# Detecting and Predicting

# Extremes in a Changing Climate

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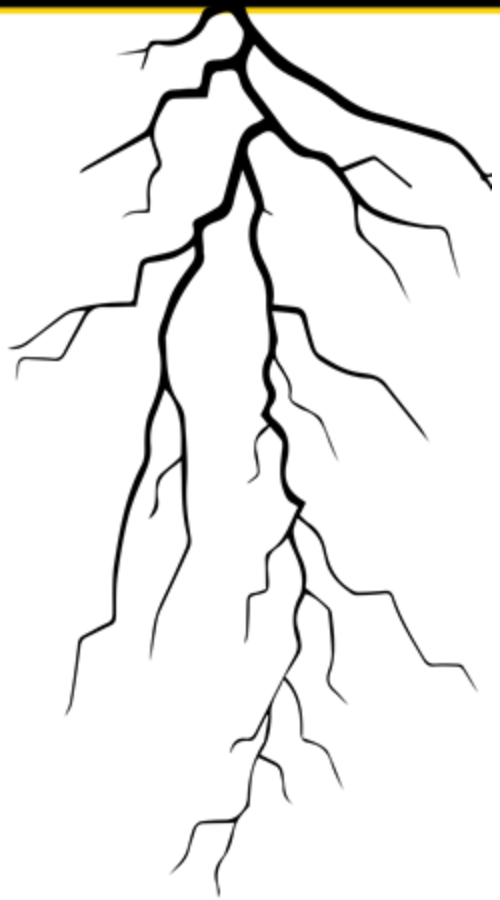

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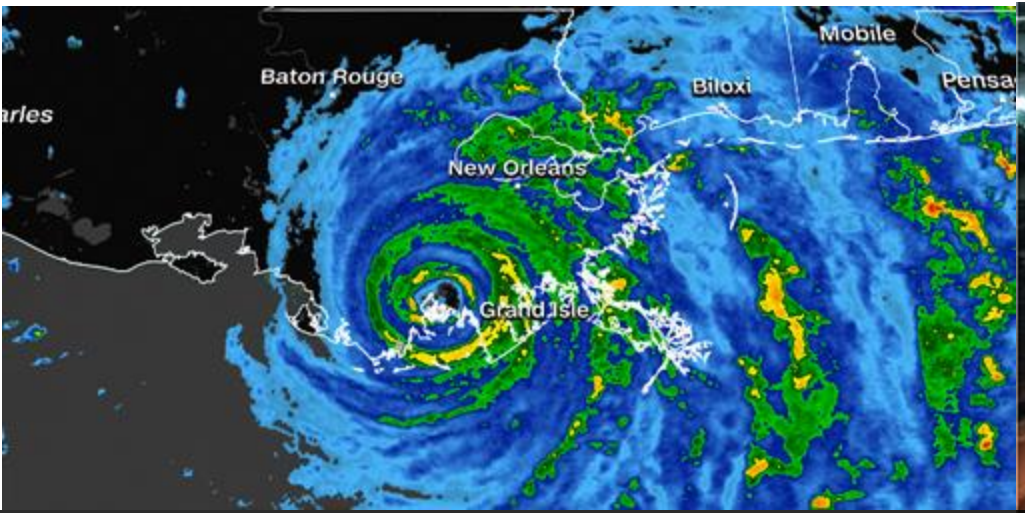
# Extremes exceeding a billion dollars in losses are **rising.**

Operational Land Imager on Landsat 8
NASA Observatory, Joshua Stevens; April 28, 2020.

**NYPD rescues more than 800 passengers from city's subways, chief says**

From CNN's Mark Morales



Ida (2021) remained a Category 4 hurricane for about

**6 hours after landfall.**

"Homes and businesses from North Dakota to Texas are losing power in the middle of an unprecedented deep freeze that has broken daily temperature records in hundreds of places." Time Magazine FEBRUARY 15, 2021

Historically marginalized communities experience **disproportionate vulnerability** to extreme weather events and climate change (Thomas et al. 2019).

Thomas, K., Hardy, R.D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., Roberts, J.T., Rockman, M., Warner, B.P. and Winthrop, R., (2019). Explaining differential vulnerability to climate change: A social science review. Wiley Interdisciplinary Reviews: Climate Change, 10(2), p.e565.

# ML in traditional physics-based modeling

## Initial State

- Data Assimilation
- Parameter Estimation
- Sensor Placement

## Run Model

- Physical Parameterizations
- PDE Acceleration
- Emulation
- Online Bias Correction

## Output

- Information Extraction
- Offline Bias Correction
- Data fusion
- Downscaling

**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.

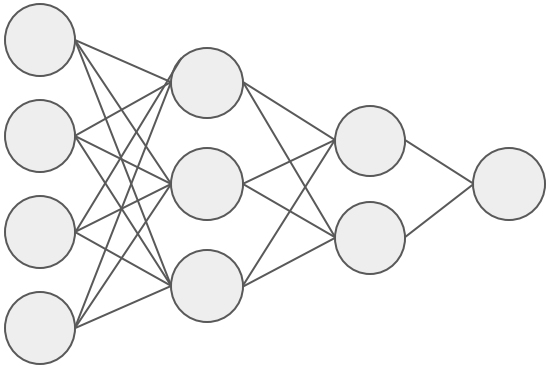
# ML-based weather and climate prediction

