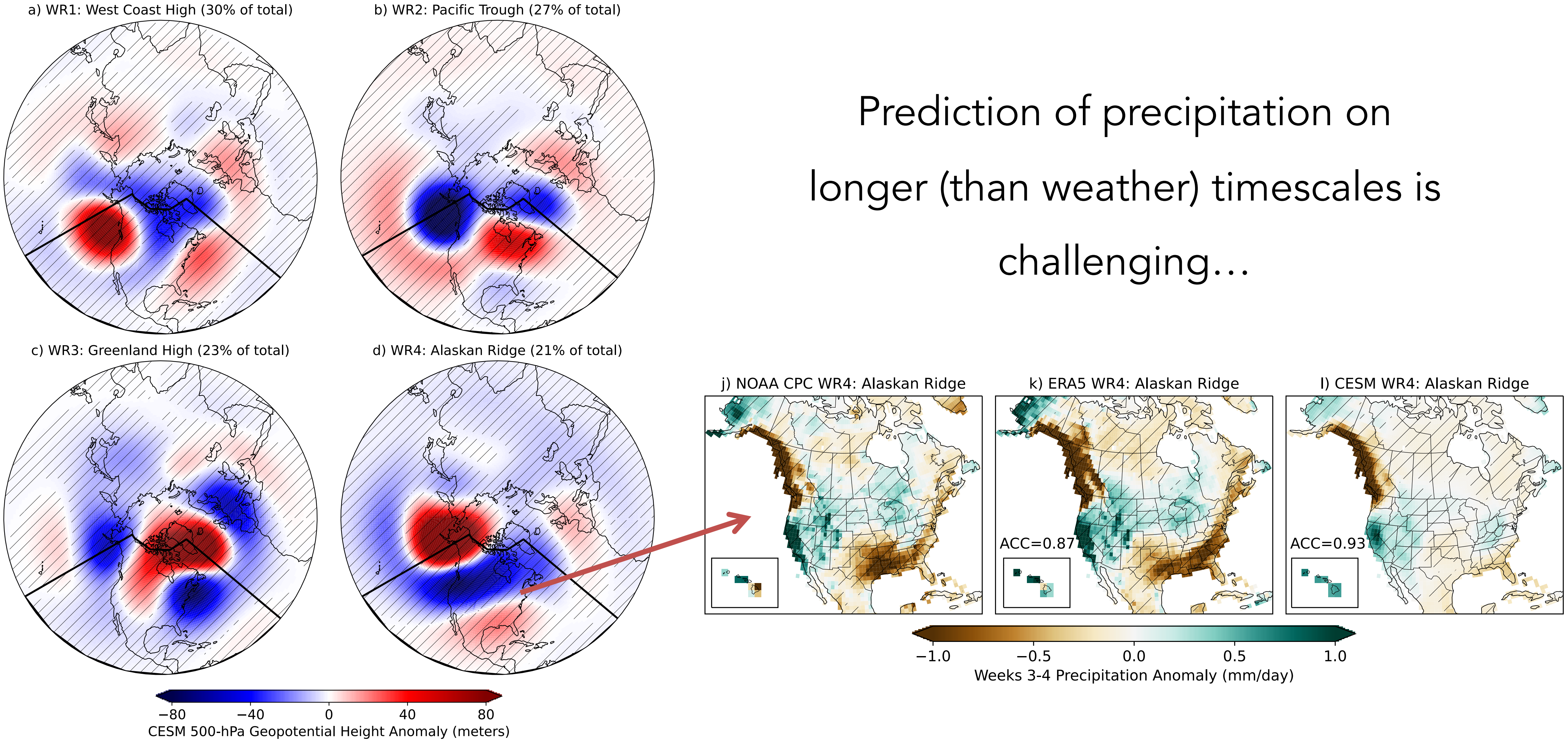
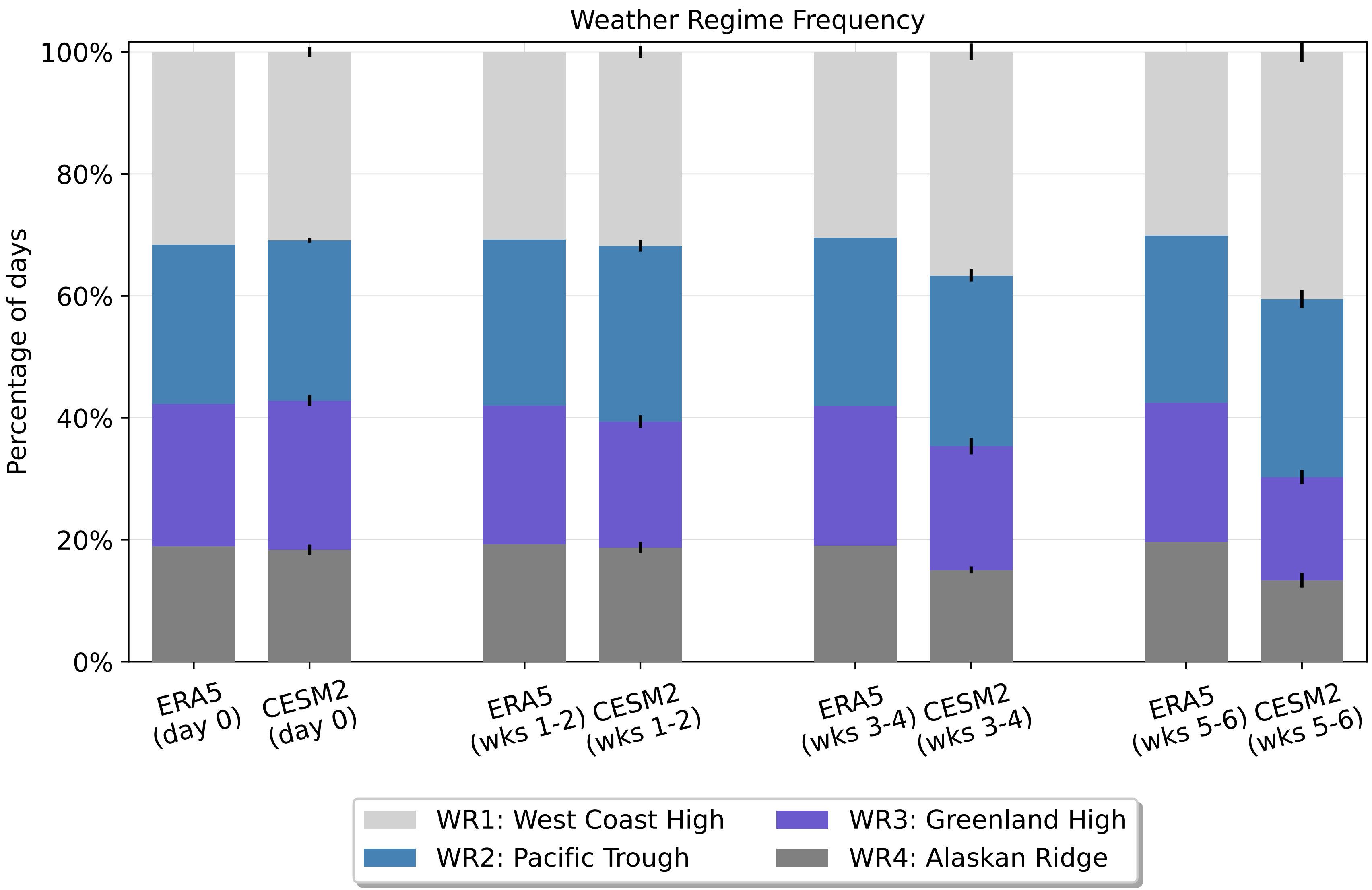

Subseasonal Prediction
Climate Variability
Extreme Weather Prediction




# Prediction of precipitation on longer (than weather) timescales is challenging…

Molina, M. J., Richter, J.H., Glanville, A.A., Dagon, K., Berner, J., Hu A., Meehl, G.A., 2023. Subseasonal Representation and Predictability of North American Weather Regimes using Cluster Analysis. AMS AI for the Earth Systems.

