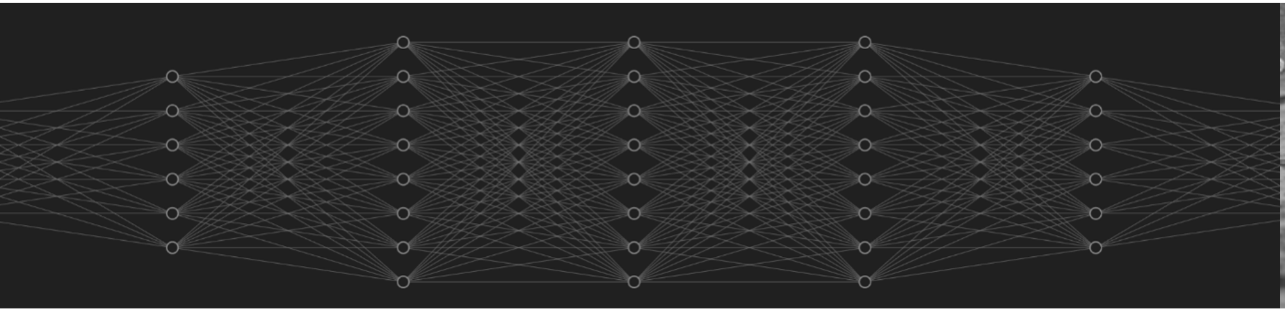
Deep Learning for Subseasonal Global Precipitation Prediction

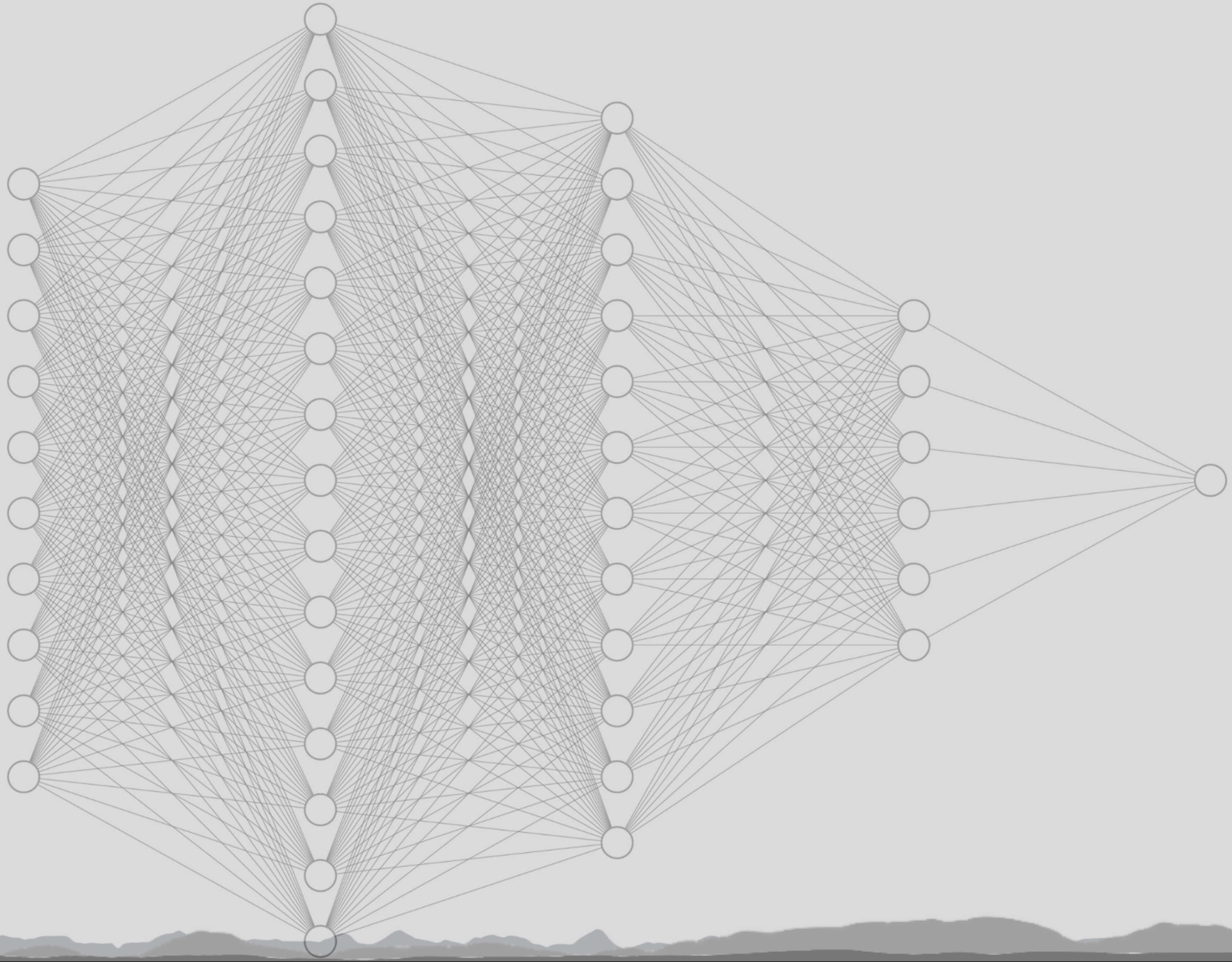


Maria J. Molina

National Center for Atmospheric Research, Boulder, Colorado

In collaboration with Jadwiga Richter, Judith Berner, Anne Sasha Glanville, Katie Dagon, Abby Jaye, Aixue Hu, Gerald Meehl, and others

NCAR U.S. DEPARTMENT OF ENERGY Office of Science NSF catalyst



1959, ML defined

1986,

Backpropagation

Since 1990s,

GPUs

ImageNet

DL advances

Where does machine learning fit in Earth system modeling?

Input
Observations
Initialization

→

Run Model
Parameterizations
HPC Costs

→

Output
S2S Predictions
Feature Detection

Where does machine learning fit in Earth system modeling?

Input
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S2S Predictions
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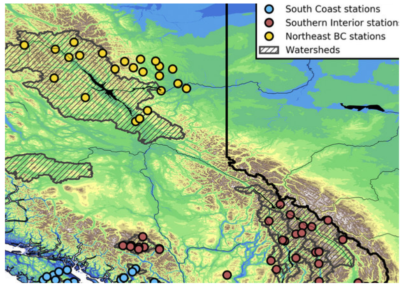
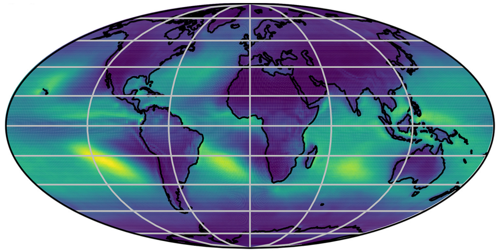
Sha, Y., Gagne, D.J., West, G. and Stull, R., 2021. **Deep-learning-based precipitation observation quality control.** Journal of Atmospheric and Oceanic Technology.



Where does machine learning fit in Earth system modeling?

Input	Run Model	Output
Observations	Parameterizations	S2S Predictions
Initialization	HPC Costs	Feature Detection

Gettelman, A., Gagne, D.J., Chen, C.C., Christensen, M.W., Lebo, Z.J., Morrison, H. and Gantos, G., 2021. **Machine learning the warm rain process.** Journal of Advances in Modeling Earth Systems.



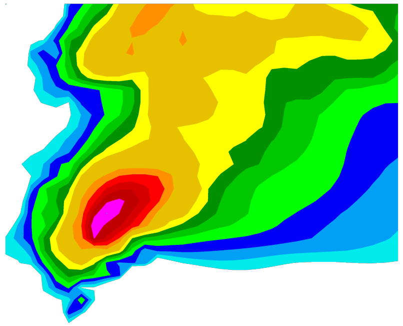
Where does machine learning fit in Earth system modeling?

Input
Observations
Initialization

Run Model
Parameterizations
HPC Costs

Output
S2S Predictions
Feature Detection

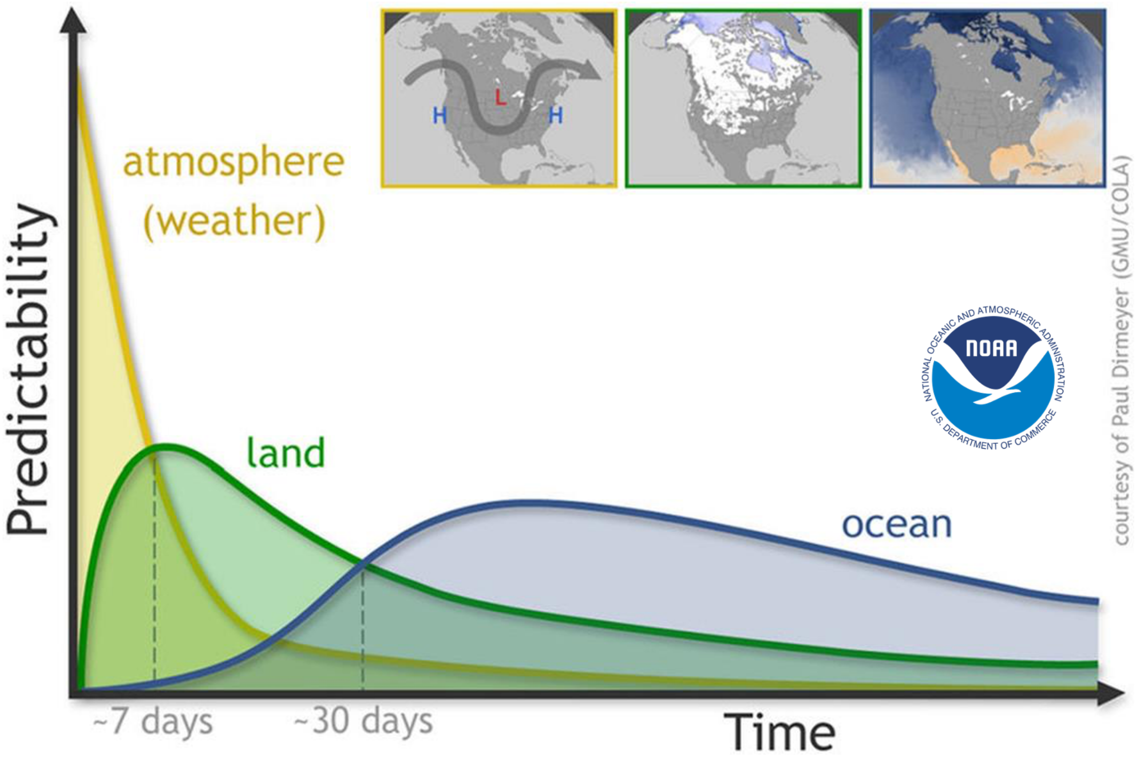
Molina, M.J., Gagne, D.J., Prein, A.F., 2021. **A benchmark to test generalization capabilities of deep learning methods to classify severe convective storms in a changing climate.** Earth and Space Science.