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

**Run Model**
Computing

**Output**
Predictions with a Certain Lead Time (e.g., S2S)

**Initial State**



**Future**

**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.

## Data Availability

| Data Rich | Moderate | Data Poor |
|---|---|---|

Neural Networks

PINNs

Symbolic Regression

*Transfer Learning*
*Meta-learning*

XGBoost

Gaussian Processes

## Use of Domain Knowledge

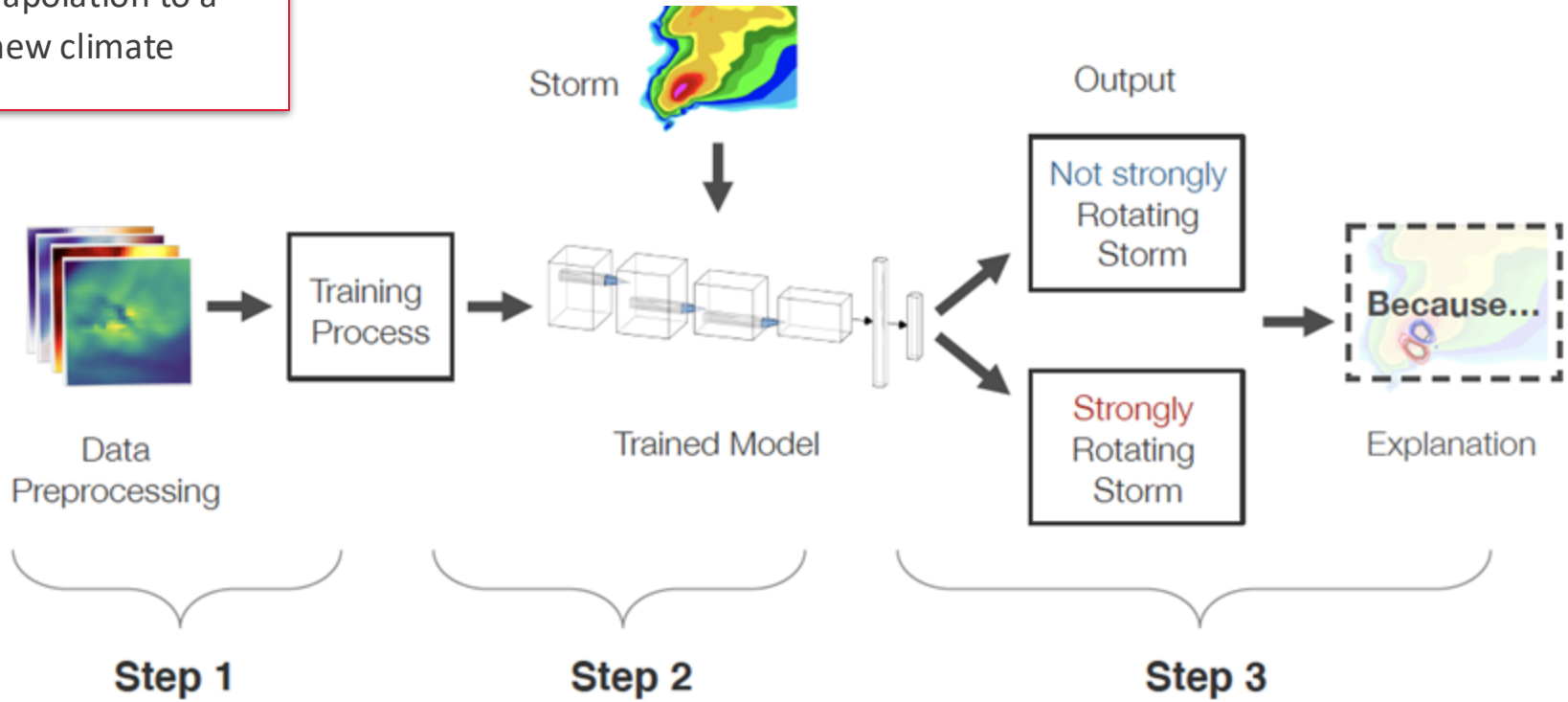
*Adapted and Inspired from*

# Questions to consider…

- Can machine learning extrapolate skillfully to new climates?
- Does machine learning remain performant with new datasets?
- What are some examples of unsupervised and supervised learning for detecting and predicting extremes?