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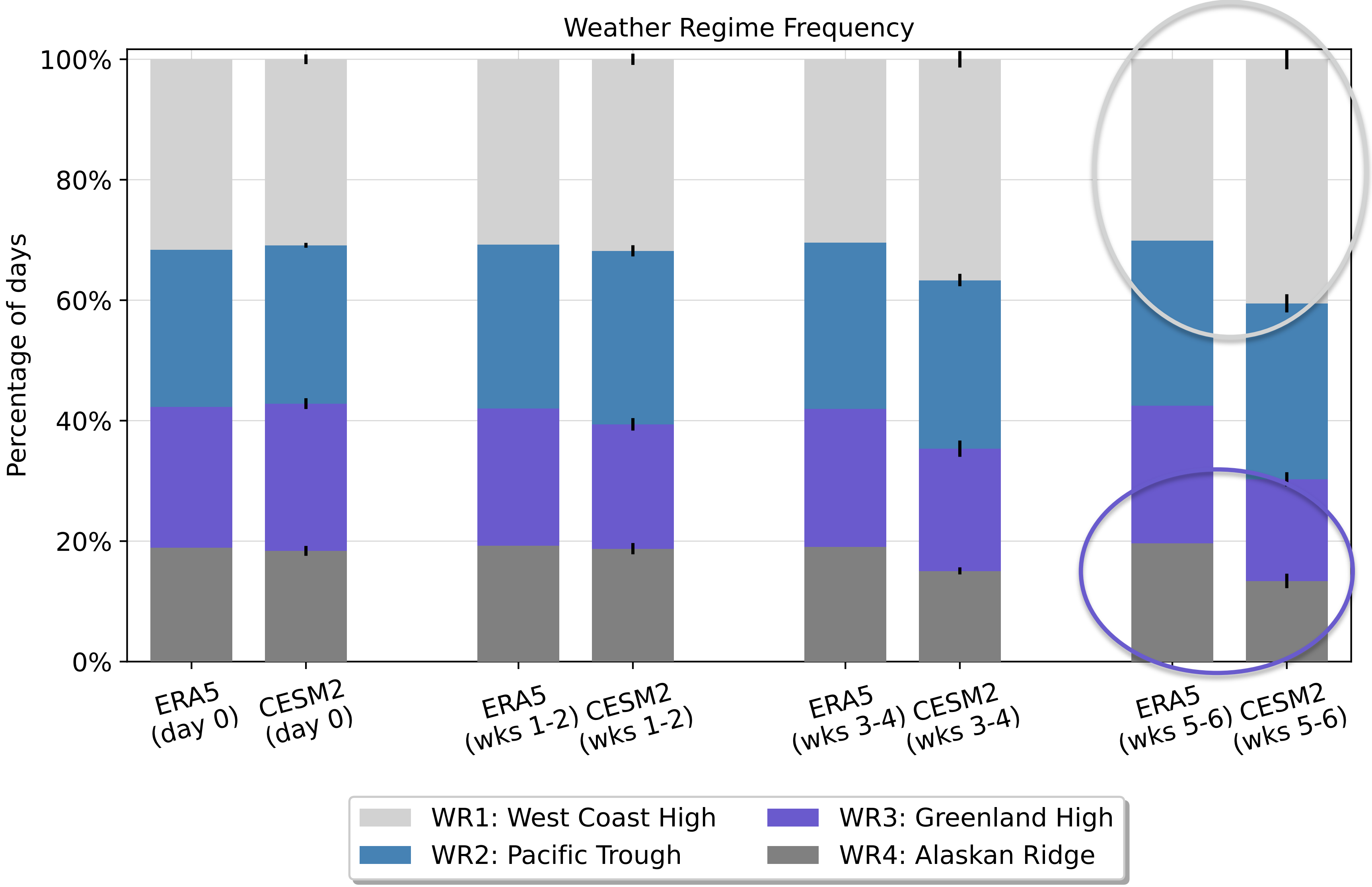


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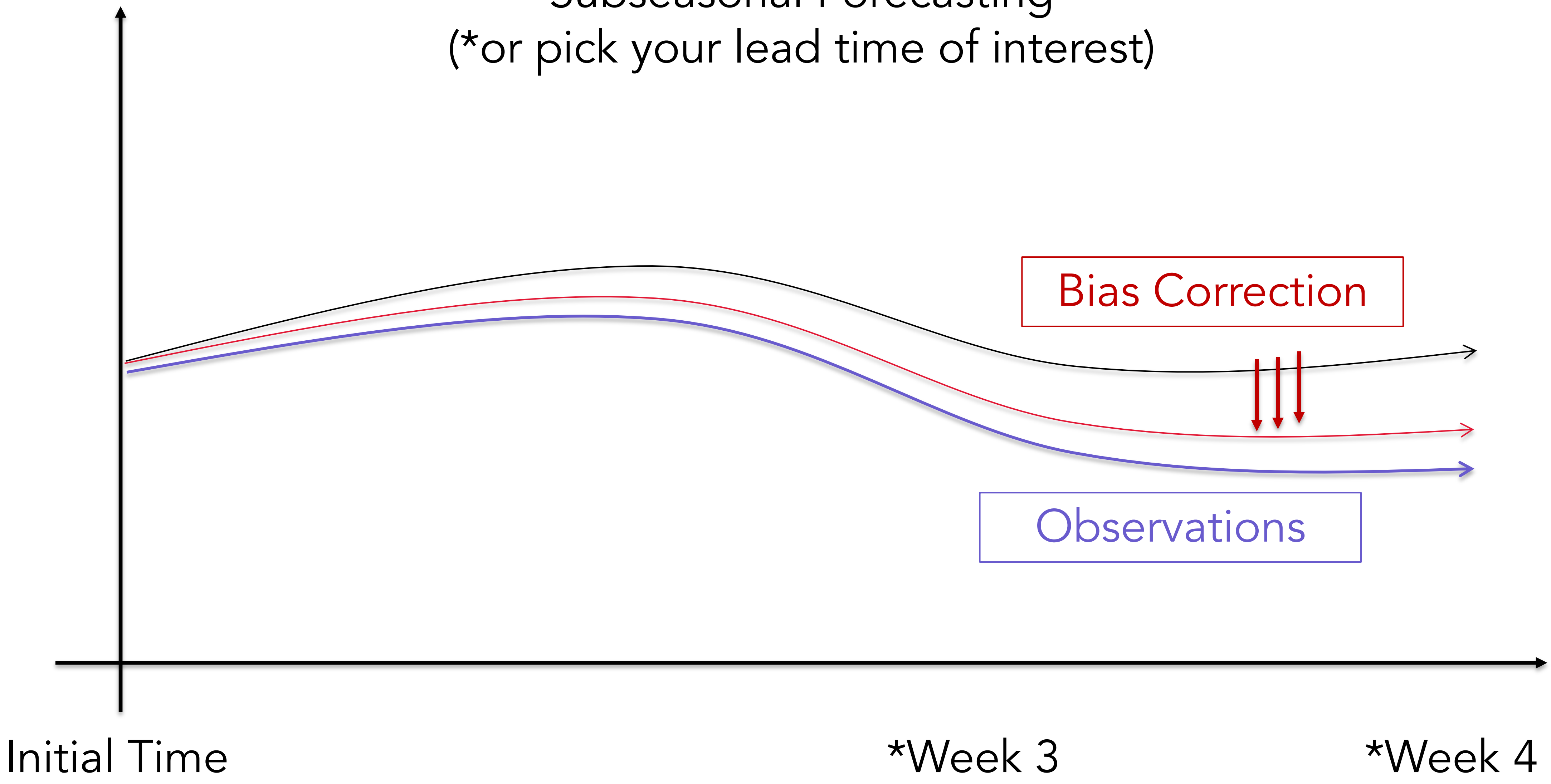
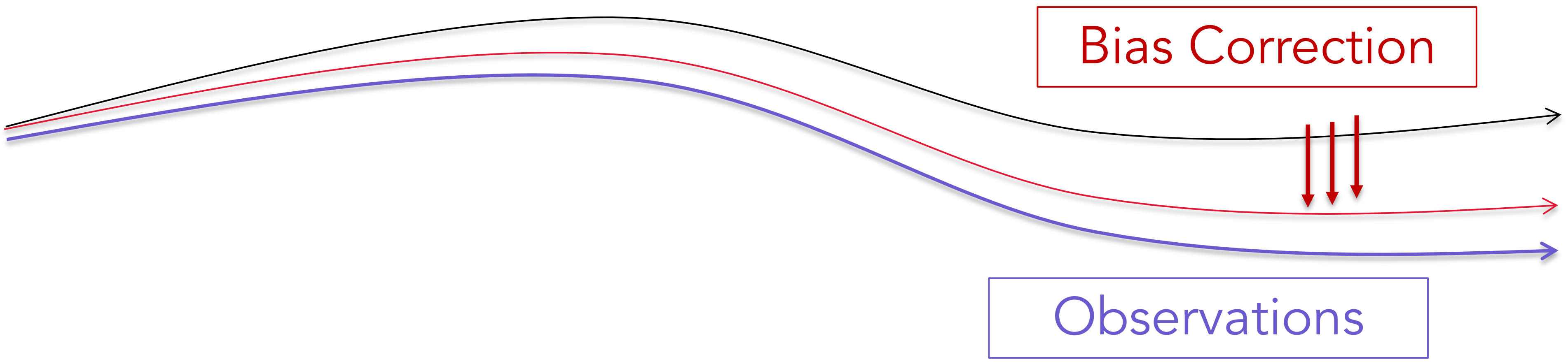
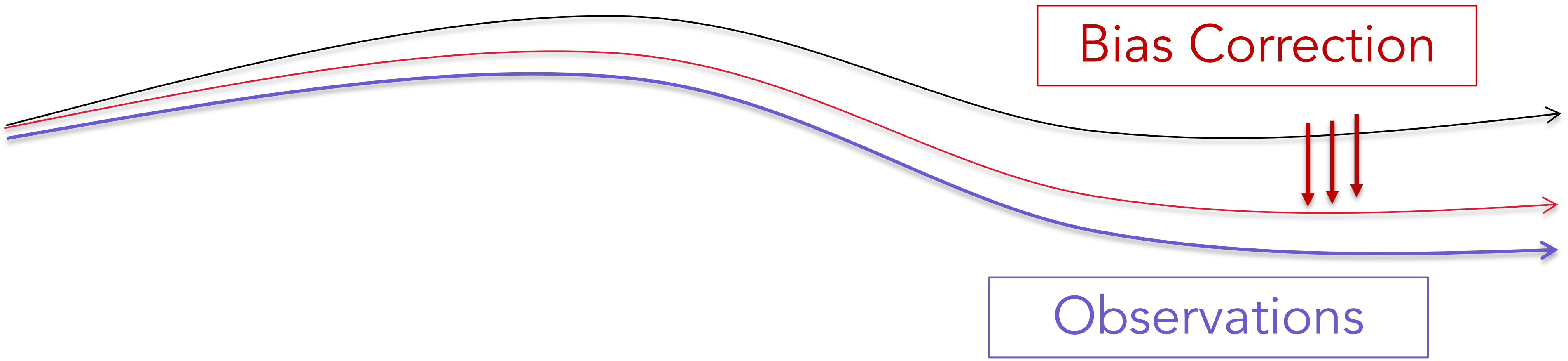
Subseasonal Forecasting
(*or pick your lead time of interest)




