Accomplishments of the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES)

Amy McGovern, University of Oklahoma
Director, AI2ES

Representing all of the members of AI2ES (see next slides!)

Slides, talks, and publication links

Senior Leadership Team

Amy McGovern, University of Oklahoma - **Director**

Ann Bostrom, University of Washington

Phillip Davis, Del Mar College

Imme Ebert-Uphoff, Colorado State University

Julie Demuth, NSF National Center for Atmospheric Research

David John Gagne, NSF National Center for Atmospheric Research

Ruoying He, North Carolina State University

John Allen, Central Michigan University Associate director

Nathan Snook, University of Oklahoma

Monica Youngman, NOAA

Rob Redmon, NOAA

Philippe Tissot, Texas A&M University, Corpus Christi

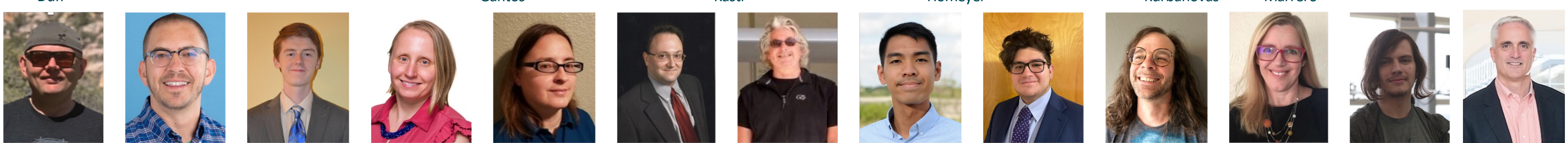
Christopher Thorncroft, University of Albany, SUNY

John Williams, The Weather Company

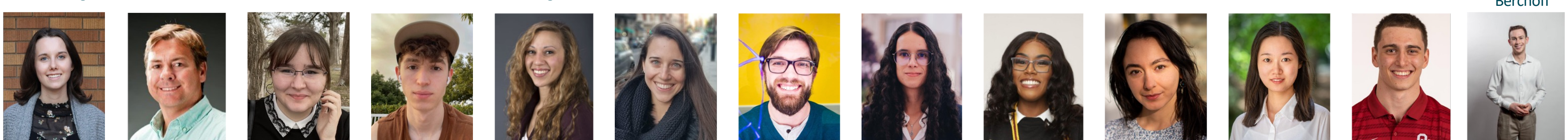
AI2ES Current Members and Collaborators

Marina Alchirch | Nick Bassill | Charlie Becker | Dara Betz | Susan Campbell | Korinne Caruso | Jorge Celis | Katie Colburn | Jose Congo | Gao Dalie | ChenRui Diao | Dimitrios Diochnos | Jacob Radford

Christian Duff | Stuart Edris | Aaron Evans | Andrew Fagg | Gabrielle Gantos | Kyle Hilburn | Matthew Kastl | Aaron Hill | Cameron Homeyer | Scott King | Arnoldas Kurbanovas | Hector Marrero | Bowen Chen | Monte Flora



Brandon McClung | Antonio Medrano | Nathan Erickson | Kristina Moen | Kate Musgrave | Henry Neeman | John J. Nelson | Son Nguyen | Christian Quintero | John Schreck | Andrea Schumacher | Luke Sewell | Don Berchoff



Erin Smith | Michael Starek | Savannah Stephenson | Evan Sudler | Kara Sulia | Carly Sutter | Lander Ver Hoef | Marina Vicens Miquel | Miranda White | Mel Reyes Wilson | Yan Xie | Ignacio Yockers | Matthew Cappucci

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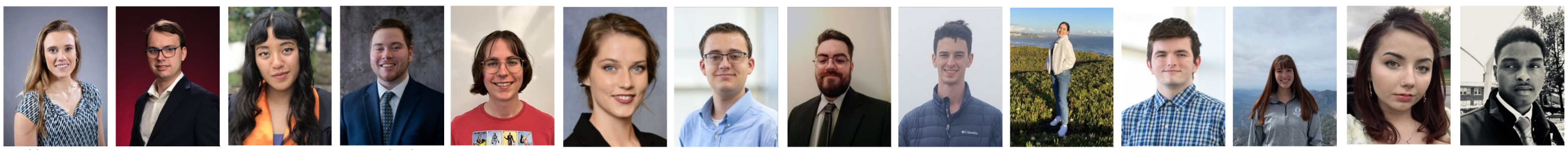
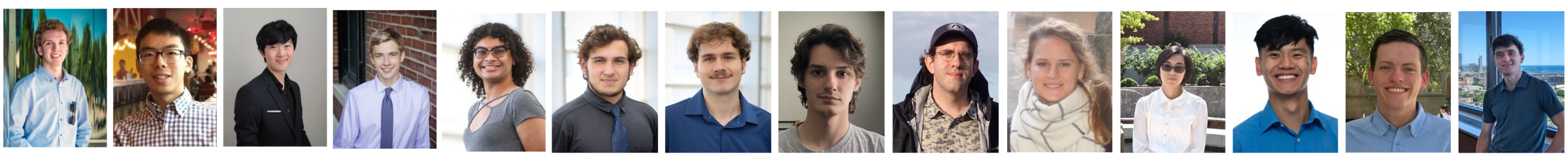
AI2ES Alumni and past Collaborators