**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.

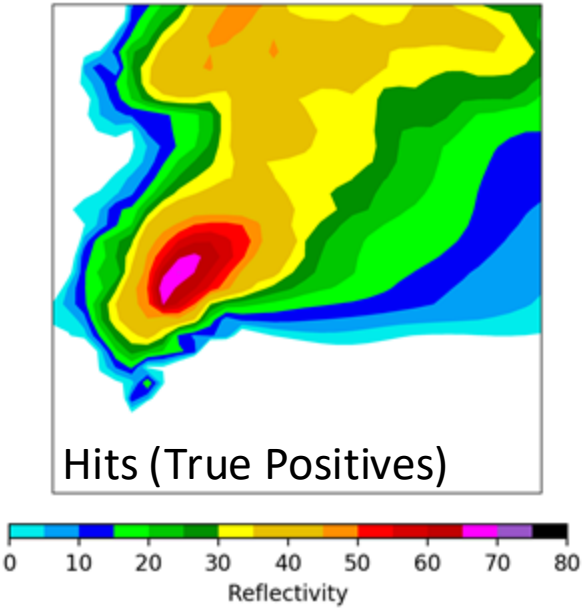
Extrapolation to a new climate

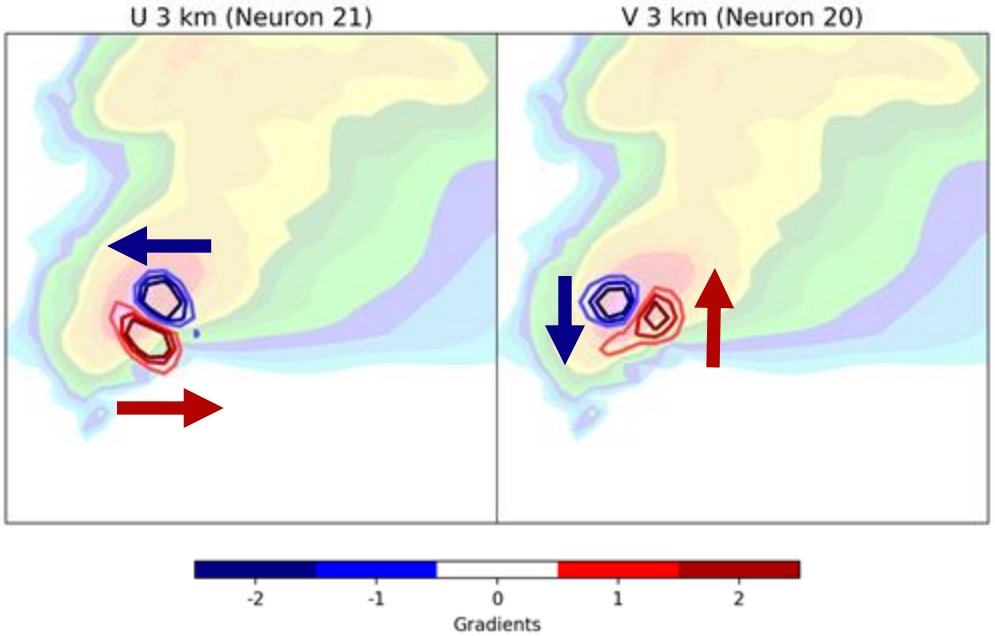



Train a model to classify organized thunderstorms in the present climate. Is the model performant in the future environment?