Bias Correction
Observations

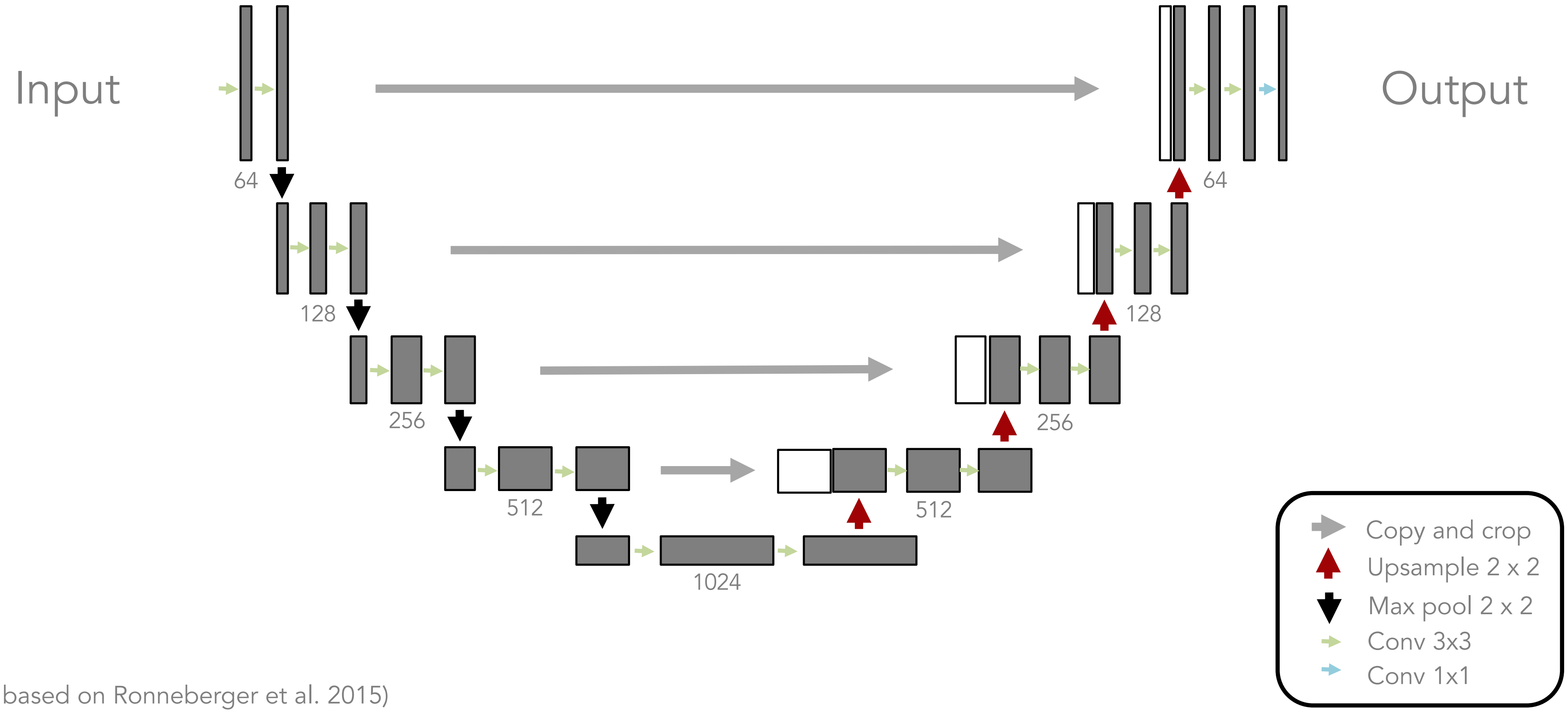



**[Online]** e.g., train ML to bias correct the numerical model *while it is running.*

**[Offline]** e.g., train ML to bias correct the numerical model *after it has run.*

Molina, M.J., K. Dagon, J. Schreck, J. S. Perez Carrasquilla, K. J. Mayer, N. Sobhani, D. J. Gagne, I. Ebert-Uphoff, C. A. Metzler, and G. A. Meehl. (In Preparation). Macro- and Micro- Large Ensemble Methods along the Pareto Frontier for Bias Correction of Subseasonal Forecasts. JAMES.