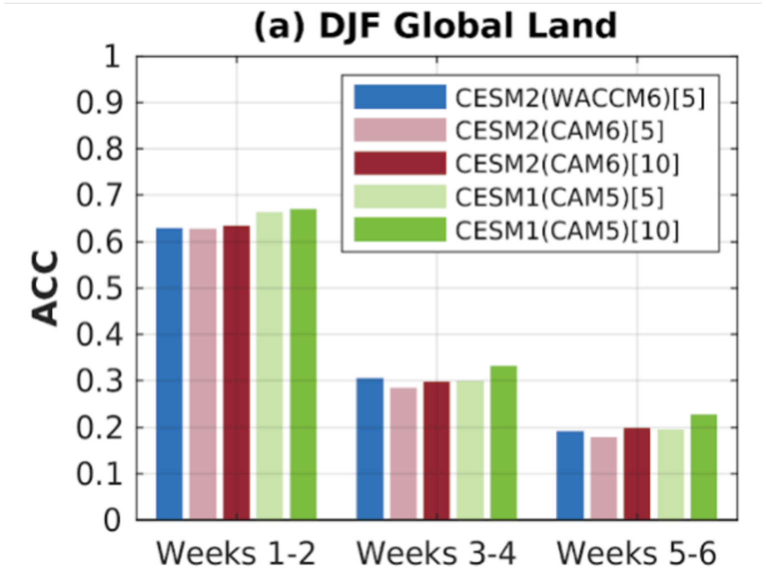
S2S simulations created using CESM2 (Richter et al. 2021; under review).

Subseasonal reforecasts follow SubX protocol (Pegion et al. 2019).

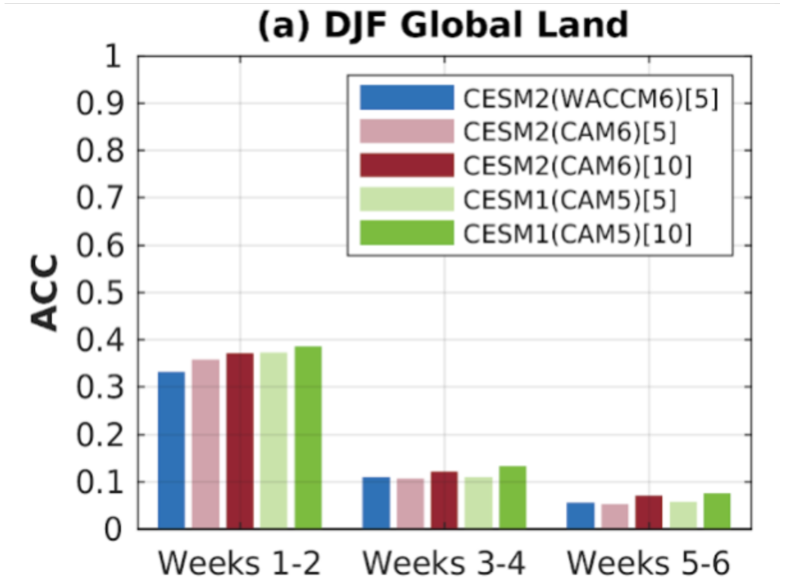
Near real-time forecasts are ongoing and contribute to the SubX multi-model mean ensemble.



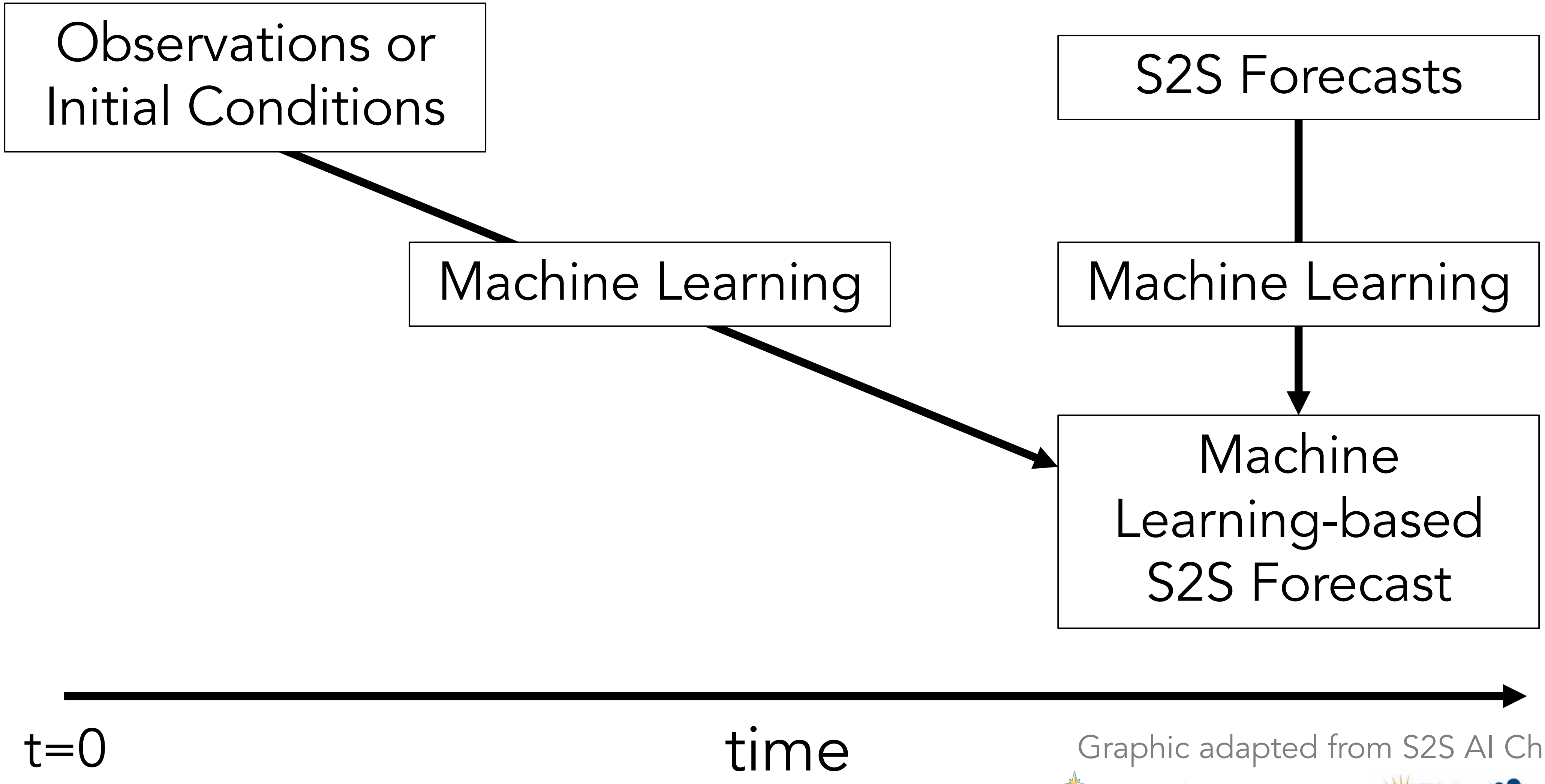
Temperature skill



Precipitation skill

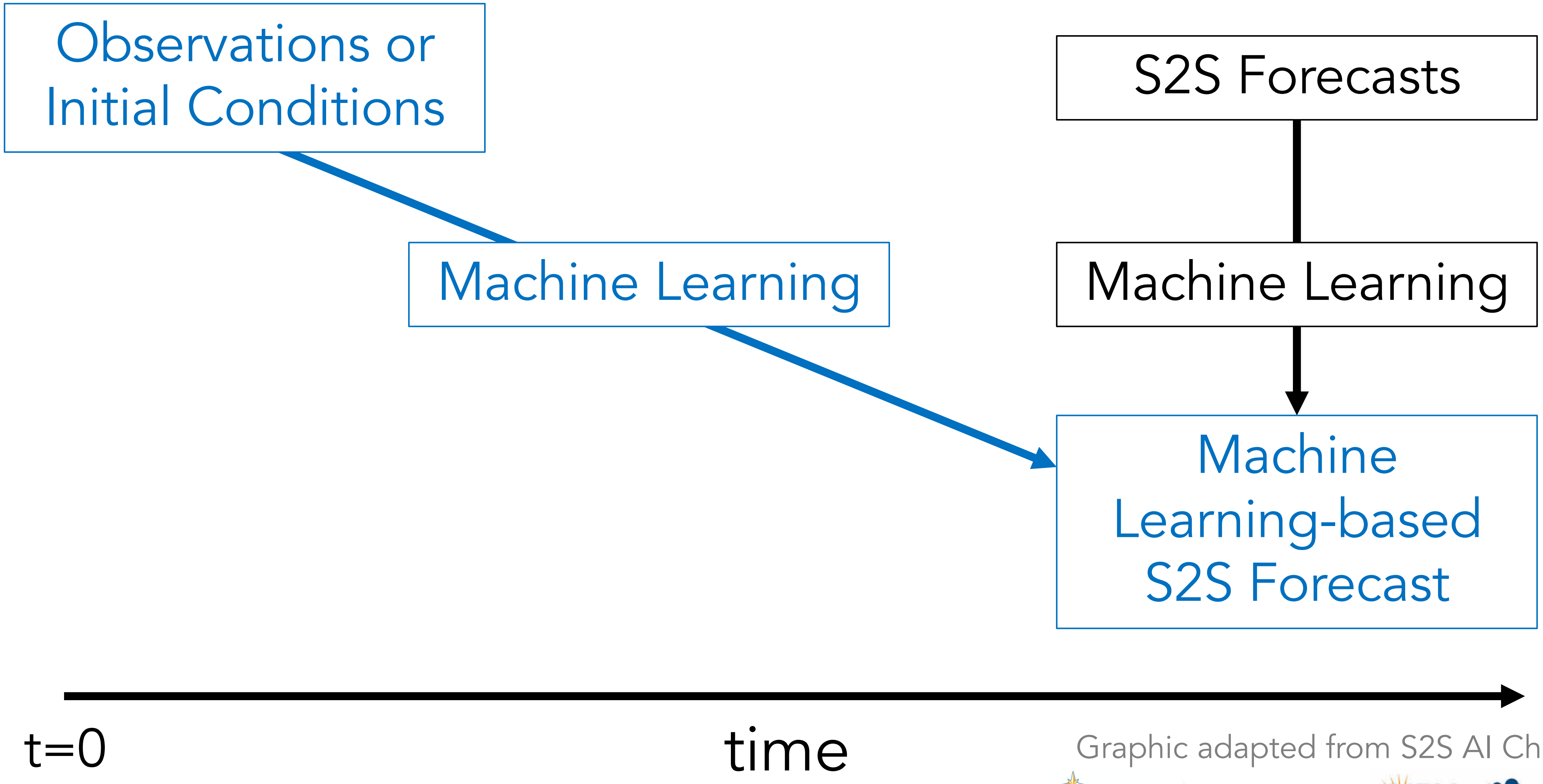


(Richter et al. 2021; under review)



Graphic adapted from S2S AI Challenge 2021

(Pegion et al. 2019, Merryfield et al. 2020, Barnes et al. 2020, Meehl et al. 2021)



Graphic adapted from S2S AI Challenge 2021

(Pegion et al. 2019, Merryfield et al. 2020, Barnes et al. 2020, Meehl et al. 2021)