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

# Extrapolation to a new climate

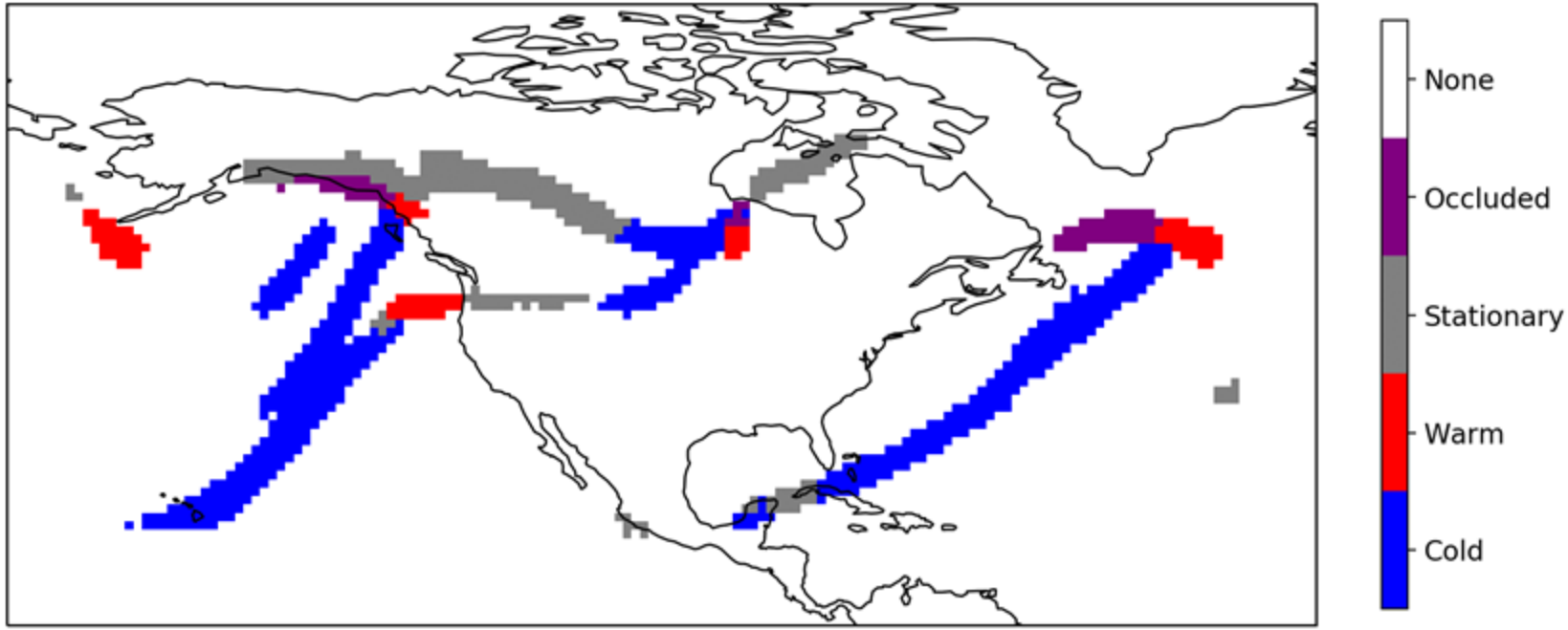



Train a model to classify organized thunderstorms in the present climate. Is the model performant in the future environment? If so, why?

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

# Generalization with a new dataset

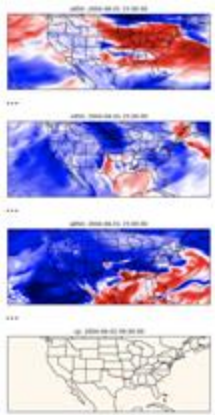


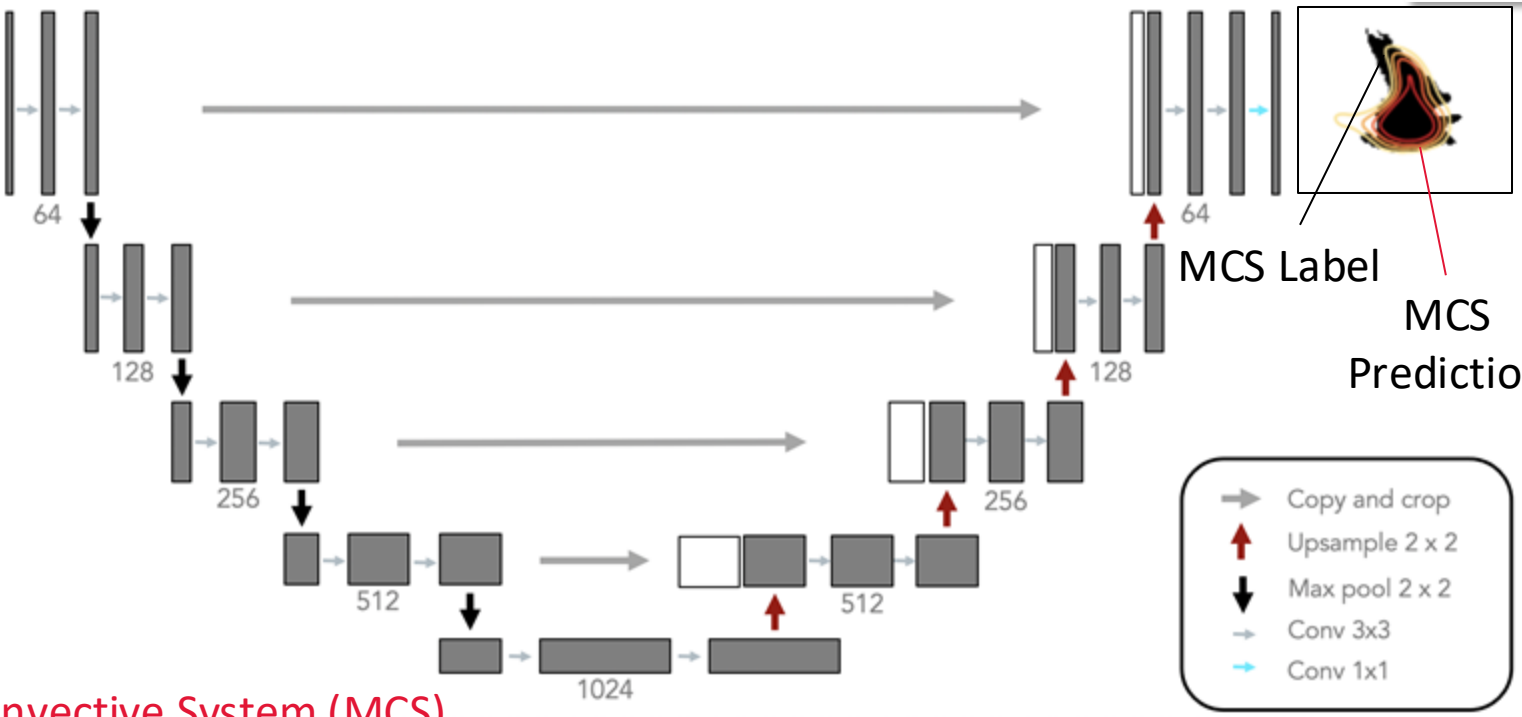

Train a model to detect fronts in a dataset, but apply it to another data product…