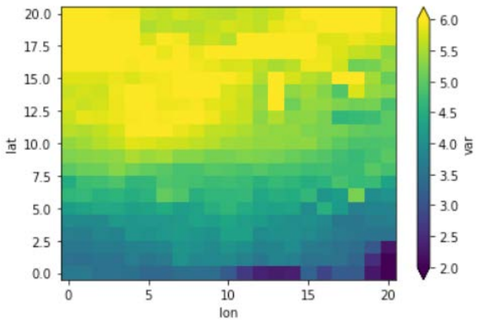
# U-Net Architecture



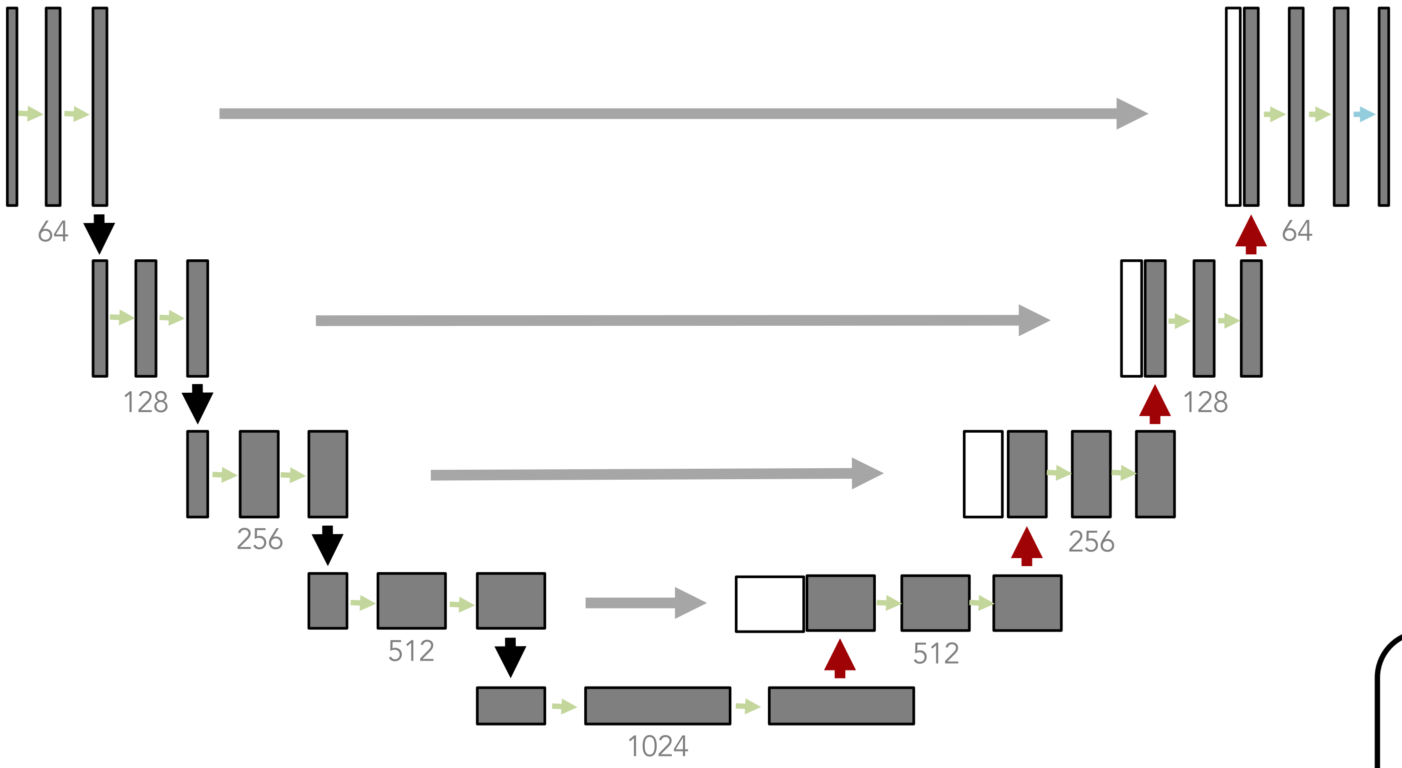

(U-Net architecture based on Ronneberger et al. 2015)

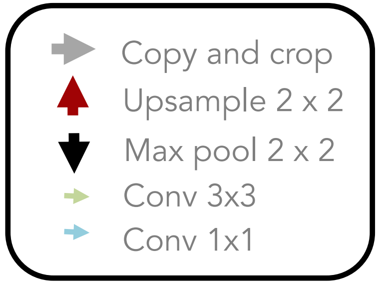
Molina, M.J., K. Dagon, J. Schreck, J. S. Perez Carrasquilla, K. J. Mayer, N. Sobhani, D. J. Gagne, I. Ebert-Uphoff, C. A. Metzler, and G. A. Meehl. (In Preparation). Macro- and Micro- Large Ensemble Methods along the Pareto Frontier for Bias Correction of Subseasonal Forecasts. JAMES.

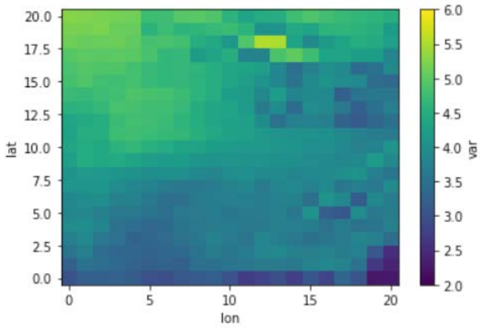
# U-Net Architecture (training and validation: 1999-2015; evaluation: 2016-2019)



CESM weeks 3,4 (temperature or precipitation)



ERA5 or NOAA CPC/GPCP

(U-Net architecture based on Ronneberger et al. 2015)

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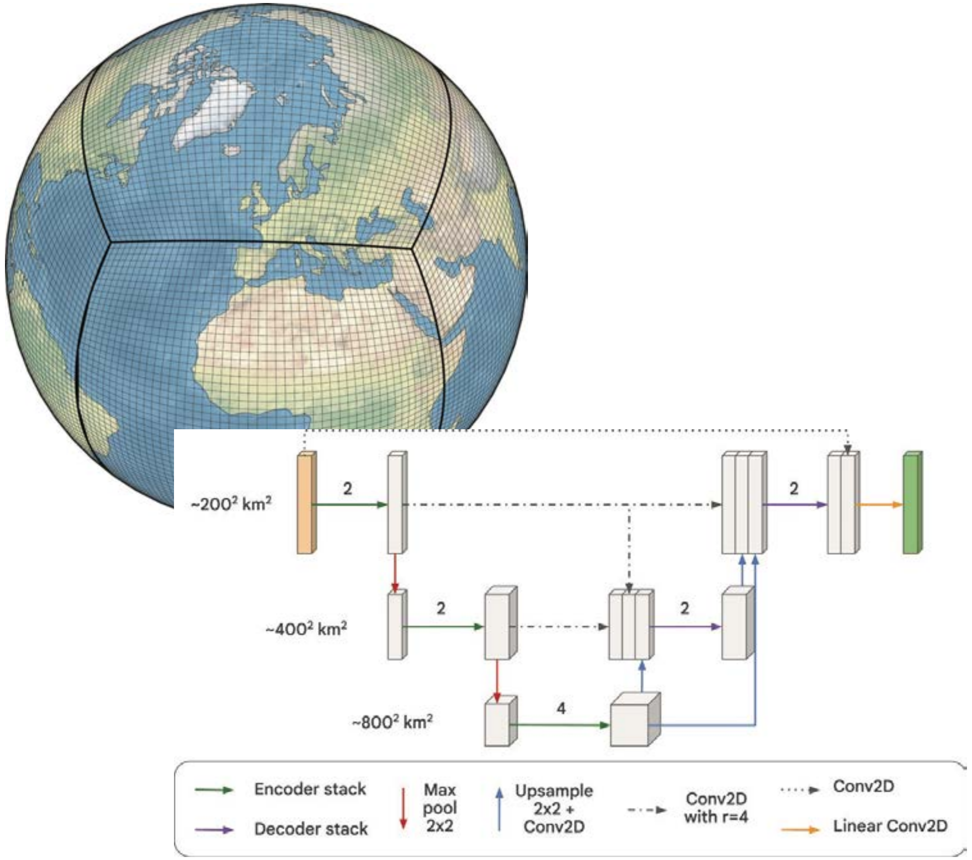
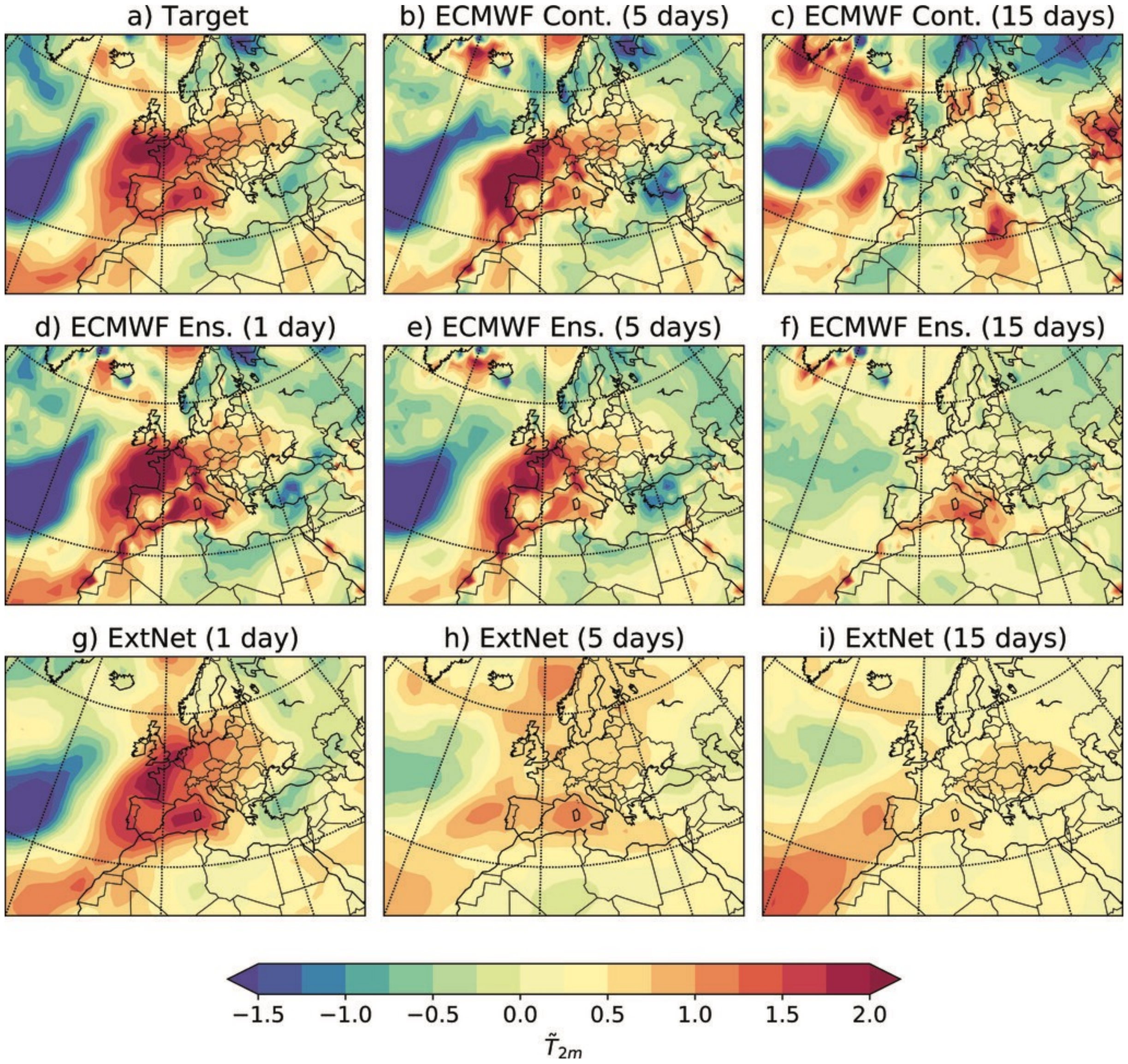
Subseasonal Prediction