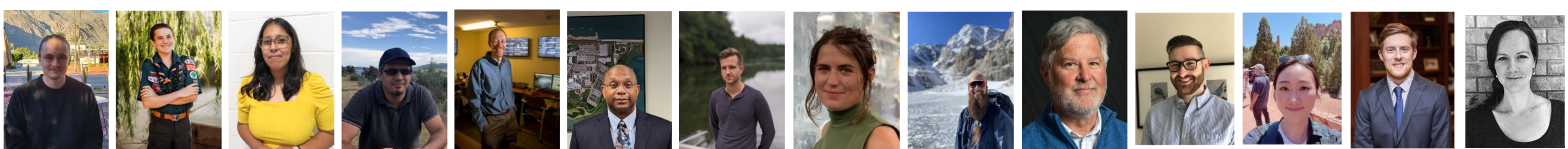
Mariana Cains | Akansha Singh Bansal | Lauriana Gaudet | Maria Madsen | Jason Stock | Monique Shotande | Antonio Mamalakis | Laura McGee | Amanda Murphy | Randy Chase



Vanessa Przybylo | Tobias Schmidt | Deianna Madlambayan | Chad Wiley | Charlotte Cabrera | Haley Perez | Vincent Ferrera | Conner Flansburg | Josh Friesen | Kayla Hoffman | Noah Lang | Kaelia Okamura | Raven Reese | Jordan Robinson



Colin Willingham | Joshua Pan | Michael Yu | Alex Nozka | Chris Cepin | Christopher Germano | Trevor Harms | Michael Gray | Evan Krell | Anna Lowe | Tiffany Le | Alberto Liu | Max Sasser | Luke Terry



Jay Rothenberger | William McGovern-Fagg | Ashley Marines | Sid Boukabara | Jerald “Jerry” Brotzge | Waylon Collins | Christopher D. Wirz | Marie McGraw | Ryan Lagerquist | Chuck Anderson | Charles “Chuck” White | Yoonjin Lee | Hunter Smith | Elizabeth Barnes

NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES)

AI2ES is developing *novel, physically based* AI techniques that are demonstrated to be *trustworthy*, and will directly improve *prediction, understanding, and communication* of high-impact weather and climate hazards, improving climate resiliency.

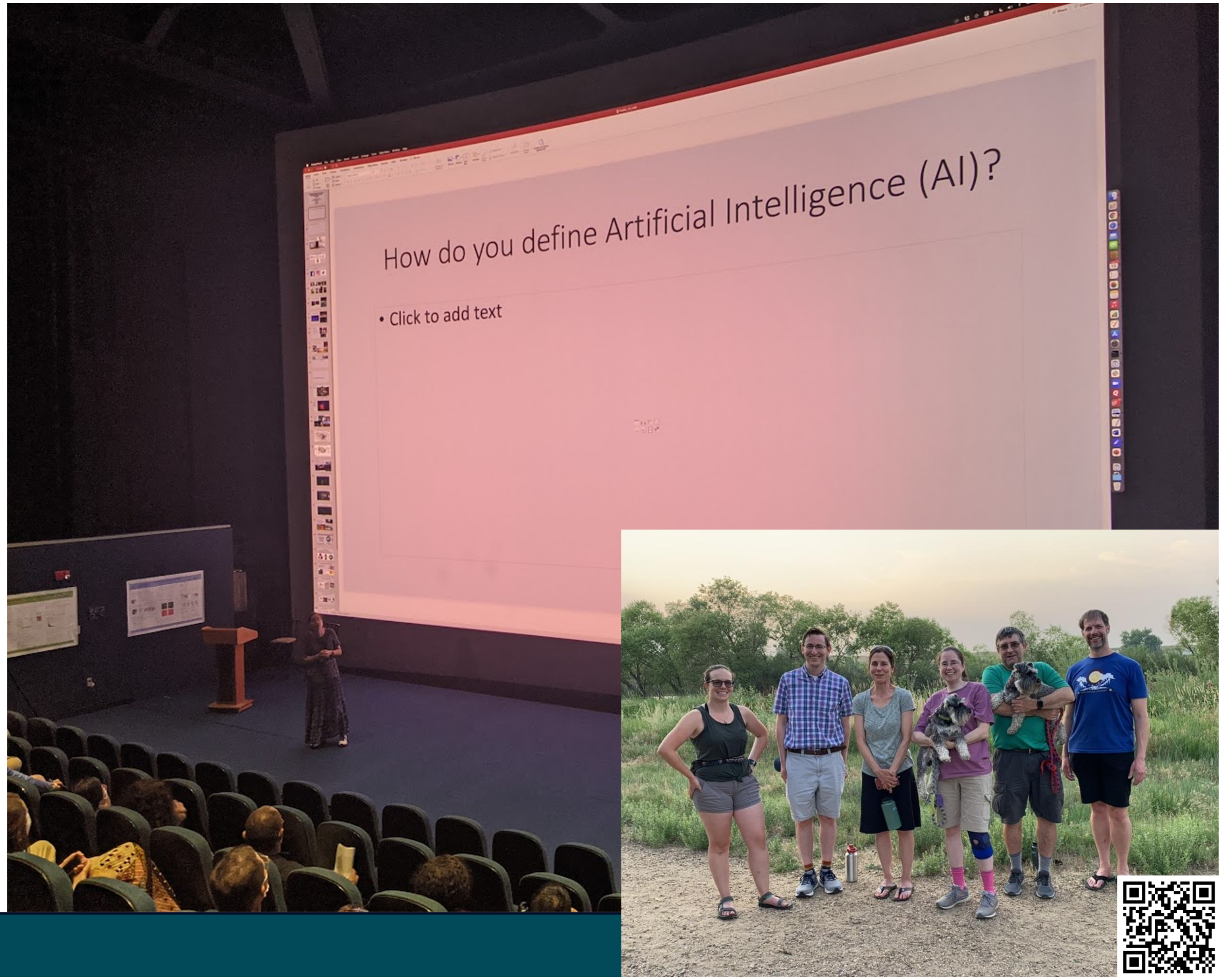
This material is based upon work supported by the National Science Foundation under Grant No. ICER-2019758

ai2es.org

AI2ES's Foundation is AMS

- Much of our original planning happened at AMS 2020
- The leadership team knew each other well from years of interacting through the AMS AI committee