Observations or Initial Conditions

Machine Learning

S2S Forecasts

Machine Learning

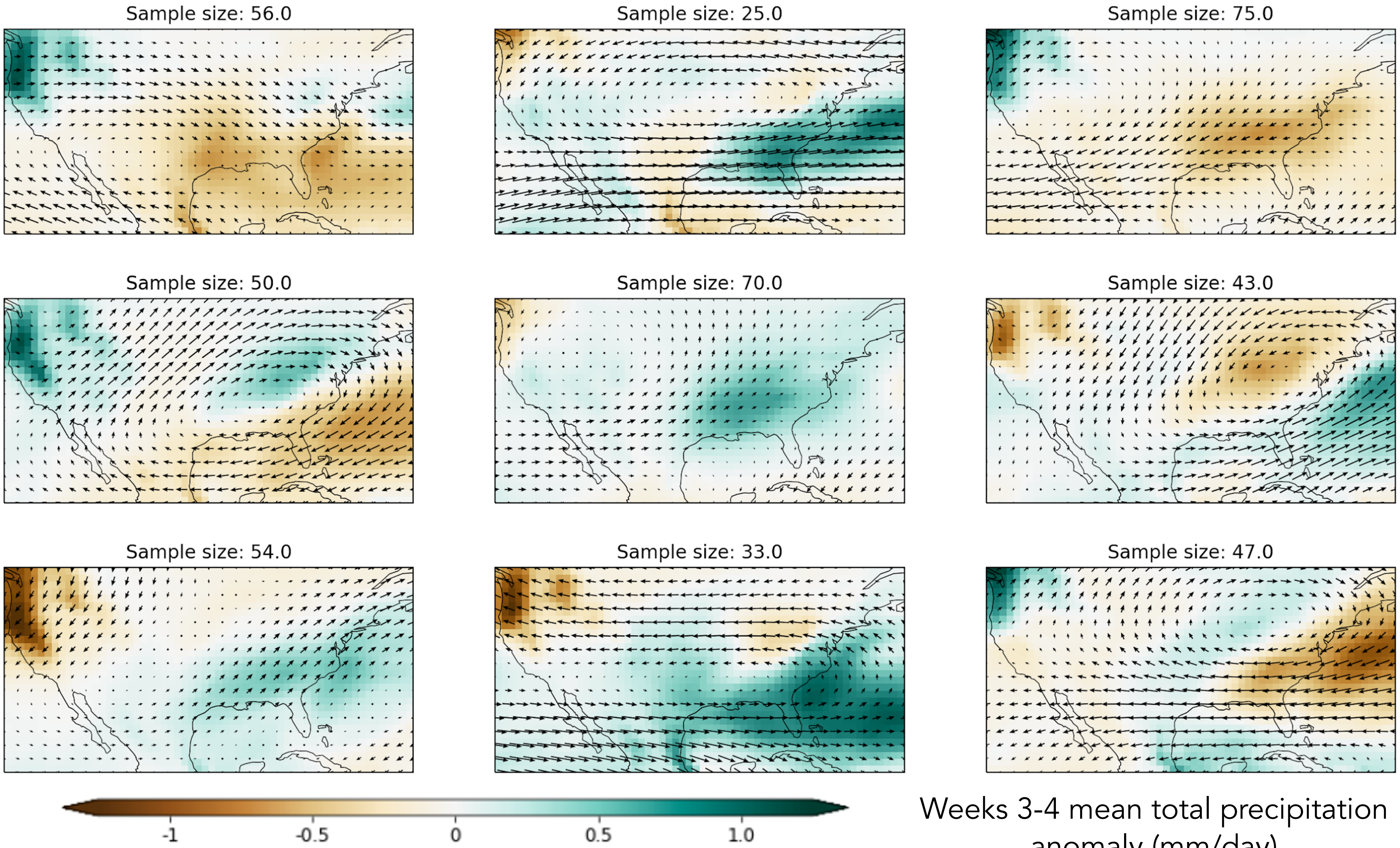
Vigaud, et al. 2018. Predictability of recurrent weather regimes over North America during winter from submonthly reforecasts. *MWR*.

Robertson, et al. 2020. Toward Identifying Subseasonal Forecasts of Opportunity Using North American Weather Regimes. *MWR*.

t=0 time

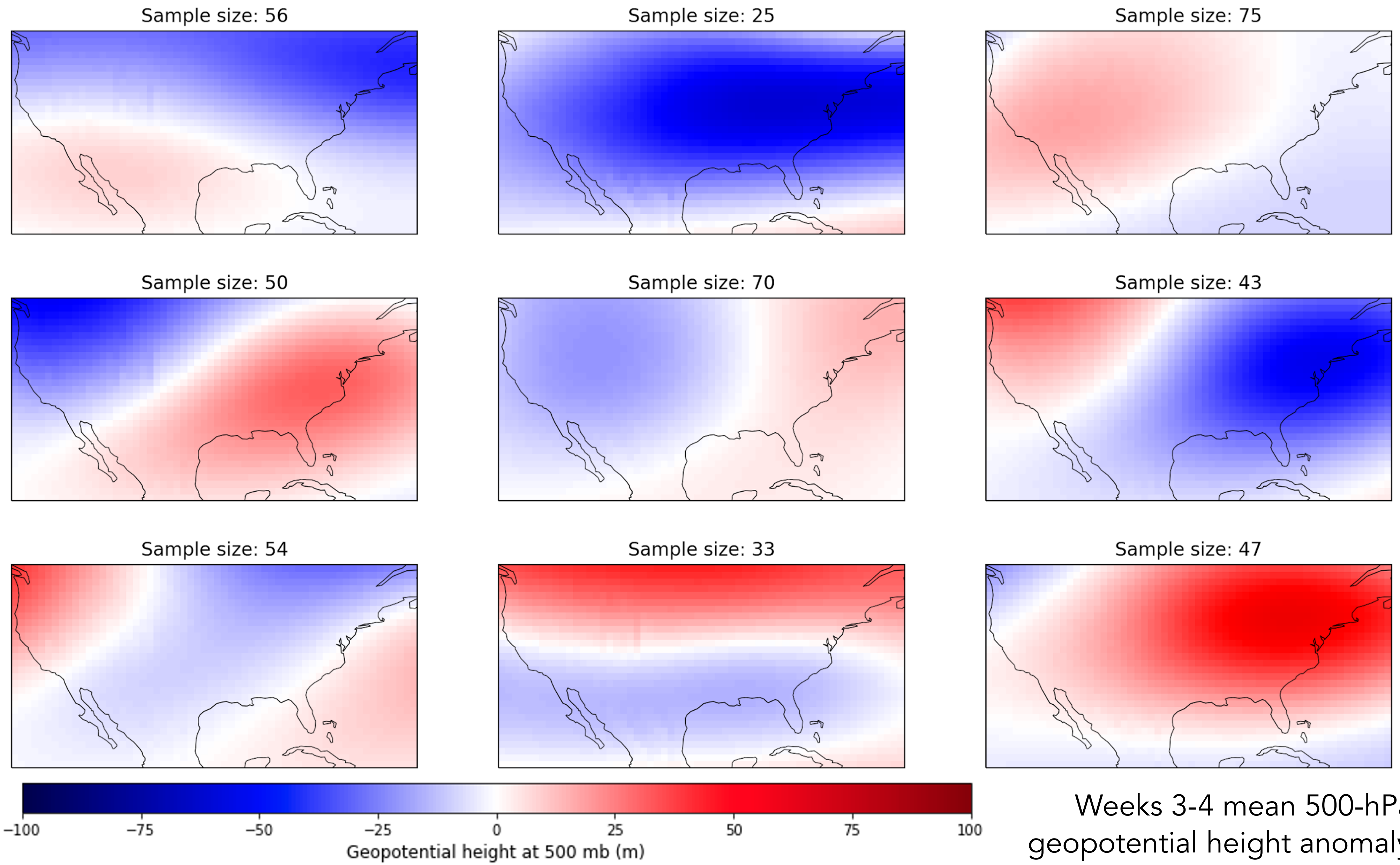
Graphic adapted from S2S AI Challenge 2021

(Pegion et al. 2019, Merryfield et al. 2020, Barnes et al. 2020, Meehl et al. 2021)



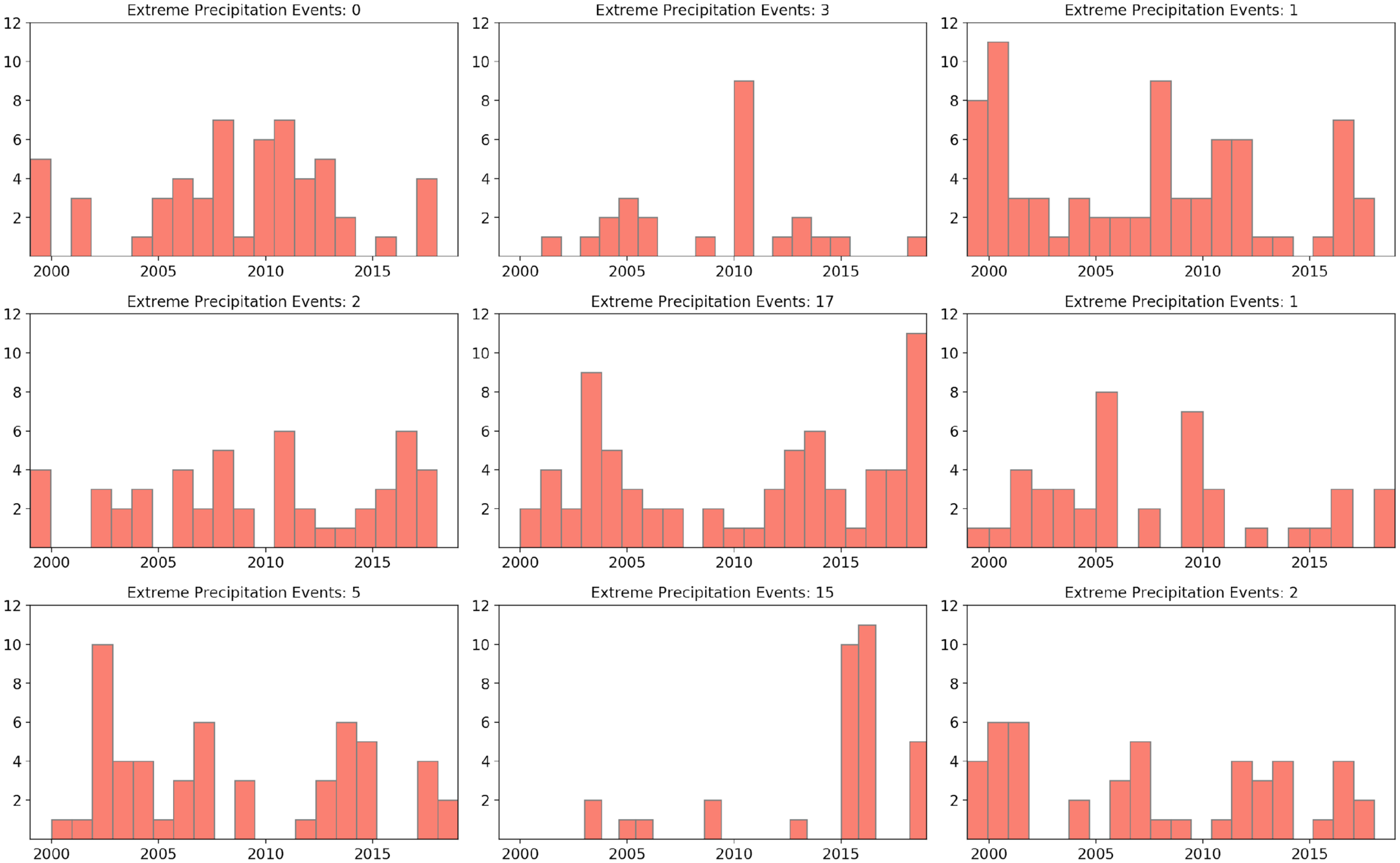
Weeks 3-4 mean total precipitation anomaly (mm/day)

Molina et al. (in prep.)