Climate Variability

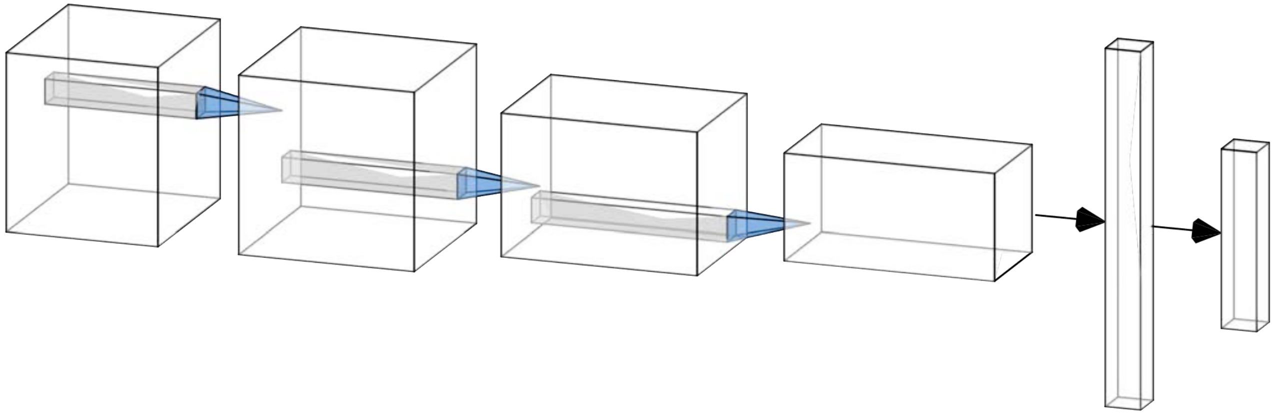
**Extreme Weather Prediction**

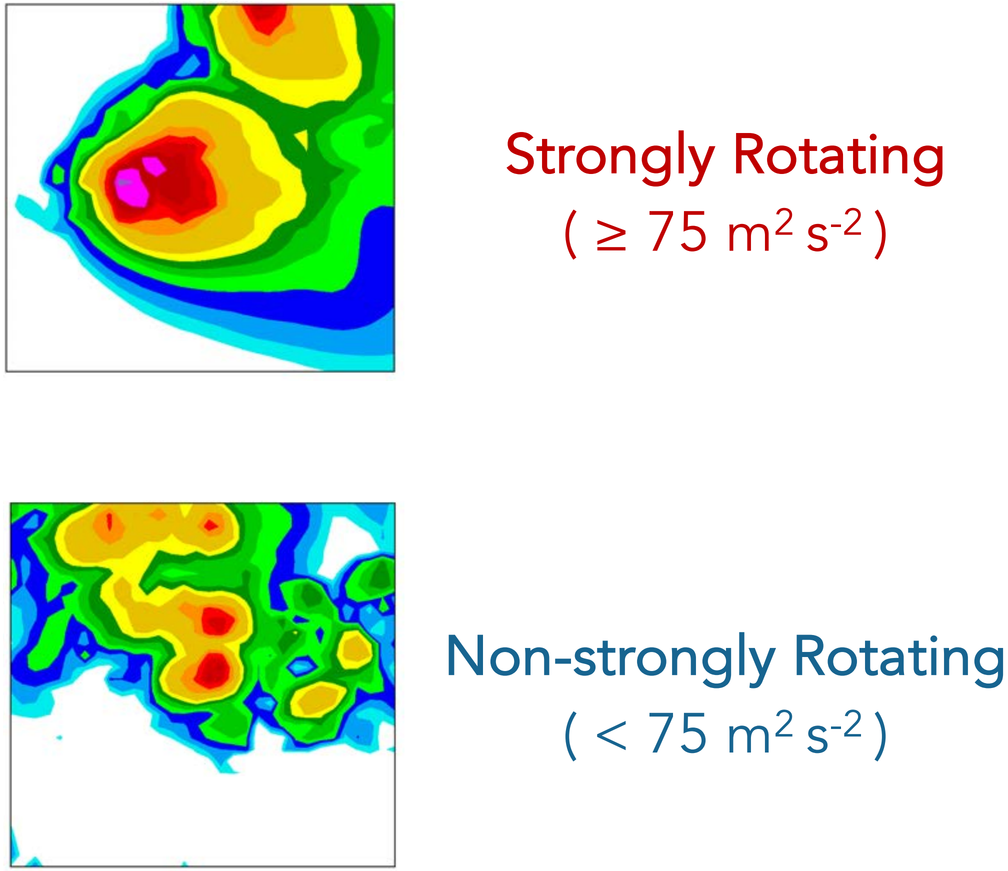



Lopez-Gomez, I., McGovern, A., Agrawal, S. and Hickey, J., 2023. Global extreme heat forecasting using neural weather models. Artificial Intelligence for the Earth Systems, 2(1), p.e220035.