Year 1: Boulder hikes and Aircraft Carrier in Corpus Christi (2021)



Year 3: Denver - NCAR (AMS Denver 2023)

Presidential panel, planning & team bus ride

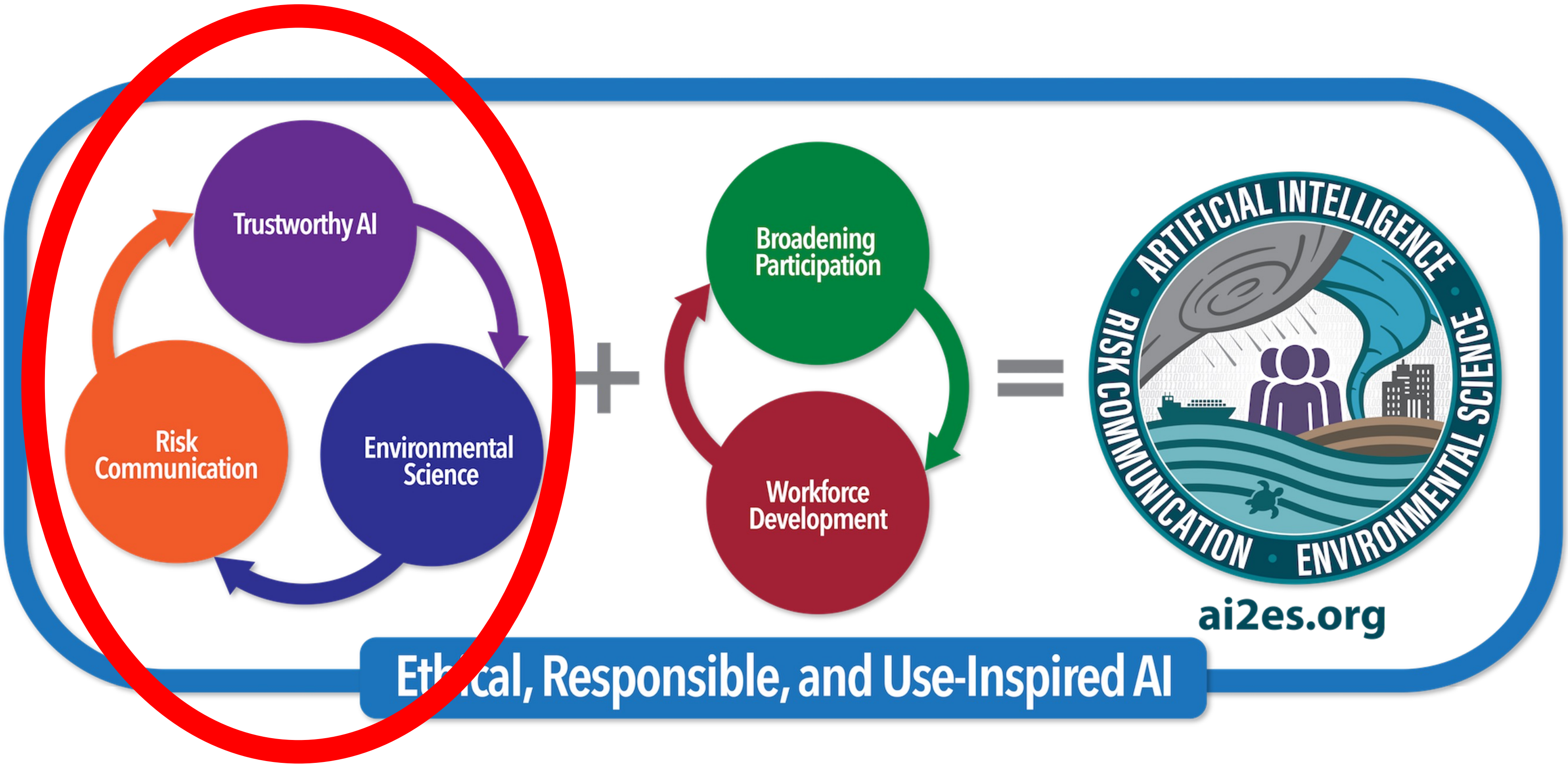
Year 4: Baltimore Convention Center (AMS 2024)

with two new Expand AI teams, FIU, SDSU

Year 5: New Orleans WWII Museum (AMS 2025)

Summarizing Research, scavenger hunt

AI2ES Key Contributions By Area

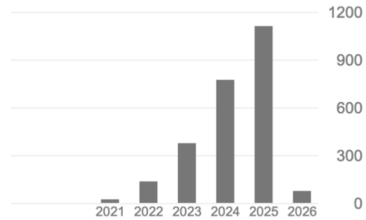


AI2ES Research Impact Summary

- Publications and presentations
  - 120+ peer-reviewed publications plus many more in review, in-prep and on arXiv
  - Over 423 presentations with **20+ student awards**
- Lives touched:
  - 24 faculty partially supported, 12 research scientists, 23 postdoctoral research associates, 46 graduate students, 83 undergraduate researchers and REU students
- R2O: Transitioned and running multiple operational products
  - Helped lead to one new startup company: Fathom Science
- Led to 7 additional funded projects (so far!): 2 ExpandAI projects, and 5 other related grants