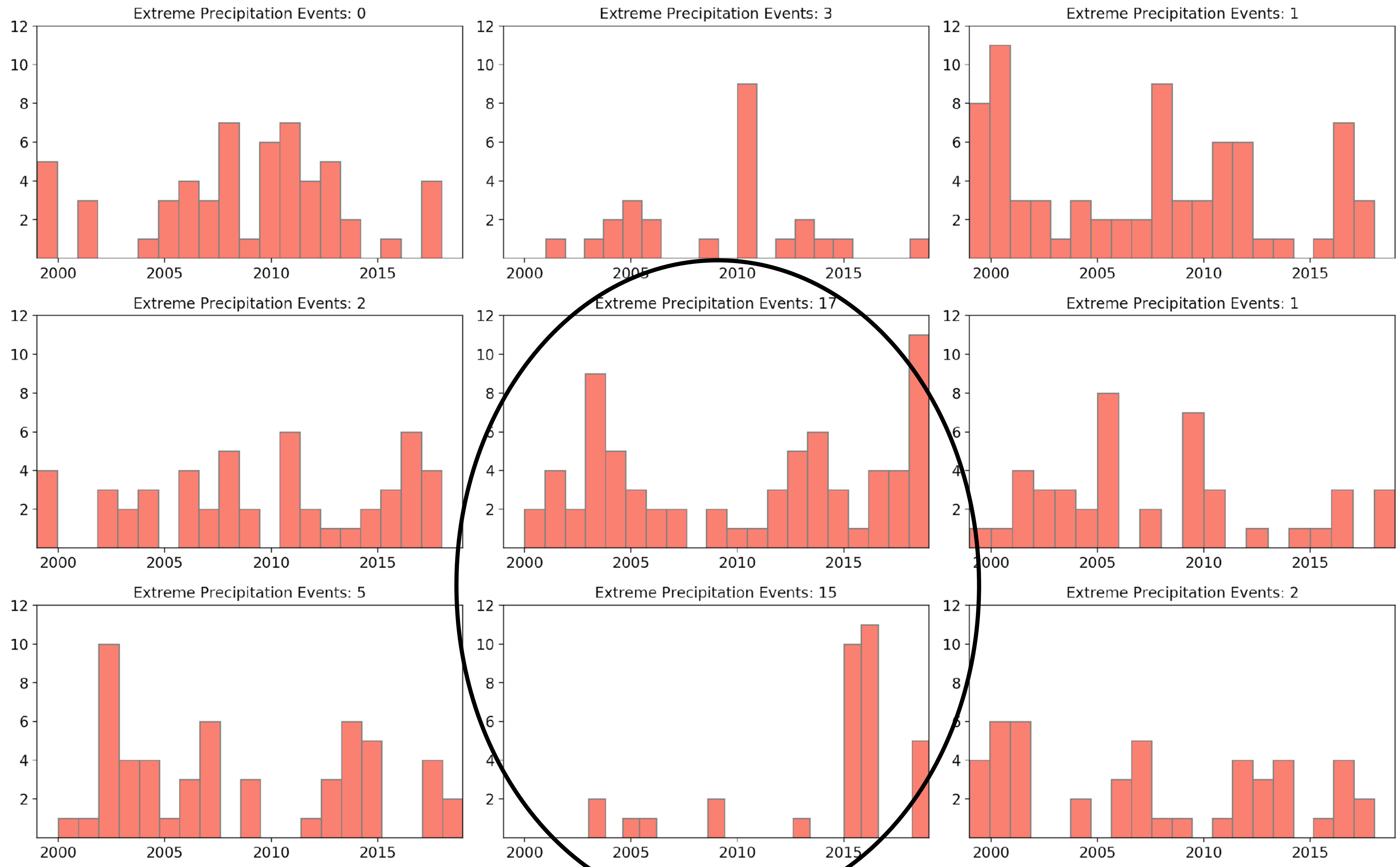


Weeks 3-4 mean 500-hPa geopotential height anomaly (m)

Molina et al. (in prep.)



Molina et al. (in prep.)

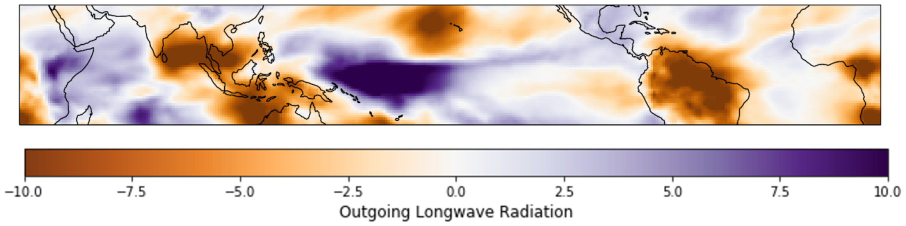


Molina et al. (in prep.)

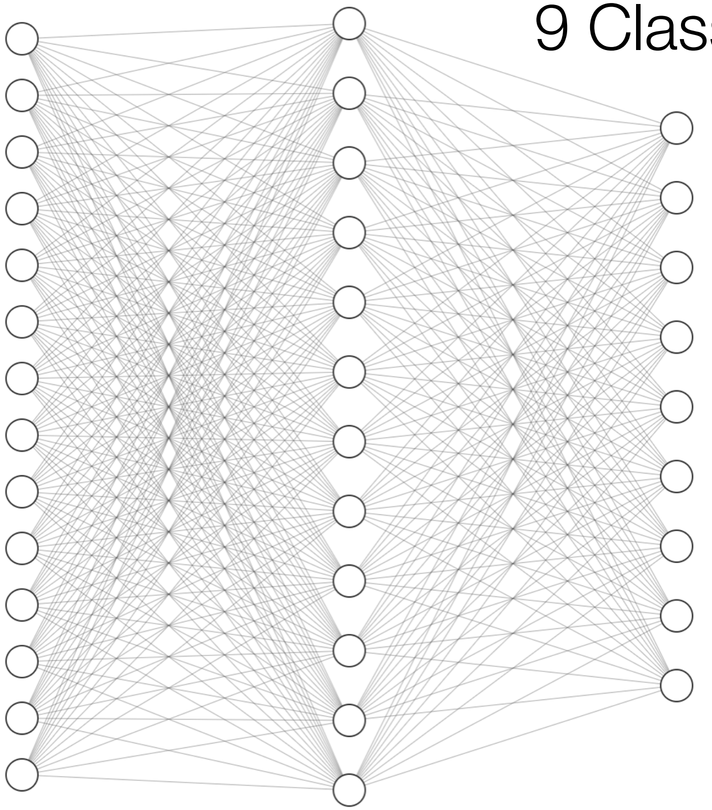
Neurons: 256, 128

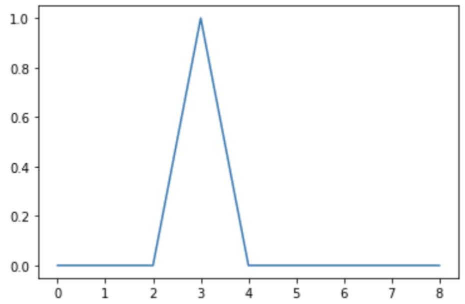
9 Classes

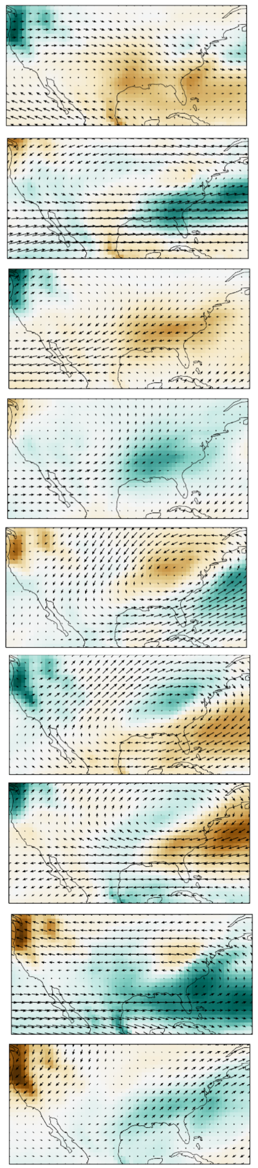
51 x 116



OLR







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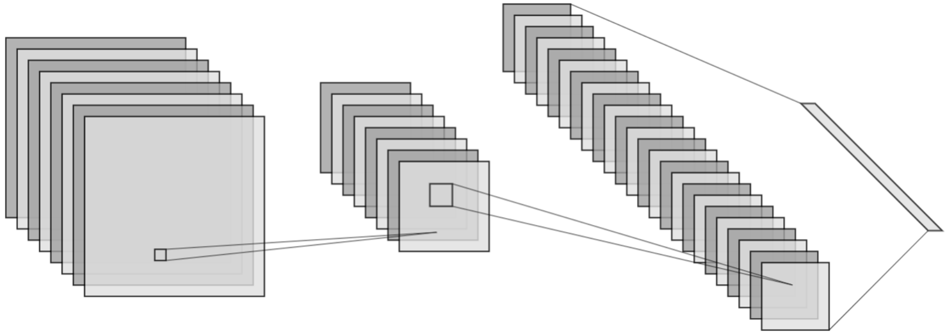
Molina et al. (in prep.)

Step 1: Train ML

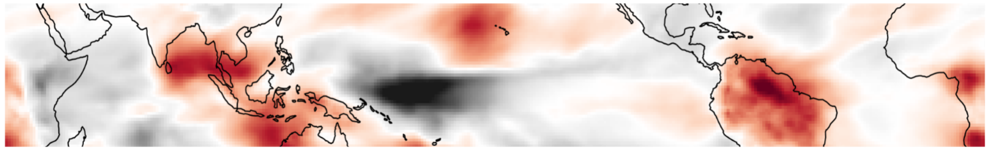
- Physically relevant upstream fields (SSTs, OLR).