## Convolutional Neural Network



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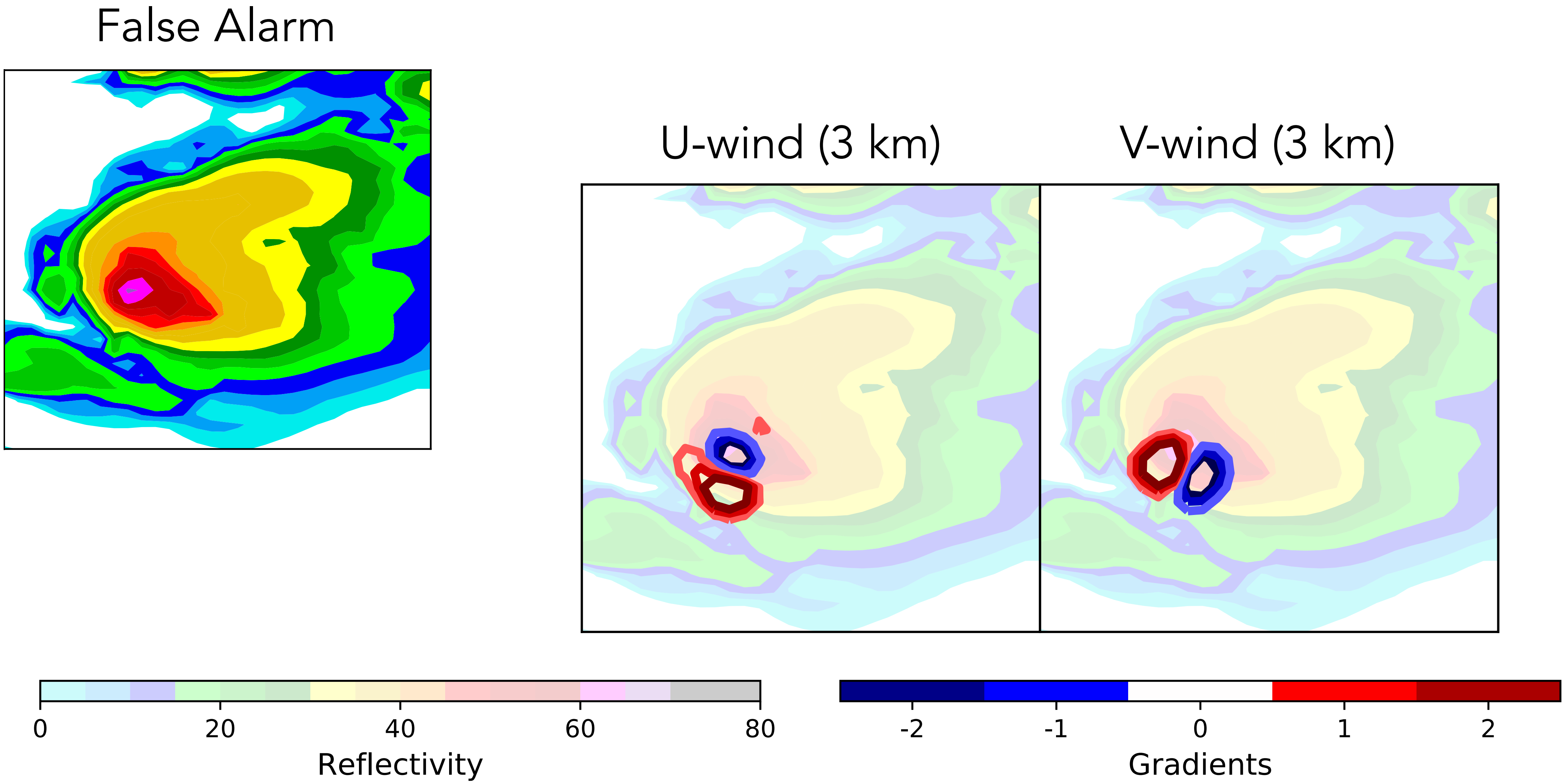


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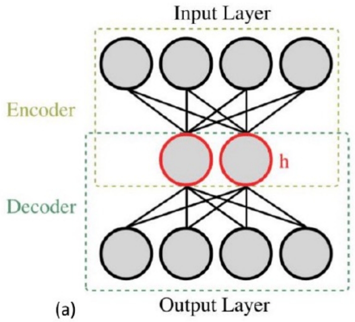