Dagon, K., Truesdale, J. E., Biard, J. C., Kunkel, K. E., Meehl, G. A., and **Molina, M. J.** (2022). Machine learning-based detection of weather fronts and associated extreme precipitation. Journal of Geophysical Research: Atmospheres

# Generalization with a new dataset

Mary Grace Albright
PhD Cand., UConn





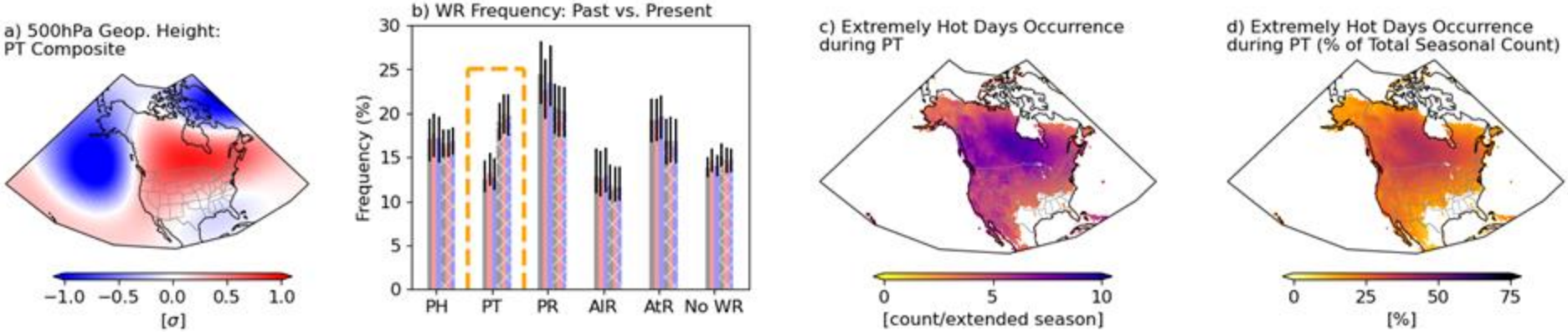

## Mesoscale Convective System (MCS)

Feng, Z., A. F. Prein, J. Kukulies, T. Fiolleau, W. Jones, B. Maybee, Z. L. Moon, K. M. Núñez Ocasio, W. Dong, **M. J. Molina**, *M. G. Albright, ..., and J. F. Mejia (2025). Mesoscale Convective Systems tracking Method Intercomparison: Application to DYAMOND Global km-scale Simulations. Journal of Geophysical Research: Atmospheres.

# Example Applications

Jhayron Steven Perez Carrasquilla

AOSC PhD Student




Detect weather regimes (WRs) using observations and unsupervised learning, then apply it to physics-based models to uncover trends and biases.


**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. Artificial Intelligence for the Earth Systems.

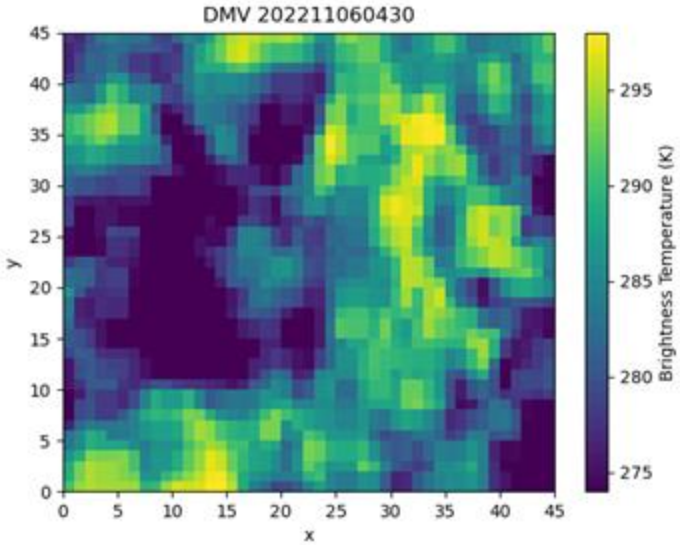
Perez-Carrasquilla, J.S., and **M.J. Molina** (under review). An Earth-system-oriented view of the S2S predictability of Weather Regimes. Artificial Intelligence for the Earth Systems.

Perez-Carrasquilla, J. S., M. J. Molina, K. J. Mayer, K. Dagon, I. R. Simpson, and J. Fasullo (to be submitted). Human-driven increase in Pacific Trough frequency intensifies winter and spring North American heat extremes. Earth's Future.

# Example Applications

Developing an AI-ready dataset to create all-weather LST products using super-resolution and gap-filling ML methods.