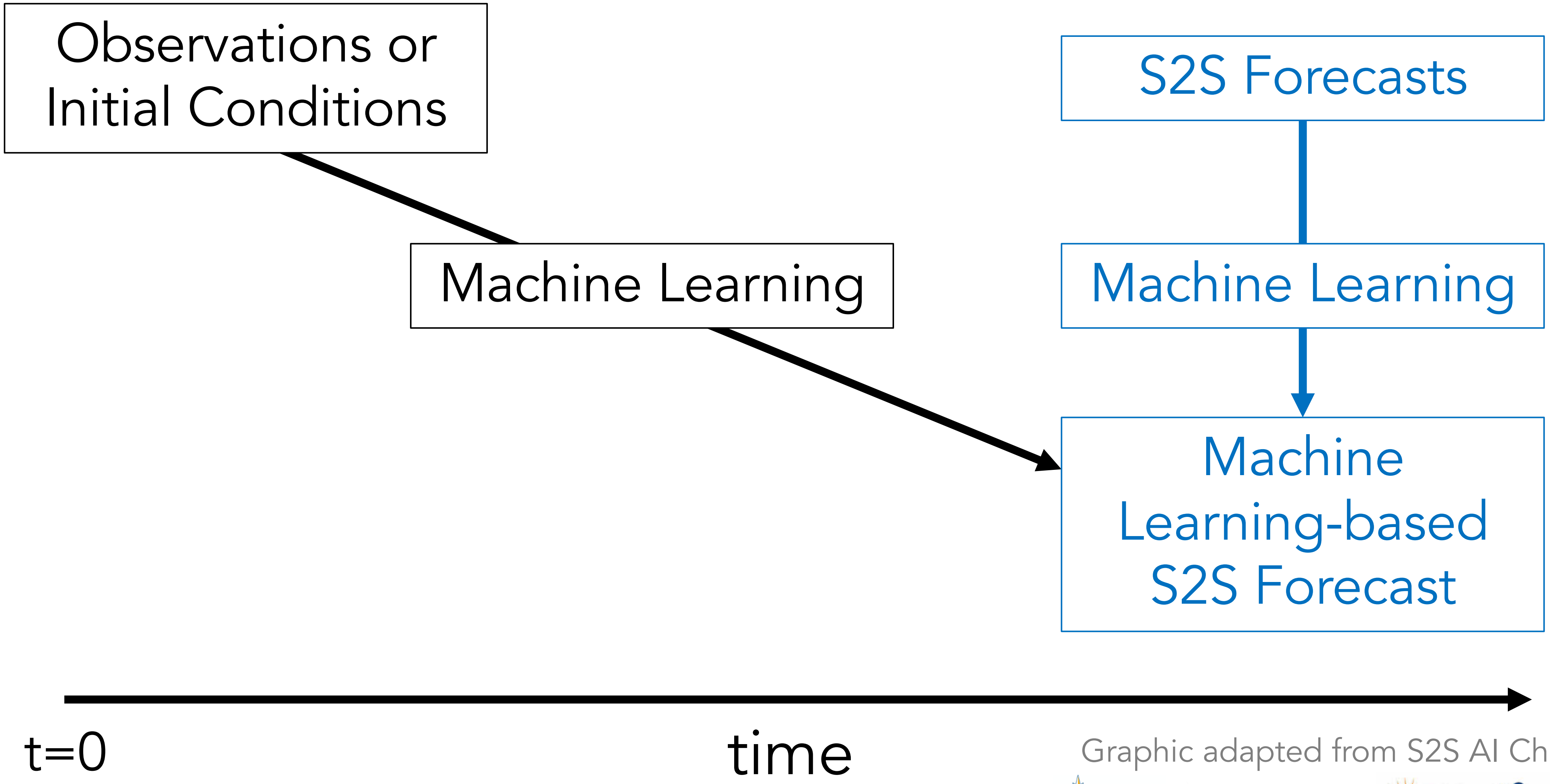
S2S/S2D Prediction

- Modes of variability (MJO, ENSO).
- Impacts (temperature, precipitation).

Step 2: Explainable AI



Generate heatmaps (saliency maps, LRP) using input fields (e.g., Barnes et al. 2020).

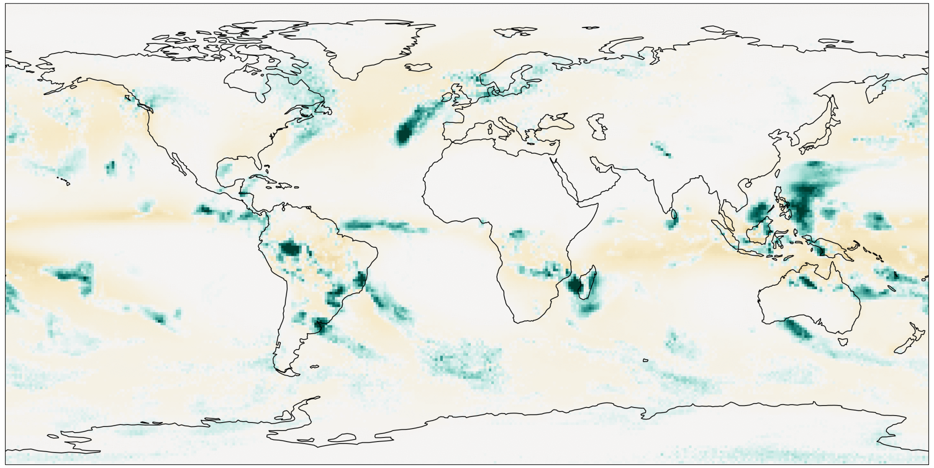


Graphic adapted from S2S AI Challenge 2021

(Pegion et al. 2019, Merryfield et al. 2020, Barnes et al. 2020, Meehl et al. 2021)

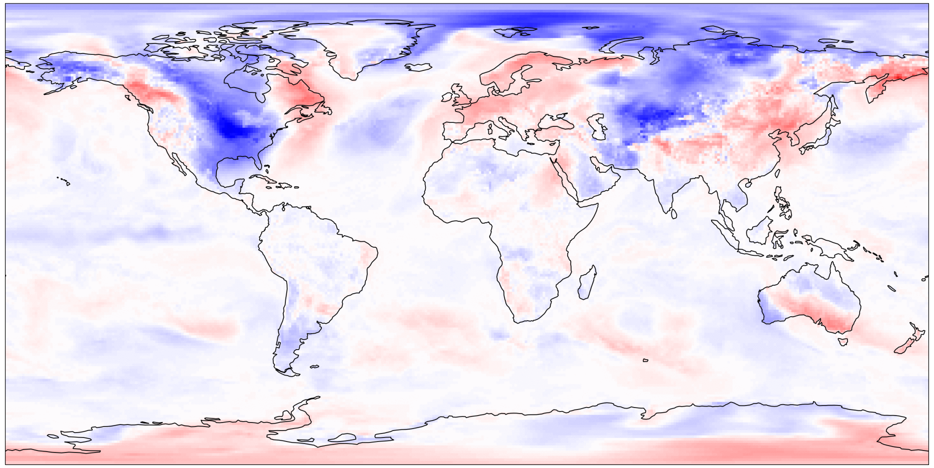
Climatology and lead time bias corrected anomalies

NOAA Global Precipitation Climatology Project (GPCP) Climate Data Record (CDR), Daily V1.3 (1999-2020).



(Adler et al. 2017)

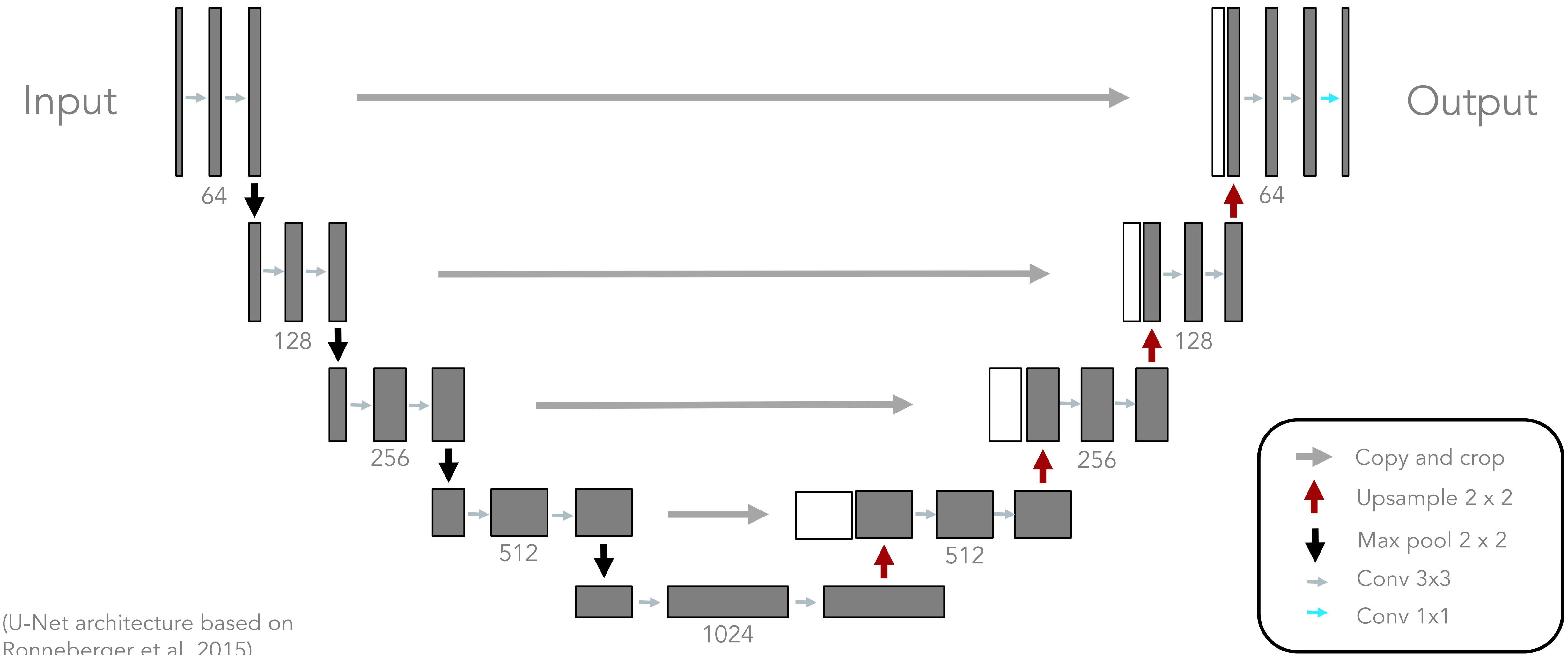
Climatology and lead time bias corrected anomalies



(Hersbach et al. 2020)

ERA5 Daily Maximum and Minimum Temperature Average (1999-2020).