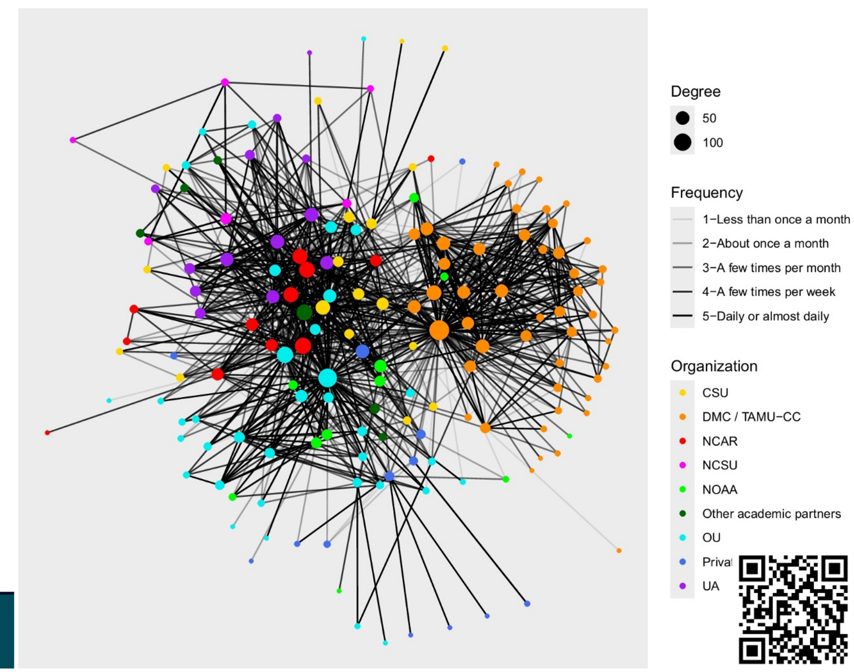
Cited by

	All	Since 2021
Citations	2538	2531
h-index	28	28
i10-index	52	52



AI2ES

Cumulative Collaboration Network



Convergence Research

Requirements for convergence research:

- Specific, compelling problem
- Diverse expertise – different disciplines, sectors, roles, etc.
- Deep integration among team

What helps makes convergence successful

- ***Sustained, large funding***
- Experience of some team members with convergence, who can guide others
- Readiness of team to work together
- Leadership that values convergence
- Involvement of next generation
- Regular, ongoing, iterative interactions

McGovern, Amy, Julie Demuth, Ann Bostrom, Christopher D. Wirz, Philippe E. Tissot, Mariana G. Cains, and Kate D. Musgrave. 2024. "The Value of Convergence Research for Developing Trustworthy AI for Weather, Climate, and Ocean Hazards." Npj Natural Hazards 1 (1): 1–6. https://doi.org/10.1038/s44304-024-00014-x.

AMS Panel Discussion & Audience Engagement – Beyond Boundaries: Mobilizing Convergence and Translational Science for Earth System Resilience
Wednesday, Jan 28, from 1:45-3:00, 342F

Sampling of Science Success Stories

Risk Communication Team

Julie Demuth

Ann Bostrom

Chris Wirz

Mariana Cains

Andrea Schumacher

Deianna Madlambayan

Jacob Radford

Susan Campbell

Erin Smith

Risk Communication team goals:

- Improve understanding of how key aspects of AI/ML models – *transparency, explanation, reproducibility, representation of uncertainty* – influence trust in AI
- Develop models of how attitudes and perceptions of AI trustworthiness influence risk perception and use of AI
- Develop principled methods of using this knowledge to inform
  - development of trustworthy AI approaches and
  - provision of AI-based information for improved decision making

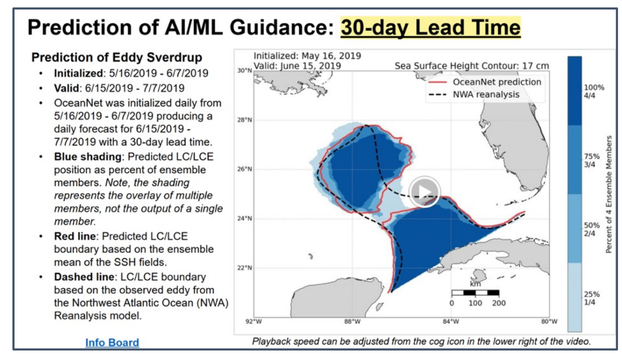
Empirical research with users

NWS forecasters' perceptions of AIML for operations

National Weather Service (NWS) Forecasters' Perceptions of AI/ML and Its Use in Operational Forecasting. Christopher D. Wirz , Julie L. Demuth, Mariana G. Cains, Miranda White, Jacob Radford, and Ann Bostrom (2024) *Bulletin of the American Meteorological Society.* https://doi.org/10.1175/BAMS-D-24-0044.1

An Assessment of How Domain Experts Evaluate Machine Learning in Operational Meteorology
David R. Harrison, Amy McGovern, Christopher D. Karstens, Ann Bostrom, Julie L. Demuth, Israel L. Jirak, and Patrick T. Marsh (2025) *Weather and Forecasting.* https://doi.org/10.1175/WAF-D-24-0144.1

Key result: "No matter if forecasters were hesitant or excited about AI/ML, they agreed they were **open to using whatever tools available** to assist them in **fulfilling the mission** that motivates them." (Wirz et al.)