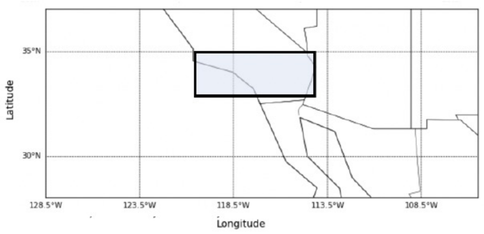


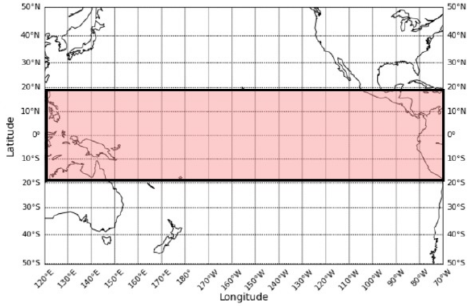


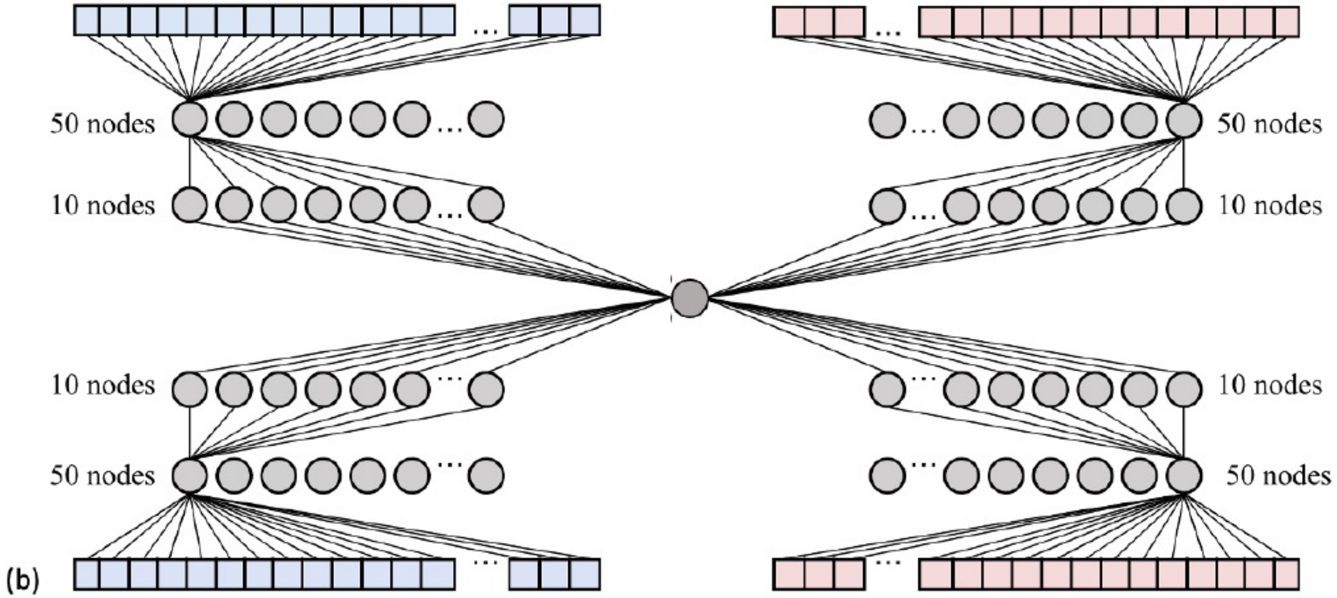


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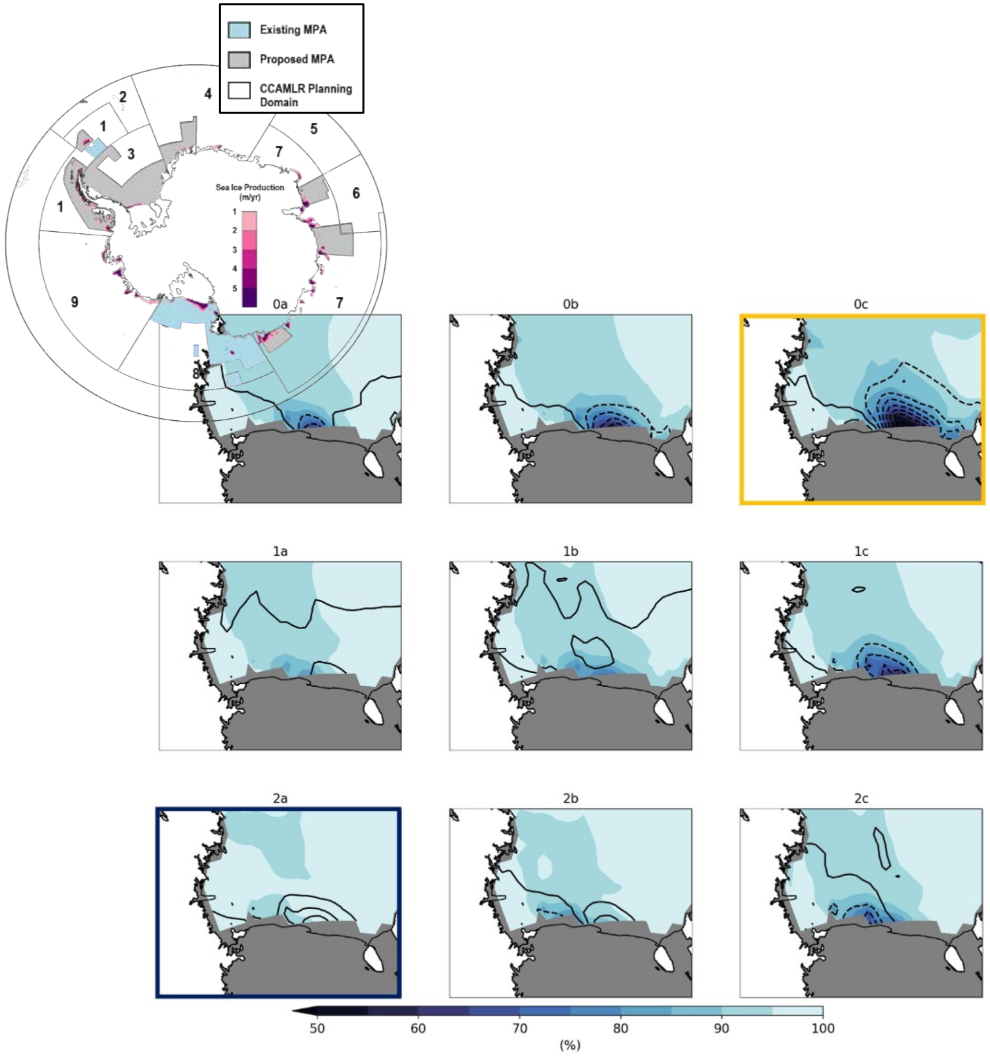


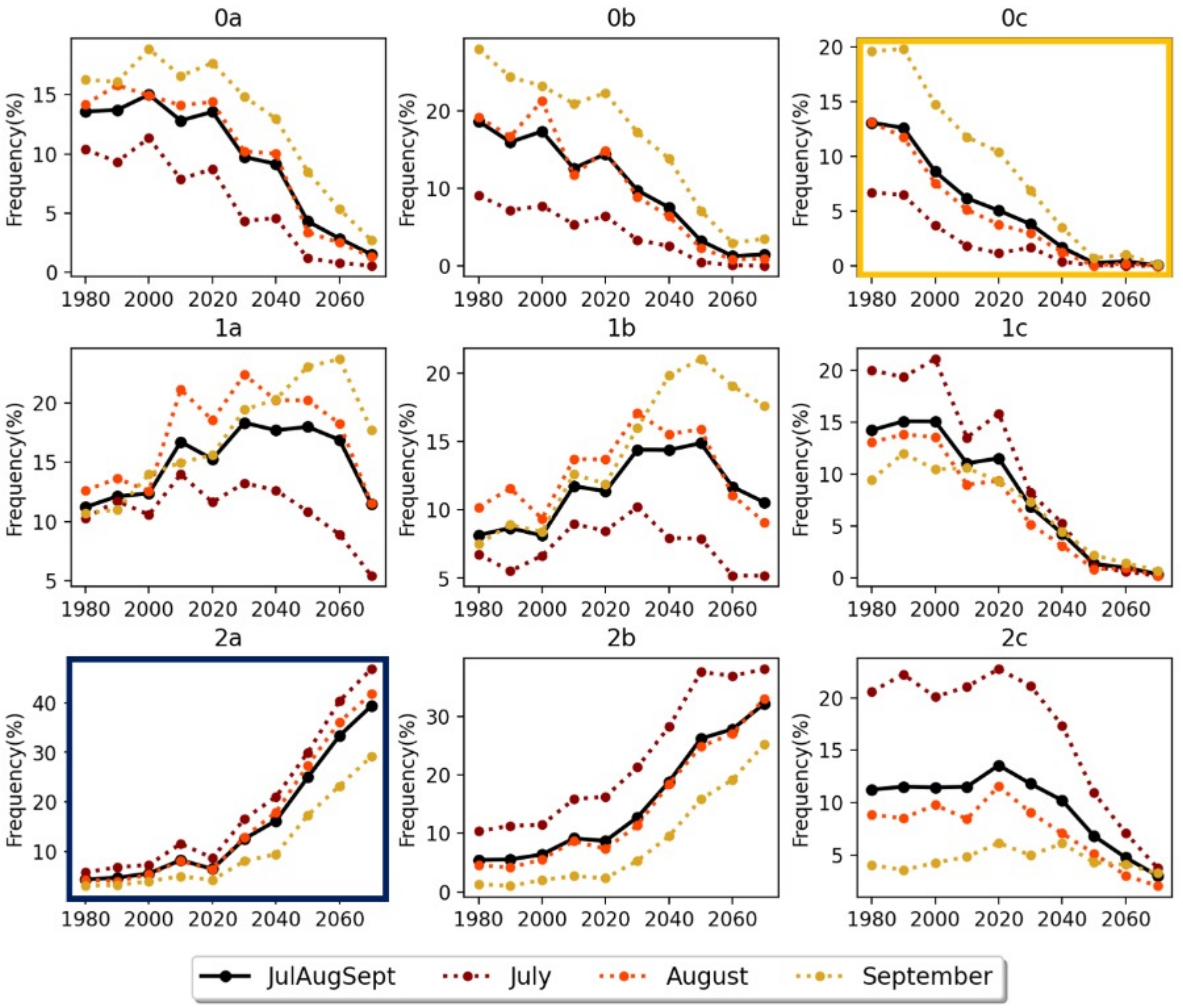


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## Subseasonal forecasting

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## Extreme weather prediction

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## Climate variability / change

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mjmolina@umd.edu

How do we rectify the need for the "best-performing" ML/AI model in a climate prediction problem vs. gaining the necessary understanding of the fundamental climate processes (i.e., is there a conflict between best prediction models and realistic ML/AI models?)