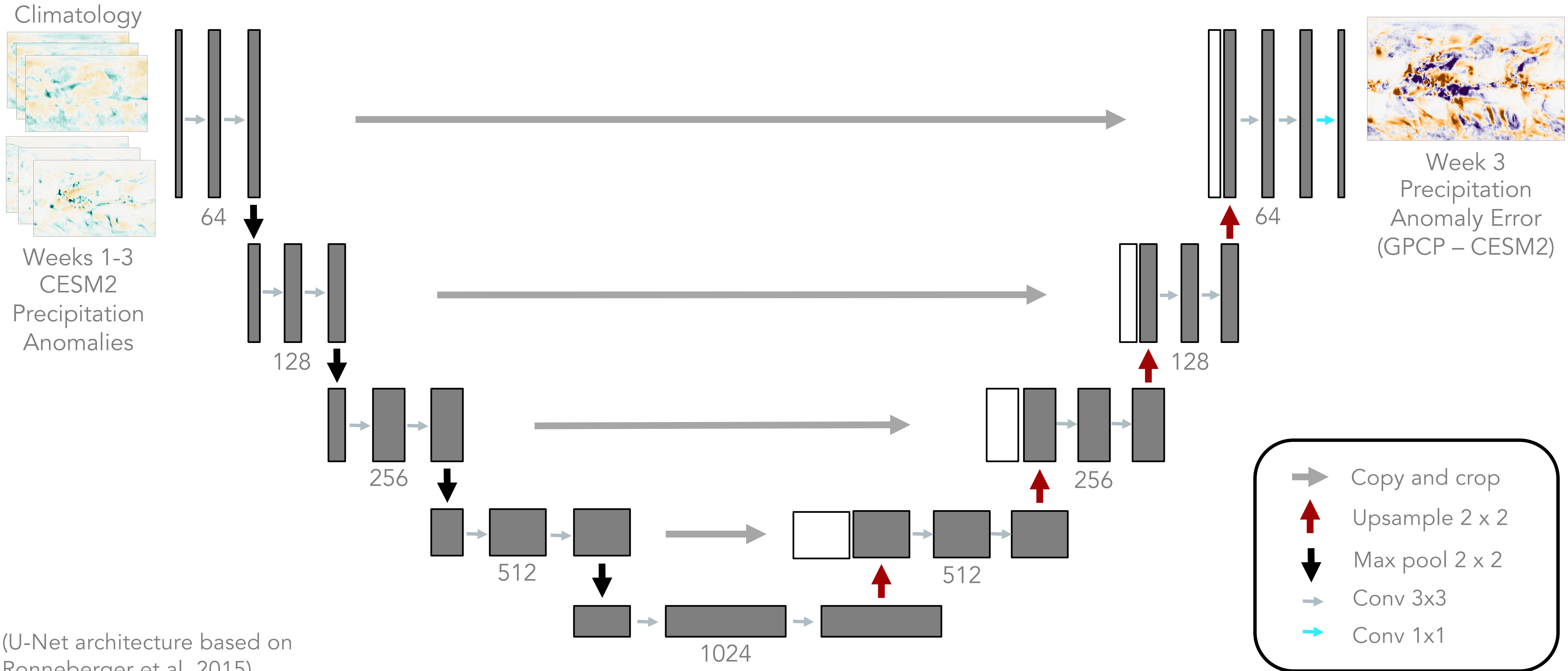
U-Net Architecture (training and validation: 1999-2015)



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

Molina et al. (in prep.)

U-Net Architecture (training and validation: 1999-2015)



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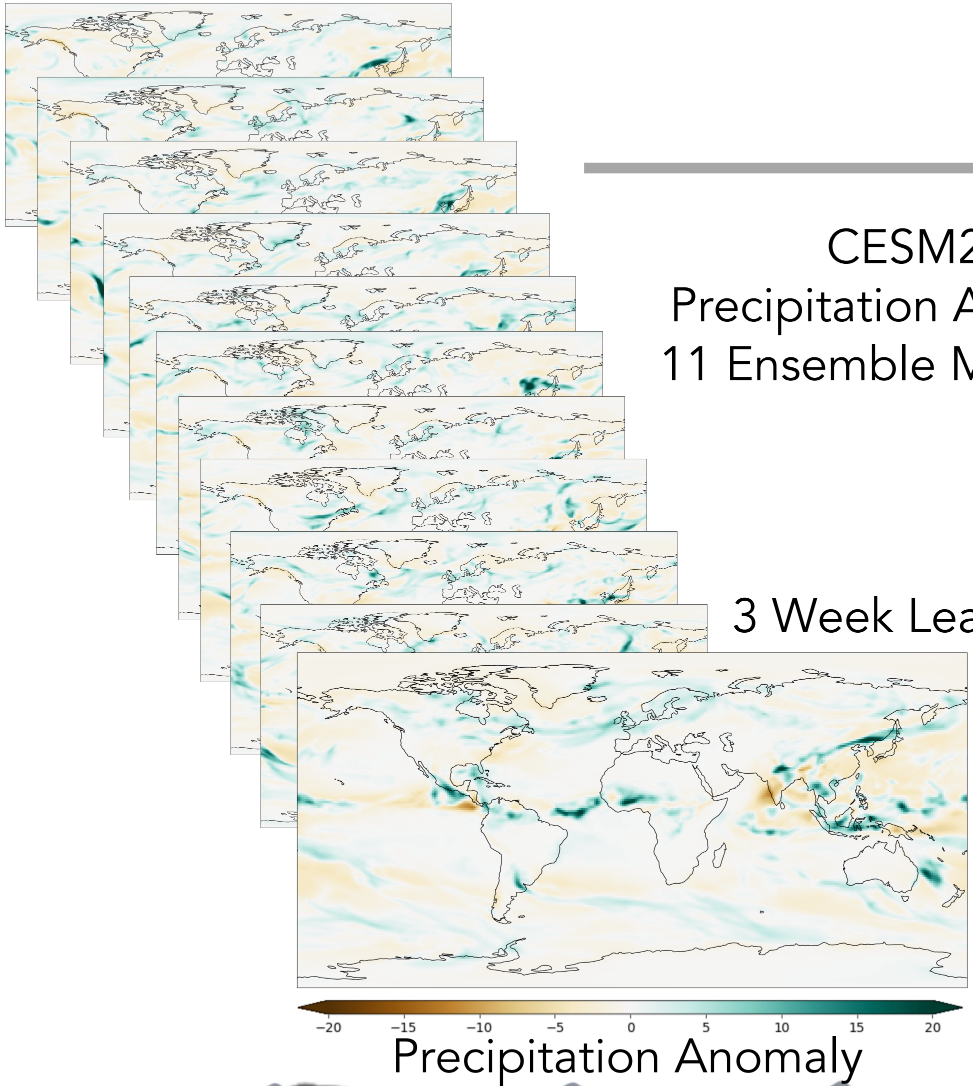
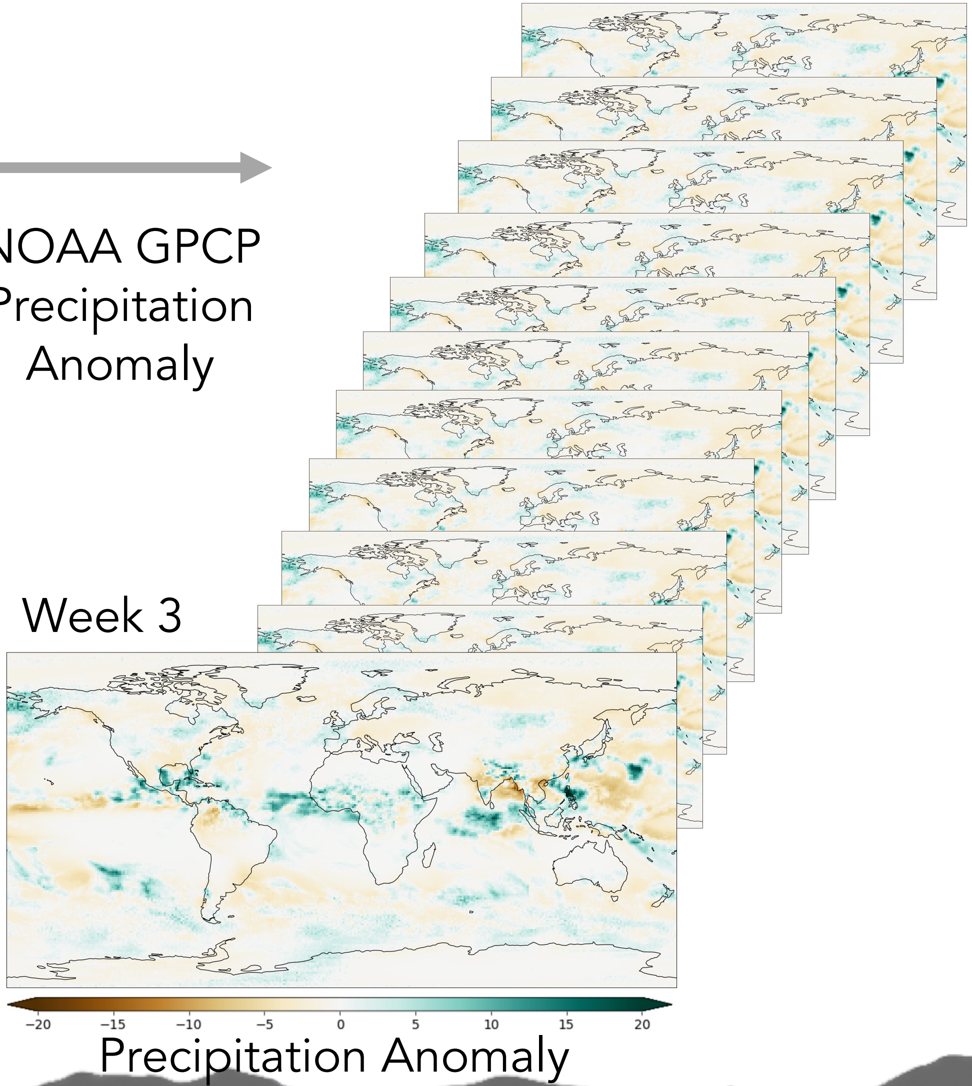


CESM2
Precipitation Anomaly
11 Ensemble Members

3 Week Lead Time

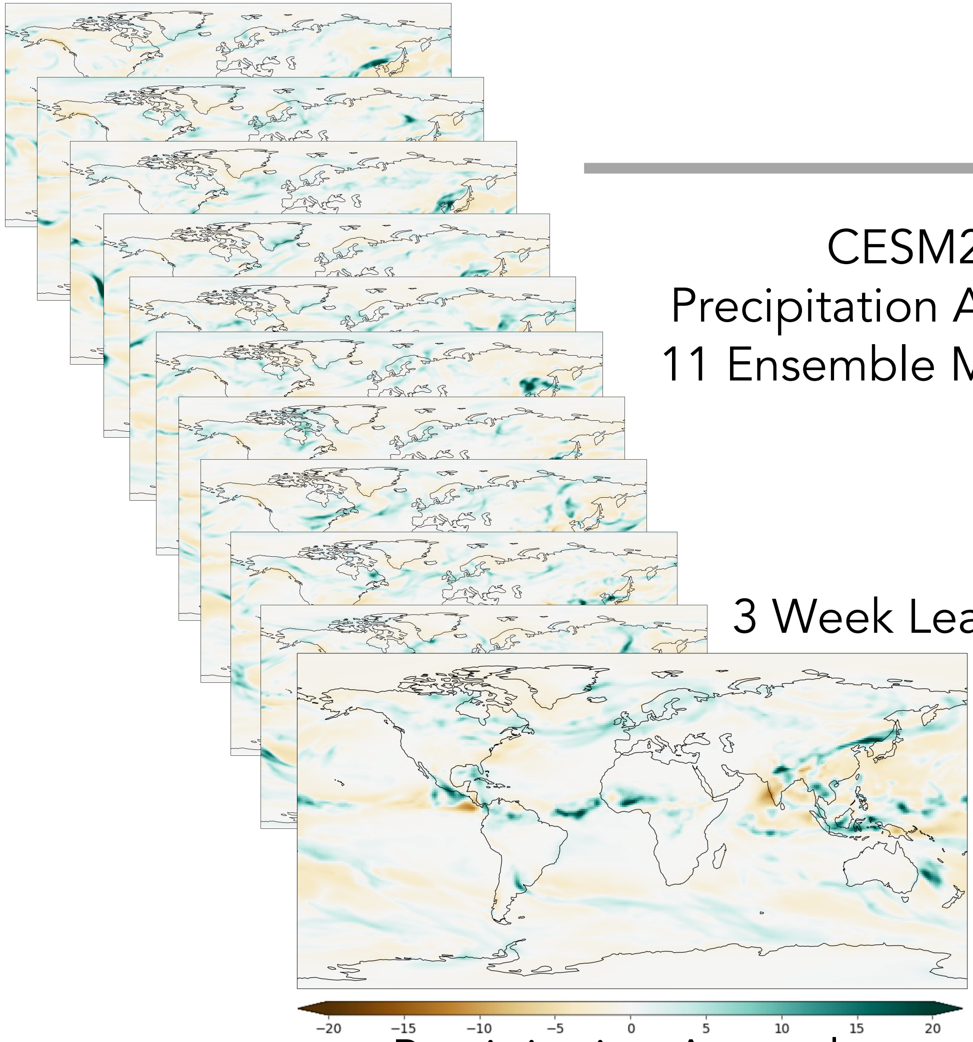
NOAA GPCP
Precipitation
Anomaly

Week 3



Molina et al. (in prep.)