Expert decision-makers' perceived trustworthiness of AIML predictions

Exploring NWS Forecasters' Assessment of AI Guidance Trustworthiness. Mariana G. Cains, Christopher D. Wirz, Julie L. Demuth, Ann Bostrom, David John Gagne II, Amy McGovern, Ryan A. Sobash, and Deianna Madlambayan (2024) *Weather and Forecasting.* https://doi.org/10.1175/WAF-D-23-0180.1

Key result: "forecasters' assessment of AI guidance trustworthiness is a **process that occurs over time** rather than automatically and suggest that **developers must center the end user when creating new AI guidance tools** to ensure that the developed tools are useful and used." (Cains et al.)

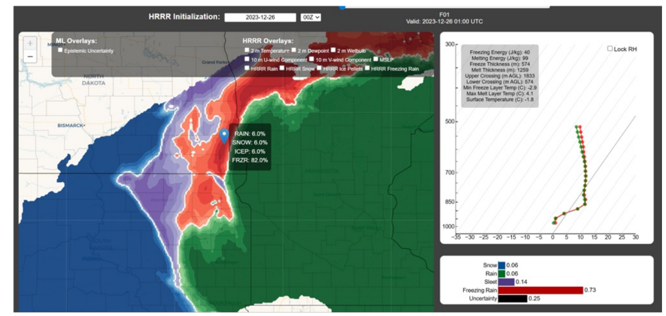
Methods transfer from social sciences to AIML

Wirz et al (2024) Increasing the Reproducibility and Replicability of Supervised AI/ML in the Earth Systems Science by Leveraging Social Science Methods, Earth and Space Science https://doi.org/10.1029/2023EA003364

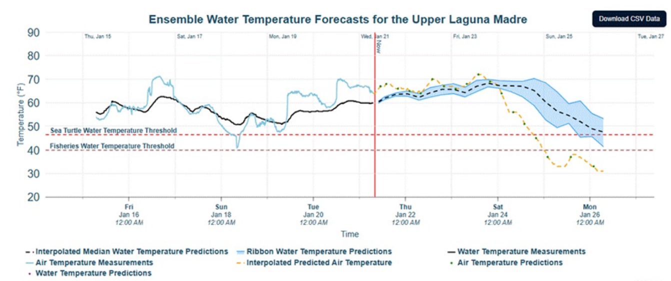
Key result: "The [quantitative content analysis]-based approach we have outlined **reduces the subjectivity of hand labeling** by creating a codebook that outlines the exact decision-making rules for assigning labels and then empirically evaluates the reliability of labelers in adhering to those rules. This process and the information it provides also **increase the reproducibility and replicability of the ML model**."

Developing new AIML models based on users' needs

Evidential dense neural network model that predicts probabilities of winter precipitation-type

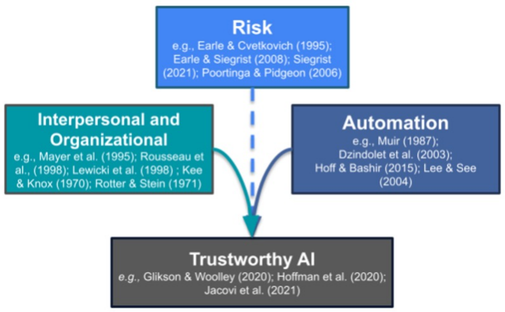


Stakeholder interviews are guiding design and deployment of operational ML with UQ: ***need to be progressive with complexity***