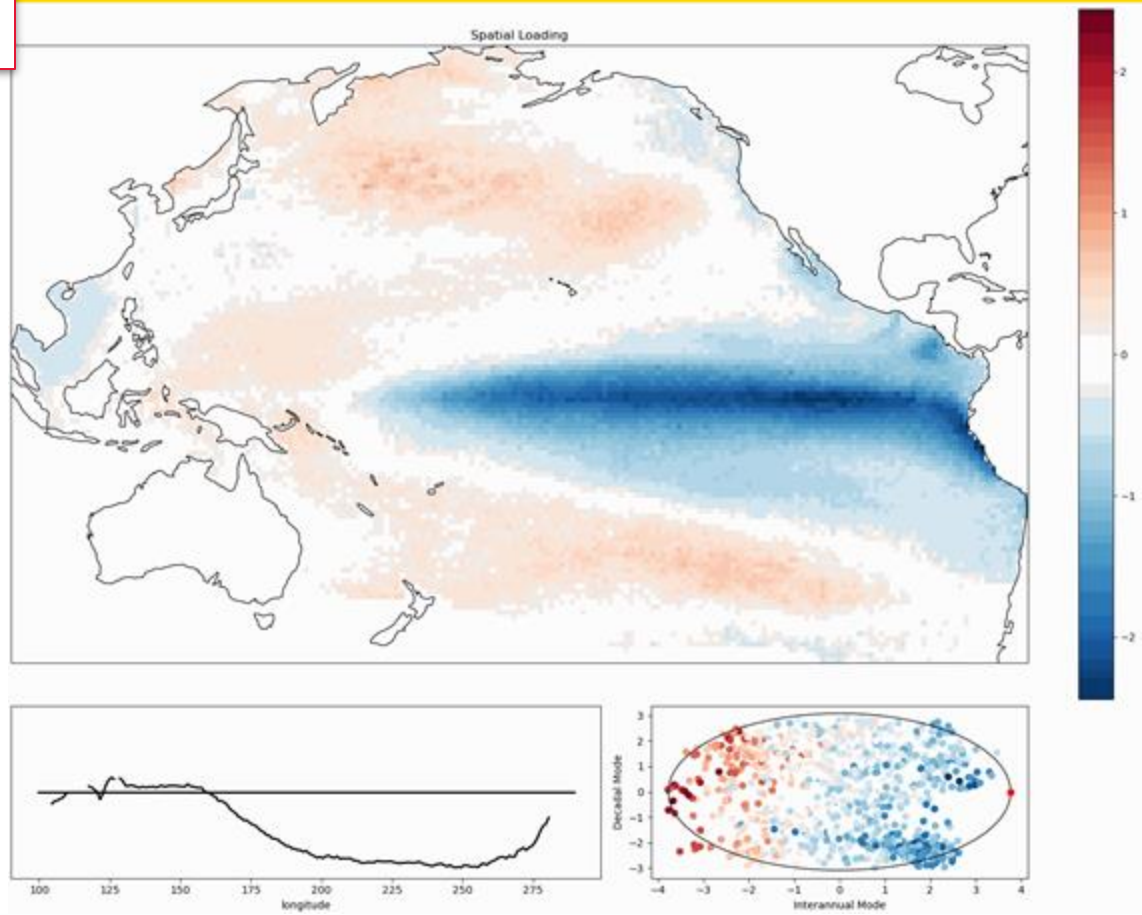
Jonathan David Starfeldt




Starfeldt, J., M. J. Molina, et al. (in preparation).

# Example Applications

Disentangling decadal, interannual, and biennial climate variability using customized, physics-guided autoencoders.