U-Net Architecture (training and validation: 1999-2015)



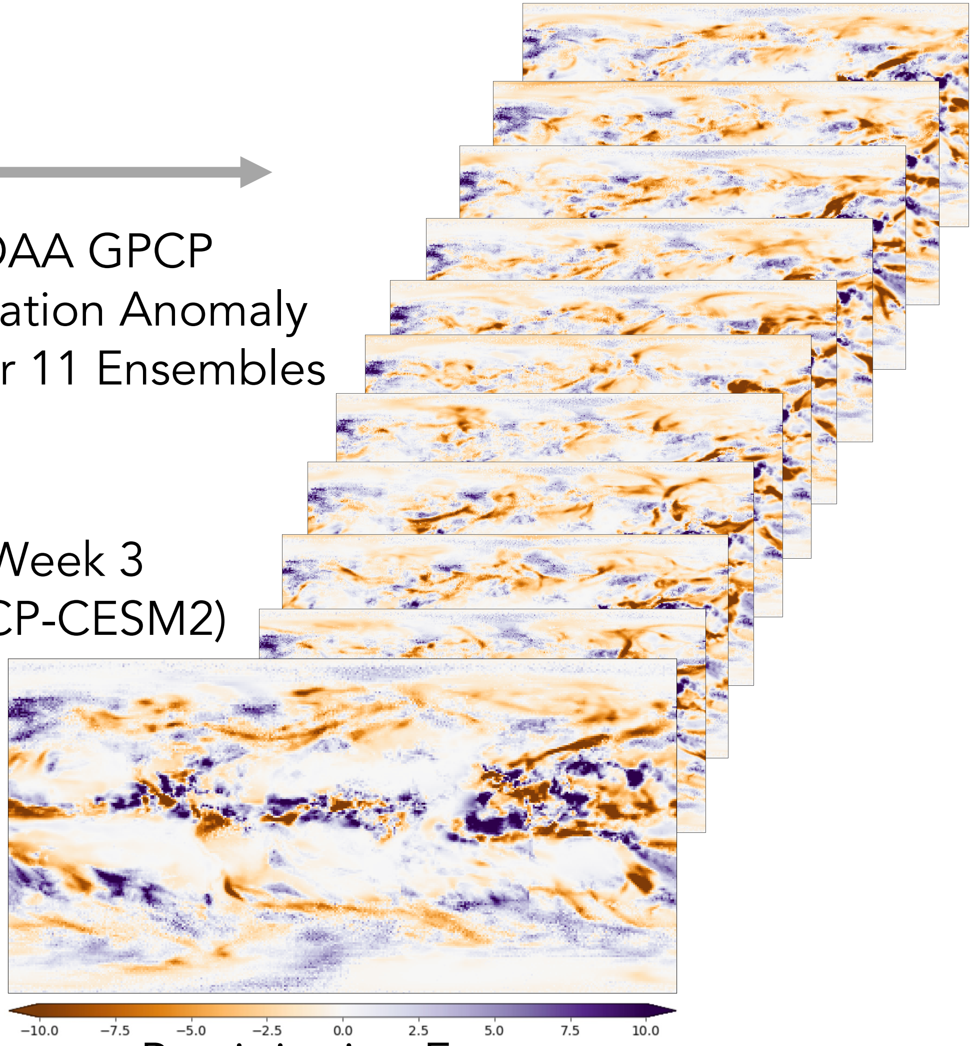
Precipitation Anomaly

CESM2
Precipitation Anomaly
11 Ensemble Members

3 Week Lead Time

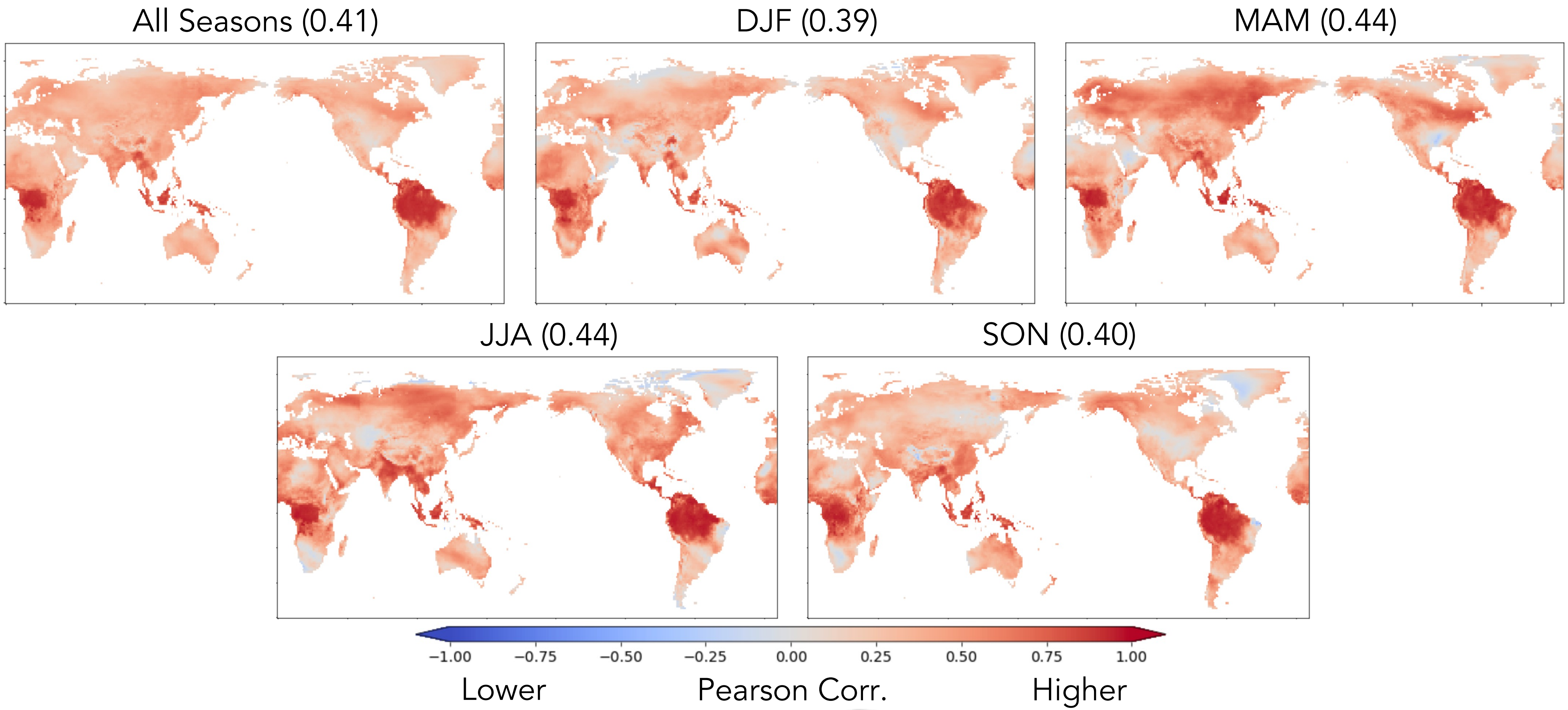
NOAA GPCP
Precipitation Anomaly
Errors for 11 Ensembles

Week 3
(GPCP-CESM2)



Precipitation Error

Skill of Week 3 Temperature Error Prediction (2016-2019)