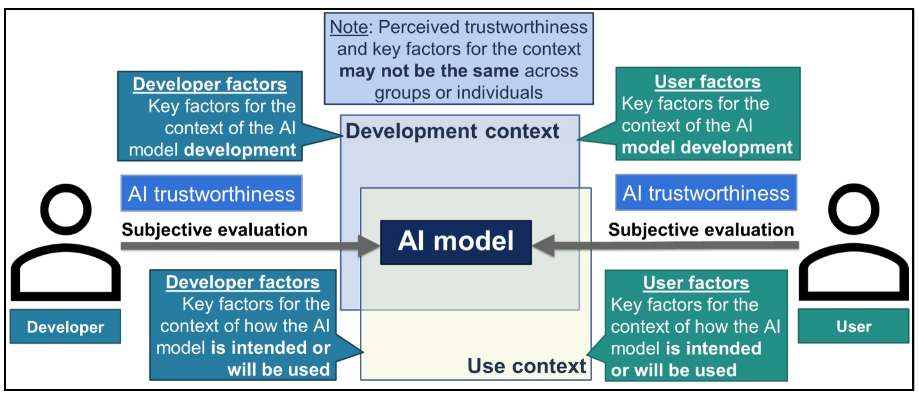


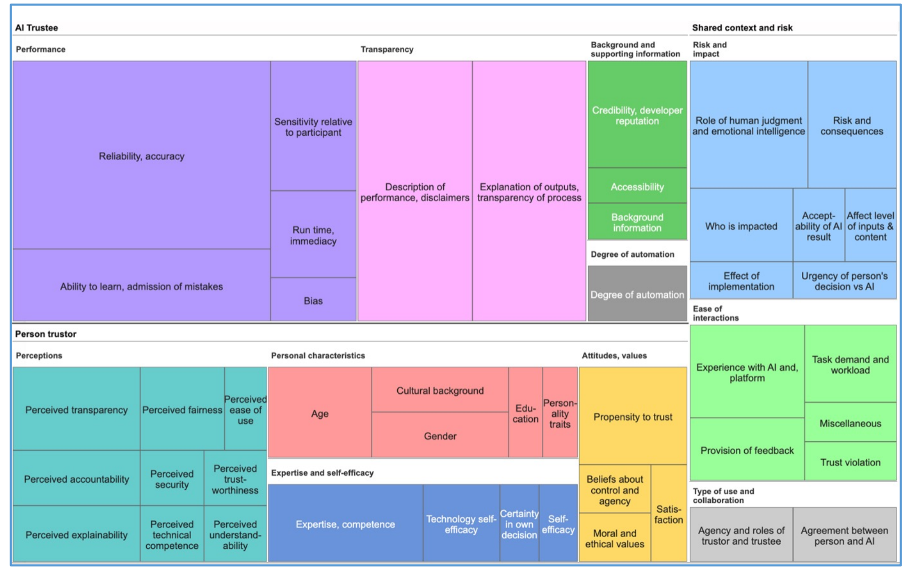
Research to advance theory

AI2ES risk communication research aims to advance theory as well as practice



Christopher D. Wirz, Julie L. Demuth, Ann Bostrom, Mariana G. Cains, Imme Ebert-Uphoff, David John Gagne II, Andrea Schumacher, Amy McGovern, Deianna Madlambayan (2025) (Re)Conceptualizing trustworthy AI: A foundation for change, Artificial Intelligence. https://doi.org/10.1016/j.artint.2025.104309





Systematic review of empirical research on trust in embedded AI, *under review*

Setting research agendas & sparking new collaborations

Organized and convened two workshops with varied expertise,
across disciplines, sectors, organizations, etc.

Bostrom and Demuth et al 2023. Trust and trustworthy artificial intelligence: A research agenda for AI in the environmental sciences. Risk Analysis, 2024 44(6),1498-1513. https://doi.org/10.1111/risa.14245

Research needs in four broad areas:

- User-oriented development and co-development
- Understanding and measuring trust and trustworthiness
- Goal alignment, calibration, and standard setting
- Integrating risk and uncertainty communication research with research on trust in AI

AI for Medicine and Meteorology (AIM^2) workshop
– To explore risk assessment, characterization, communication, trust, trustworthiness, and use of AI uncertainty predictions for high-pressure decision-making in meteorology and medicine

Foundational AI: Key Research Areas

- Earth science has different AI needs than the other fields where AI is commonly used.
- Need to develop/adjust foundations of many AI concepts for use in earth science.

Ethical use of AI in ES

Explainable AI in ES:
Which strategies did my AI model learn?

Uncertainty quantification with AI models for ES

Generative AI
How generative AI be used for foundational trustworthy science?

Physics-based AI:
integrate physics and domain knowledge

Robust AI for ES:
How to ensure consistency of AI performance?

Ethical and Responsible AI

McGovern, A., Ebert-Uphoff, I., Gagne II, D.J. and Bostrom, A., 2022. Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. Environmental Data Science, 1, p.e6. https://doi.org/10.1017/eds.2022.5

- Helped to pioneer the focus on for ethical and responsible AI for weather and climate
  - Demonstrated multiple ways in which AI can go wrong for ES
- Bad forecasts can lead to lives or property lost
  - Awareness is the first step to preventing issues

Ways in which AI can go wrong for environmental sciences

Issues related to training data:

1. Non-representative training data, including lack of geo-diversity
2. Training labels are biased or faulty
3. Data is affected by adversaries

Issues related to AI models:

1. Model training choices
2. Algorithm learns faulty strategies
3. AI learns to fake something plausible
4. AI model used in inappropriate situations
5. Non-trustworthy AI model deployed
6. Lack of robustness in the AI model

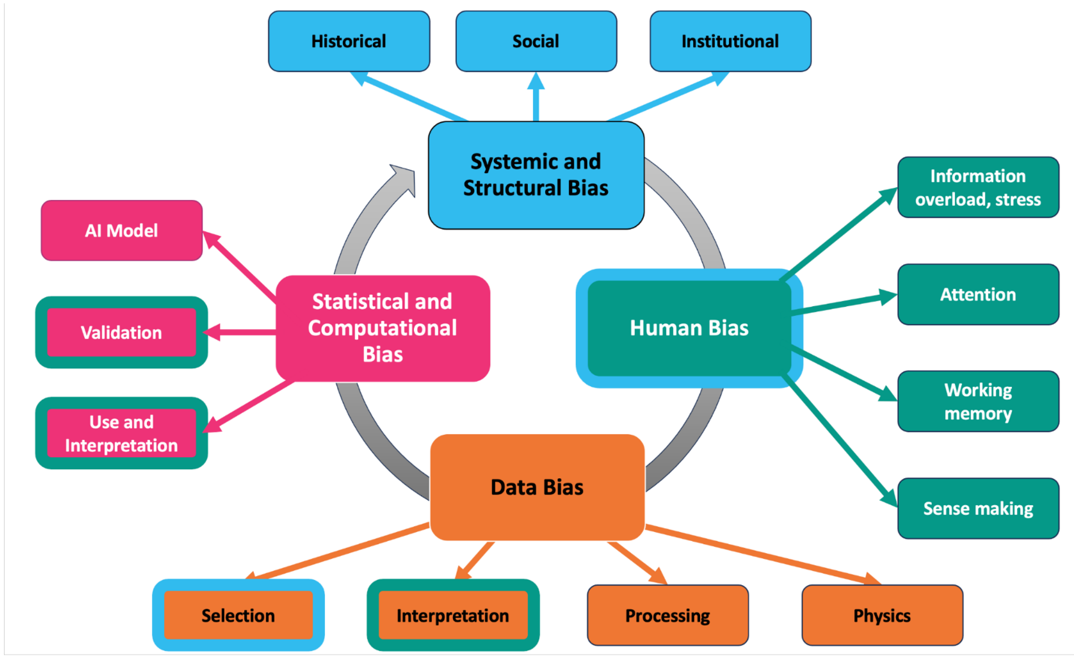
Other issues related to workforce and society:

1. Globally applicable AI approaches may stymie burgeoning efforts in developing countries.
2. Lack of input or consent on data collection and model training
3. Scientists might feel disenfranchised.
4. Increase of CO_2 emissions due to computing

Ethical and Responsible AI

McGovern, A., A. Bostrom, M. McGraw, R. J. Chase, D. J. Gagne, I. Ebert-Uphoff, K. D. Musgrave, and A. Schumacher, 2024: Identifying and Categorizing Bias in AI/ML for Earth Sciences. Bulletin of the American Meteorological Society,105, E567–E583, https://doi.org/10.1175/BAMS-D-23-0196.1.

- Developed a categorization of biases for AI for ES
- Now developing bias measurement and mitigation approaches



Categorization of bias for AI/ML for ES

12A.3 - Bias Correction in Data Preparation and Its Implications for AI Model Performance. Yan Xie. Wednesday, January 28, 2026. 5:00 PM - 5:15 PM, 330A.

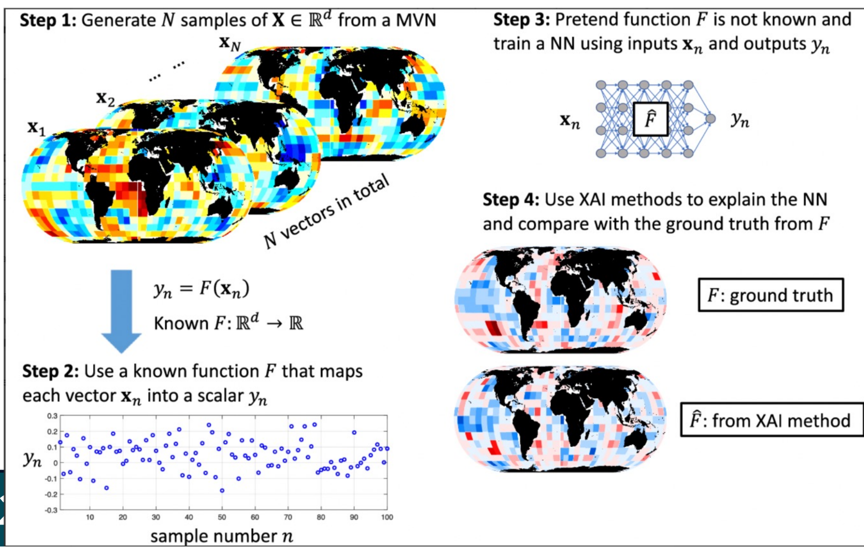
Explainable AI

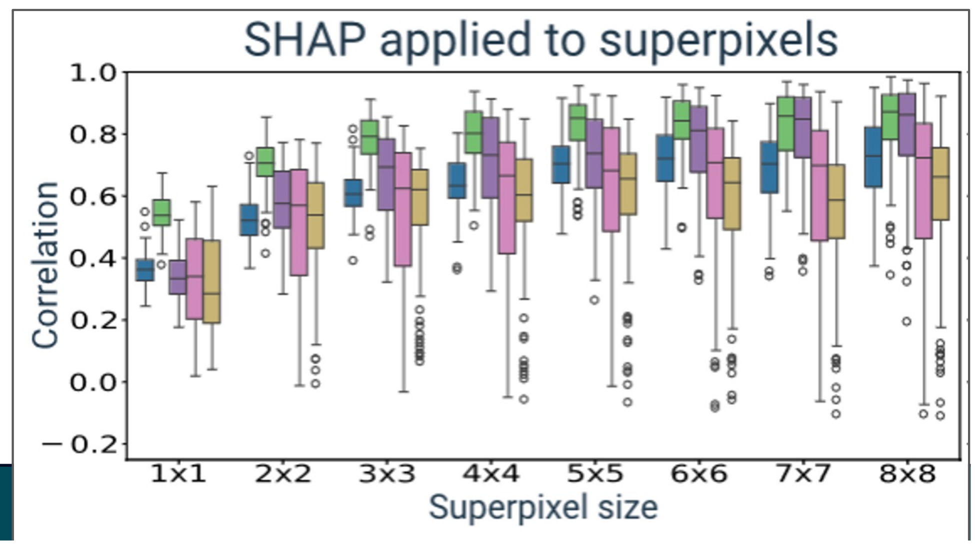
- Deep dive into XAI methods and their limitations for geosciences
- Developed benchmarks to test XAI methods
- Developed novel XAI methods

Mamalakis A, Ebert-Uphoff I, Barnes EA. Neural network attribution methods for problems in geoscience: A novel synthetic benchmark dataset. *Environmental Data Science*. 2022;1:e8. https://doi.org/10.1017/eds.2022.7

Mamalakis, A., E. A. Barnes, and I. Ebert-Uphoff, 2022: Investigating the Fidelity of Explainable Artificial Intelligence Methods for Applications of Convolutional Neural Networks in Geoscience. Artif. Intell. Earth Syst., 1, e220012, https://doi.org/10.1175/AIES-D-22-0012.1.