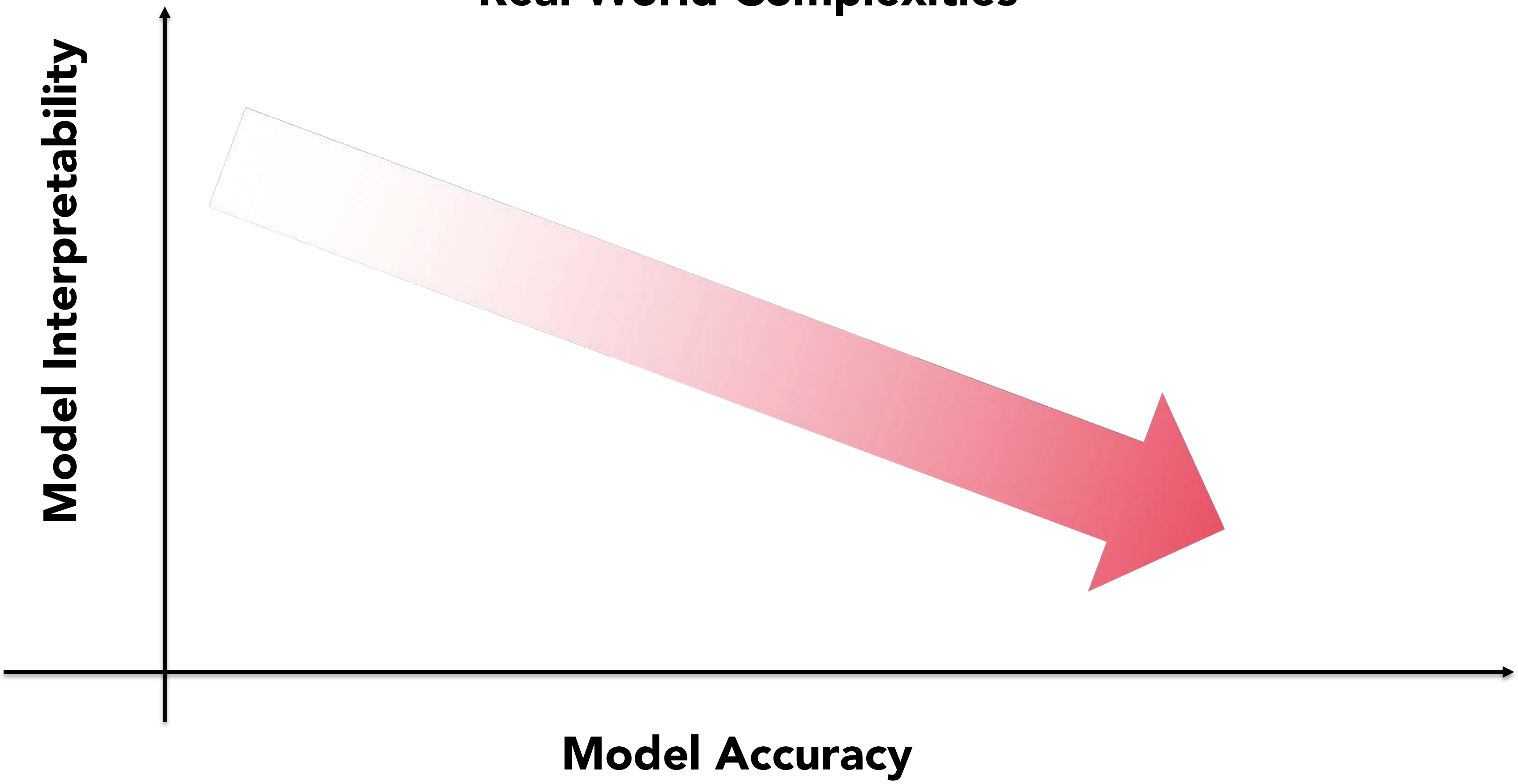
What is a **"best-performing"** weather forecast / climate projection?

How do we rectify the need for the "best-performing" ML/AI model in a climate prediction problem vs. gaining the necessary understanding of the fundamental climate processes (i.e., is there a conflict between best prediction models and realistic ML/AI models?)

**Yes!** Consider image sharpness for example…

Forthcoming work led by Imme Ebert-Uphoff (CSU/NOAA CIRA)

# Real World Complexities*




*this is for illustration purposes (not real data)

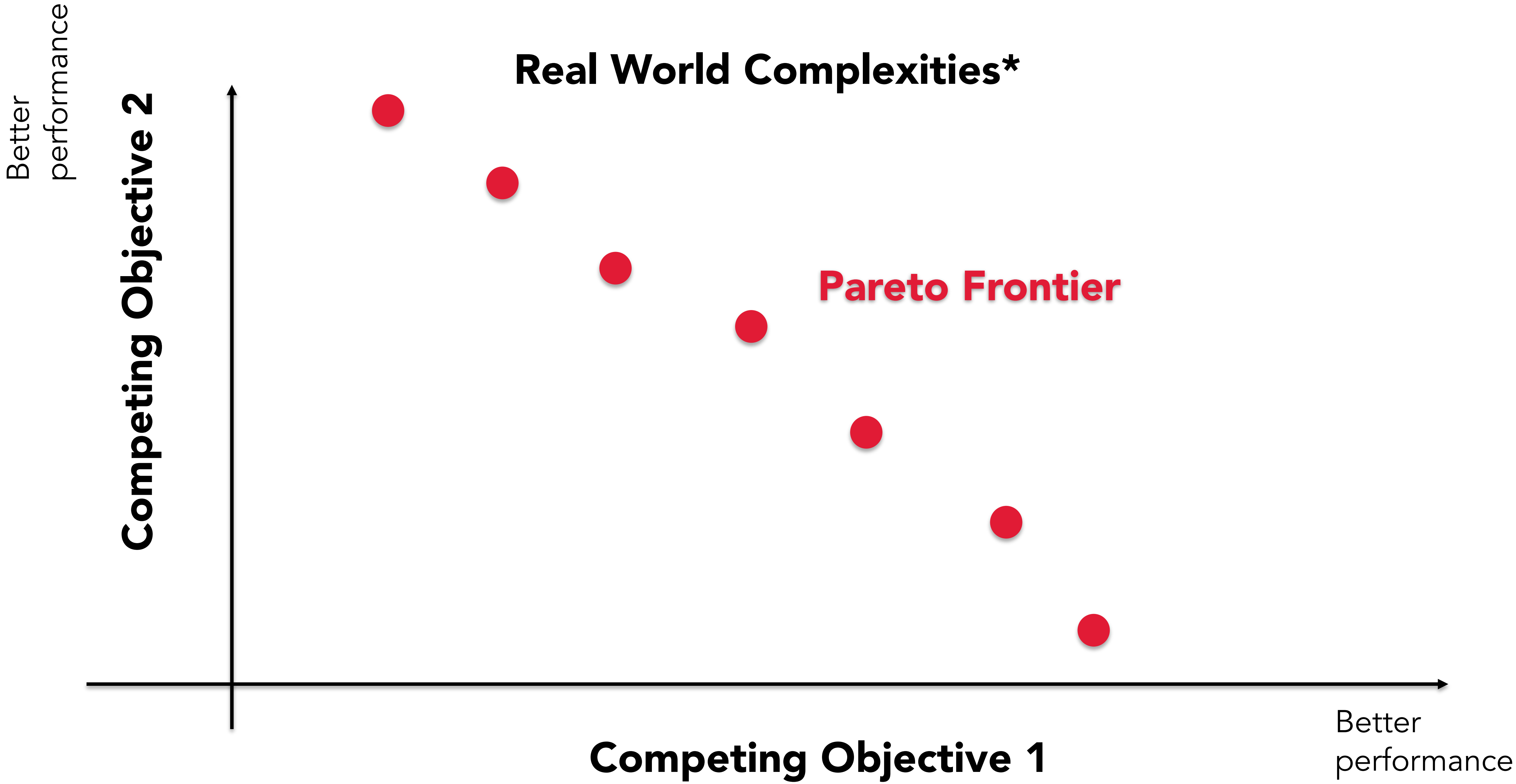
What "best practices" should we implement for performing ML studies in climate prediction? Are there specific metrics, verification datasets, and problems that should be considered?

Very problem specific. Plus, how do you do this without **stifling creativity?**

What "best practices" should we implement for performing ML studies in climate prediction? Are there specific metrics, verification datasets, and problems that should be considered?

On the use of **metrics...**

# Real World Complexities*

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What can US CLIVAR and others do to promote the open and free distribution of datasets (reanalysis, observations, model output) to use for ML/AI applications in climate prediction?

Don't do this **alone!**
(Also, software!)

What can US CLIVAR and others do to promote the open and free distribution of datasets (reanalysis, observations, model output) to use for ML/AI applications in climate prediction?

- Home
- Meeting Notes
- Membership
- Upcoming Events
- Short Courses
- AI Datasets
- Past Conferences and Events
- Terms of Reference

## Committee on Artificial Intelligence Applications to Environmental Science

Important Dates

**Updates**

1. 2-4-2022: Machine Learning in Python 2022 Short Course materials now available on our Short Course page.
2. 7-19-2021: AMS Annual Meeting submission deadline extended to Sept 1 with new virtual option available.
3. 1-10-2021: New web
community: http://ml

PANGEO ML DATASETS

TOPS NASA

AGU

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GRAND CHALLENGES GRANTS

U.S. DEPARTMENT OF ENERGY

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