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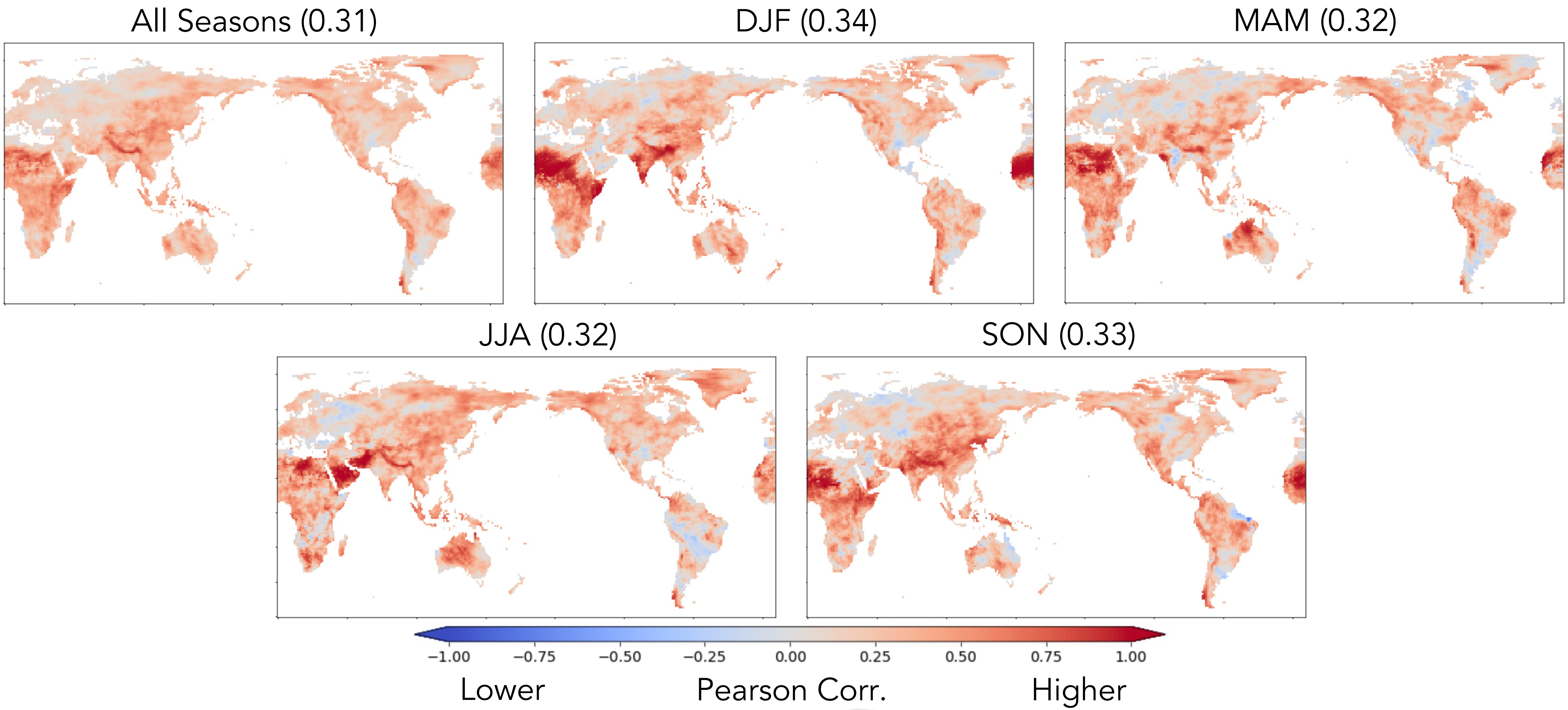
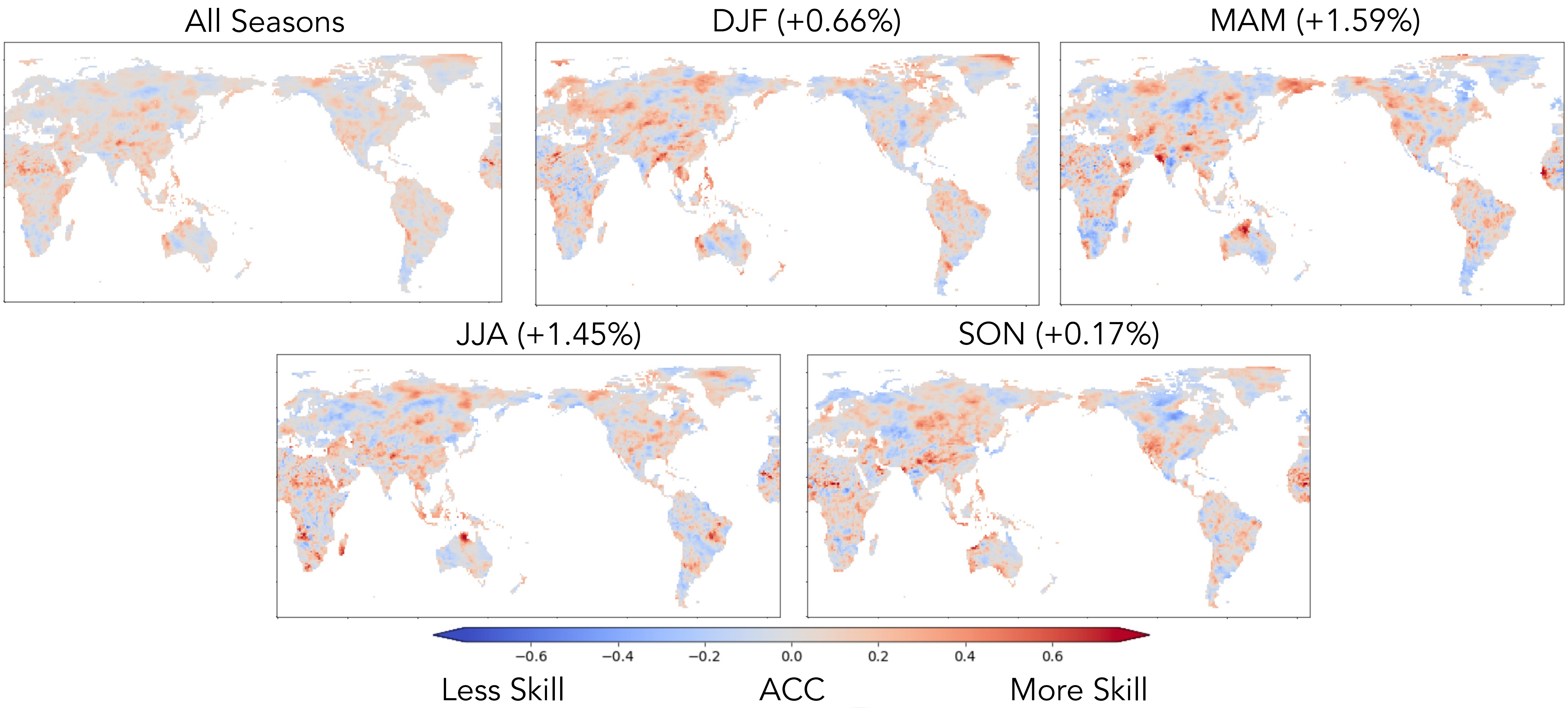
Skill of Week 3 Precipitation Error Prediction (2016-2019)



Molina et al. (in prep.)

Skill of Week 3 Precipitation Prediction (2016-2019)



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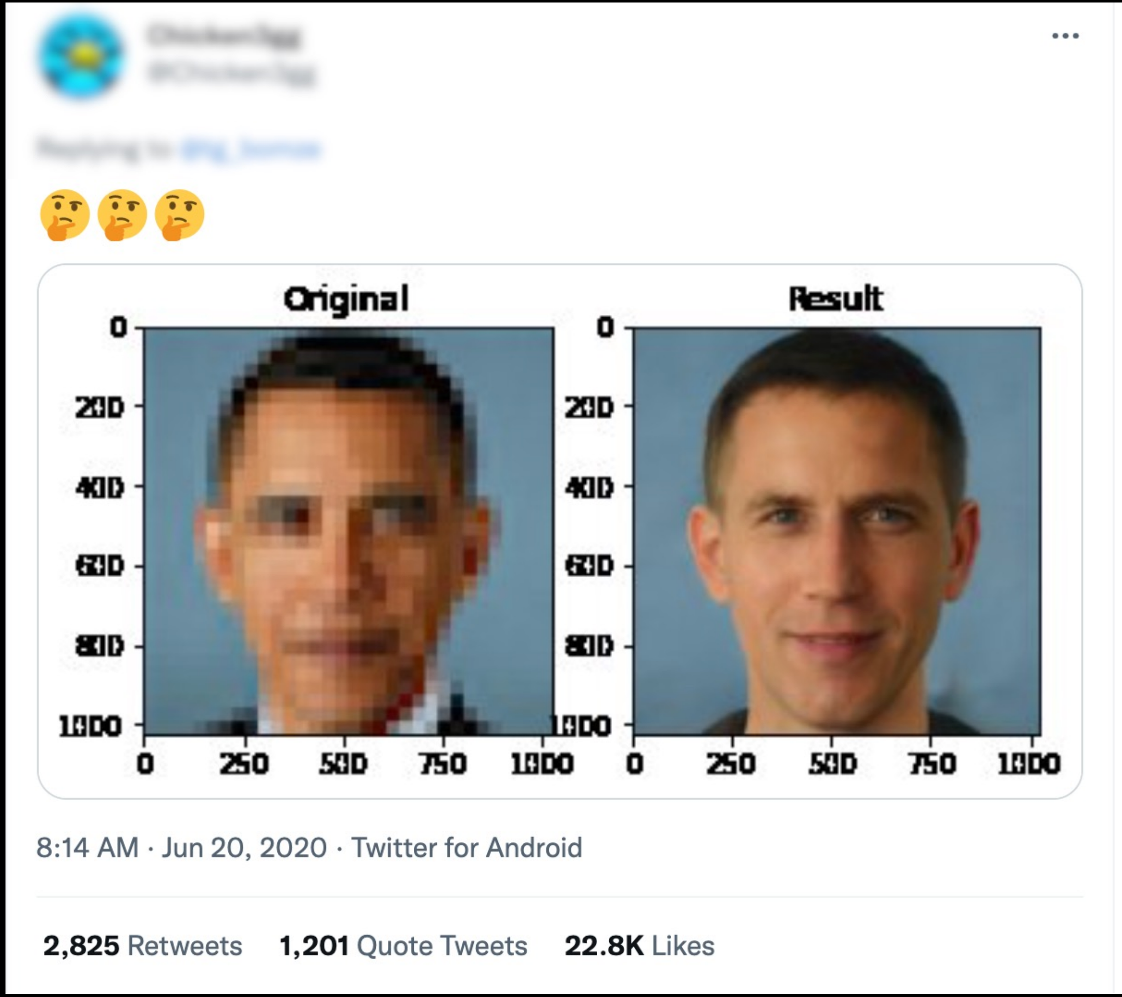
Molina et al. (in prep.)

Future work and opportunities:

- Application of Explainable AI.
- Comparison to other bias correction methods.
- Creation of a large ML-based ensemble.

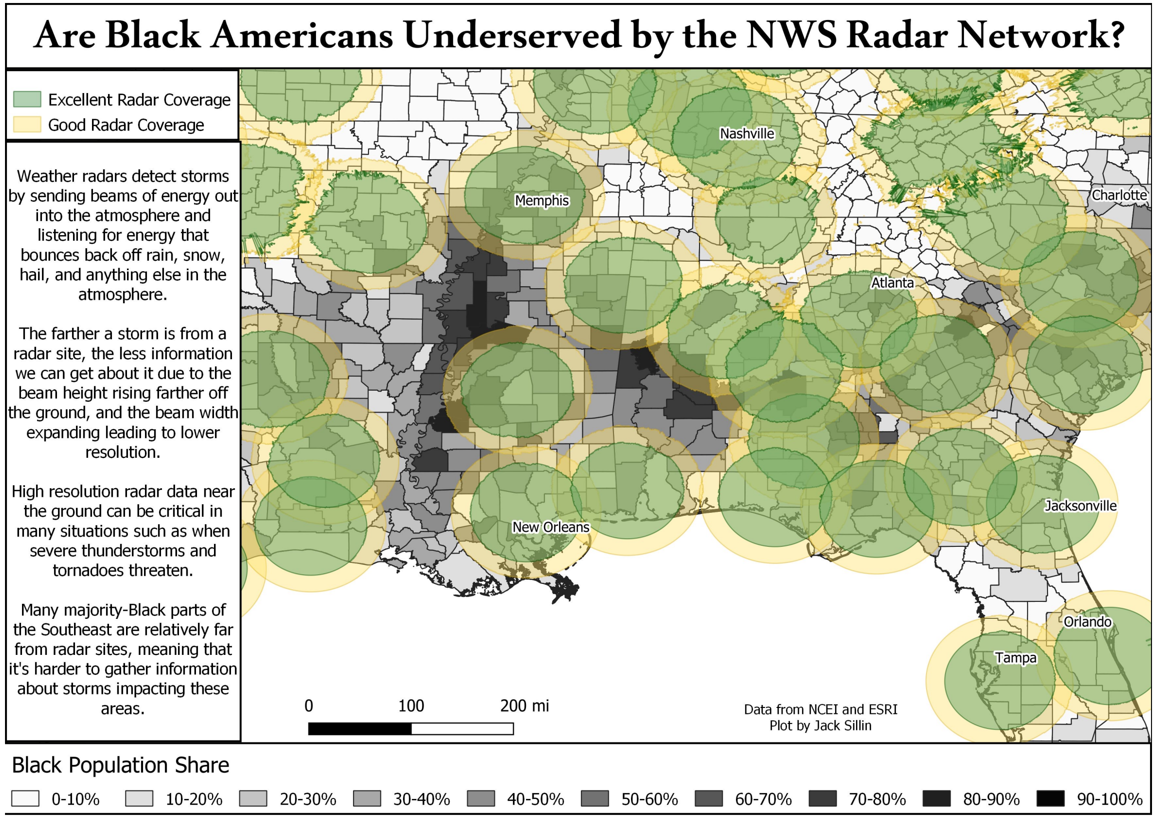
DERECHO
NCAR Supercomputer

Ethics in AI



Face-Depixelizer
https://github.com/tg-bomze/Face-Depixelizer

Ethics in AI for Weather and Climate



Funded NCAR Innovator Program grant led by Dr. Amy Yeboah (Howard University; 2021-23).

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catalyst