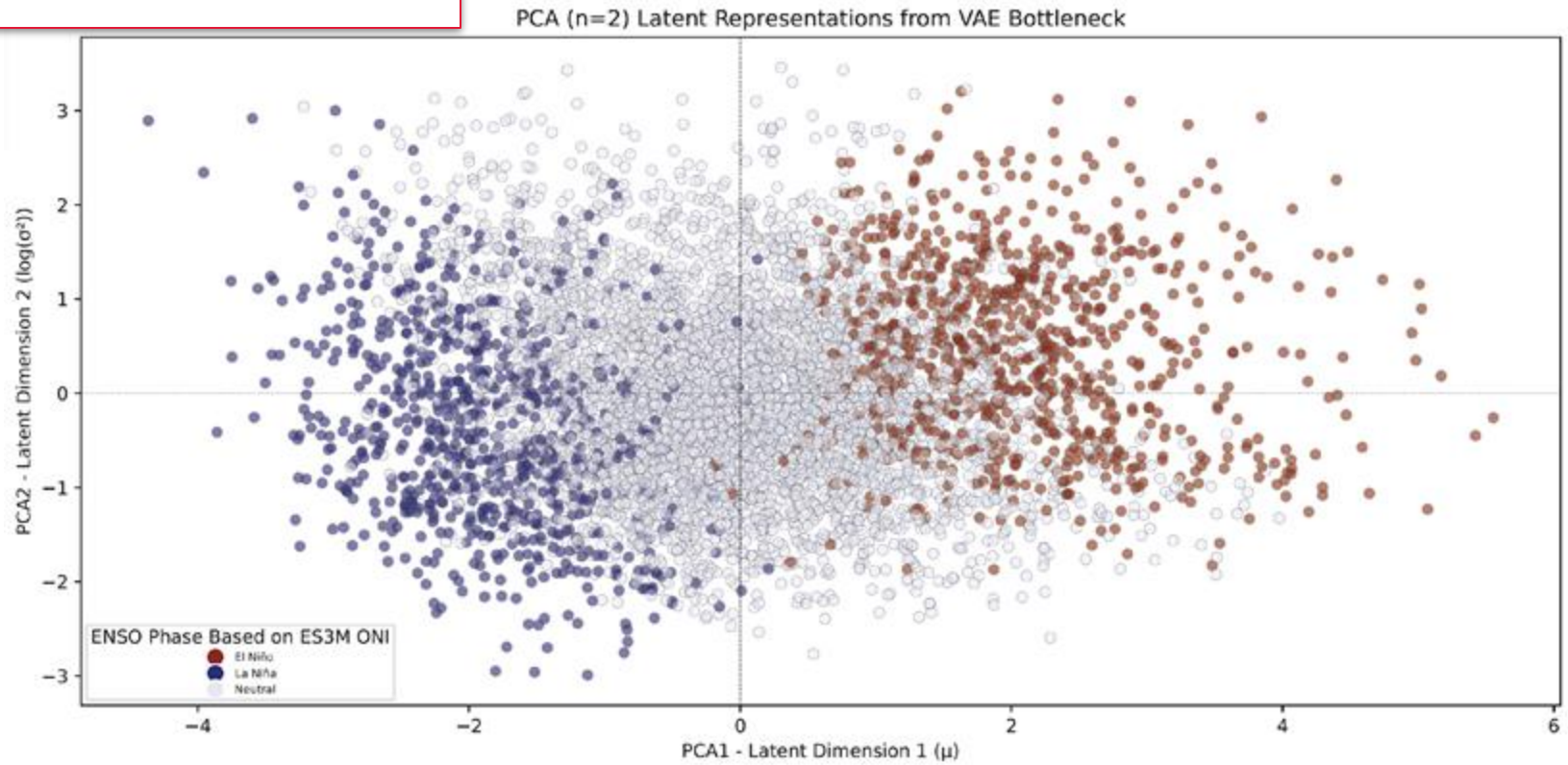


Kyle J. C. Hall

AOSC PhD Student

Hall, K., M. J. Molina, et al. (in preparation).

# Example Applications

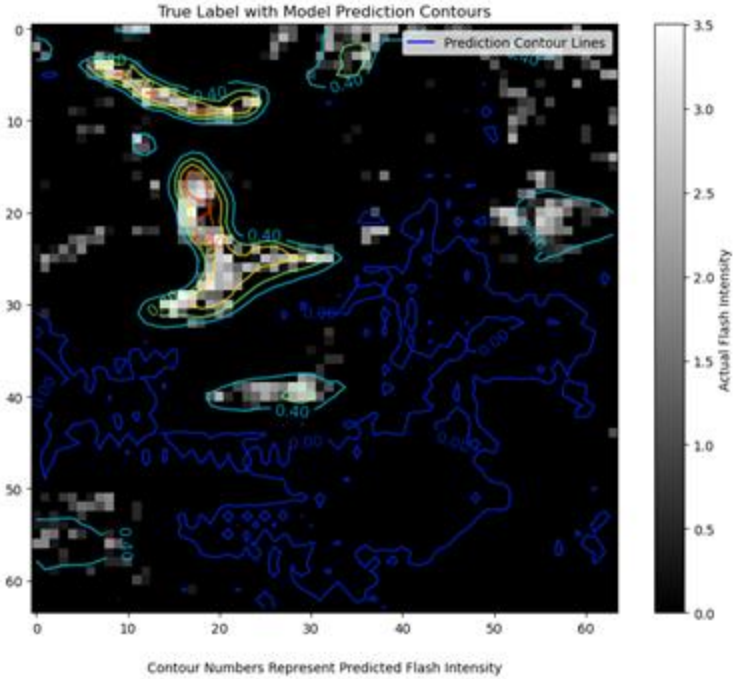


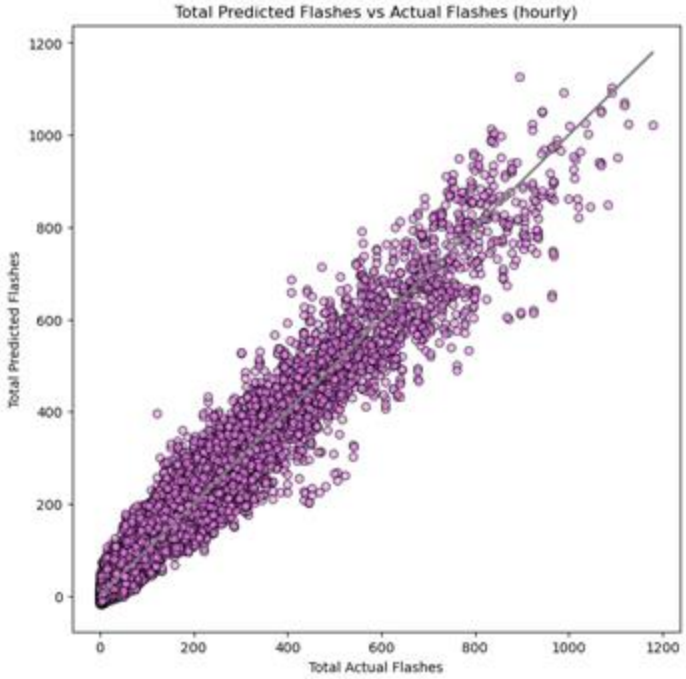
Better describing ENSO diversity with unsupervised generative AI methods (e.g., VAE).

Wisinski, E. F., M. J. Molina, et al. (in preparation).

# Example Applications

Madilynn Seiler
PhD Student, UMD

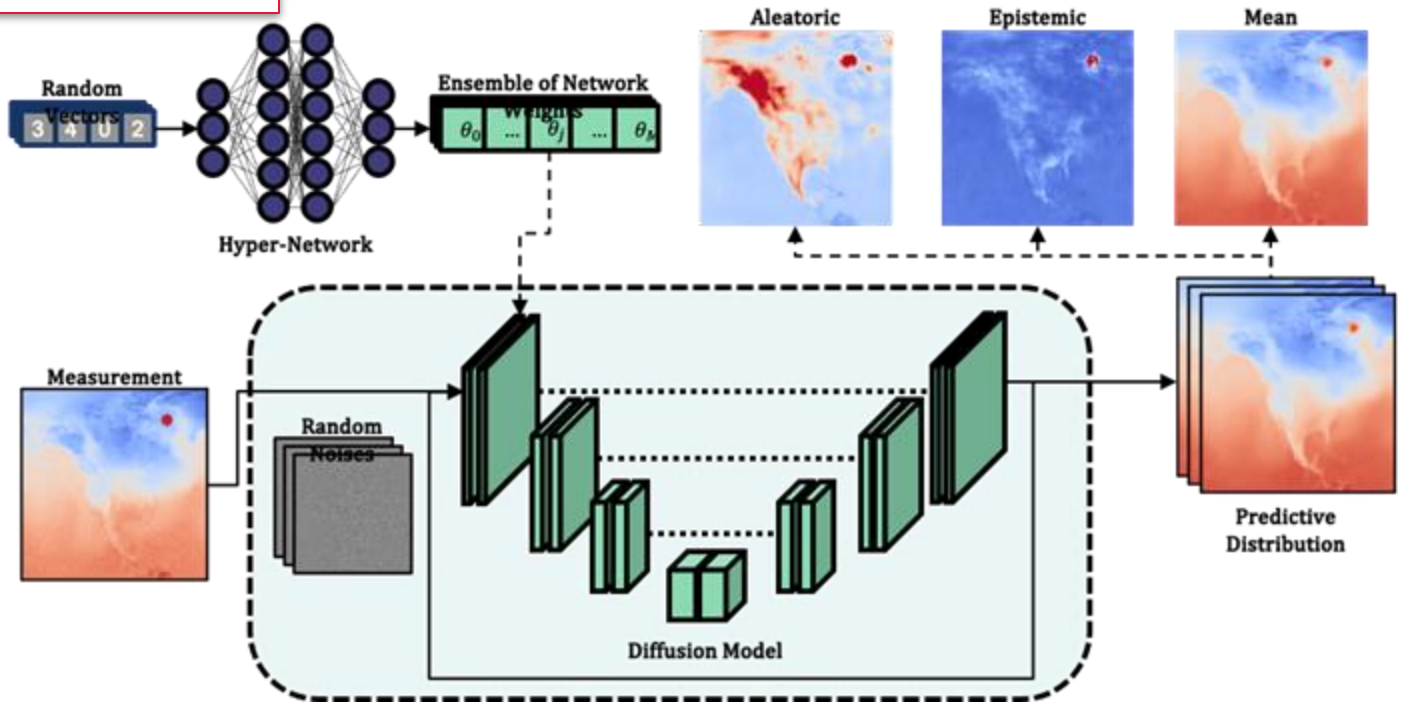



Developing a lightning parameterization scheme for the NASA GEOS model.

Seiler, M., D. Allen, K. Pickering, and M. J. Molina (in preparation).

# Example Applications



Matthew Chan
CS PhD Student

Leverage hypernetworks and diffusion models to decompose uncertainty into aleatoric and epistemic components.

Chan, M. A., **M. J. Molina,** and C. A. Metzler (2024). Estimating Epistemic and Aleatoric Uncertainty with a Single Model. Thirty-Eighth Annual Conference on Neural Information Processing Systems (NeurIPS).

ML for **extremes in a changing climate** should incorporate:

- Physics and Domain Knowledge
- Robustness
- Interpretable ML and Explainable AI

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