Krell E, Kamangir H, Collins W, King SA, Tissot P. Aggregation strategies to improve XAI for geoscience models that use correlated, high-dimensional rasters. Environmental Data Science. 2023;2:e45. https://doi.org/10.1017/eds.2023.39



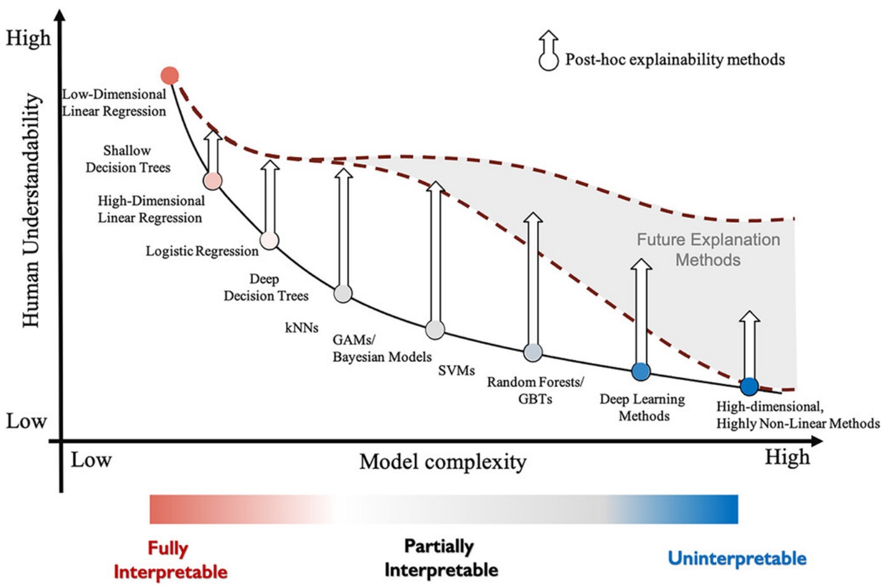


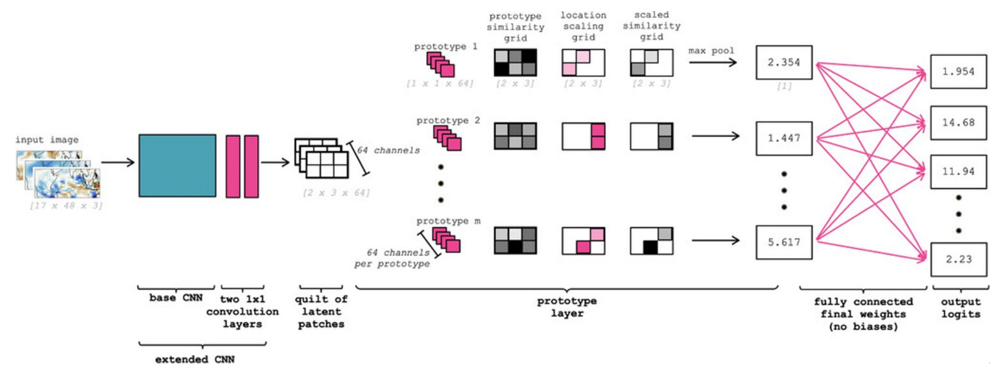
Explainable AI

- Published a tutorial on XAI methods
- Developed novel interpretable models for S2S applications

Flora, M. L., C. K. Potvin, A. McGovern, and S. Handler, 2024: A Machine Learning Explainability Tutorial for Atmospheric Sciences. Artif. Intell. Earth Syst., 3, e230018, https://doi.org/10.1175/AIES-D-23-0018.1.

Barnes, E. A., R. J. Barnes, Z. K. Martin, and J. K. Rader, 2022: This Looks Like That There: Interpretable Neural Networks for Image Tasks When Location Matters. Artif. Intell. Earth Syst., 1, e220001, https://doi.org/10.1175/AIES-D-22-0001.1.



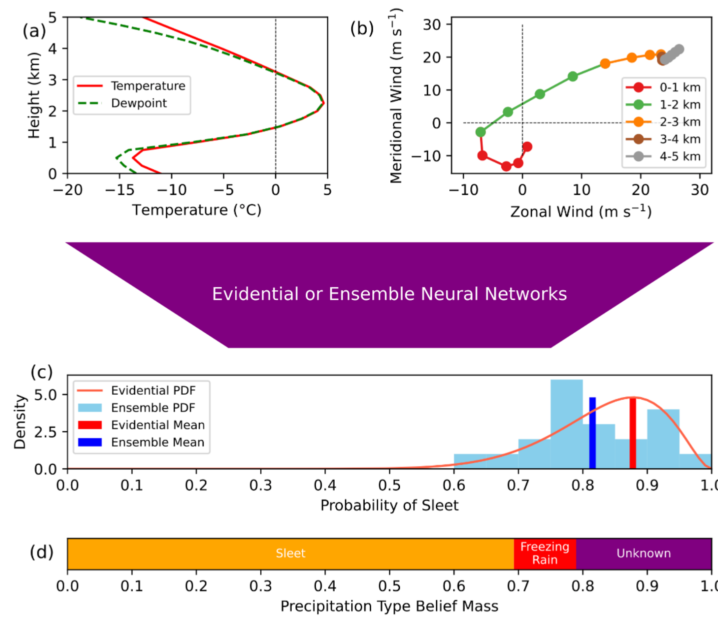


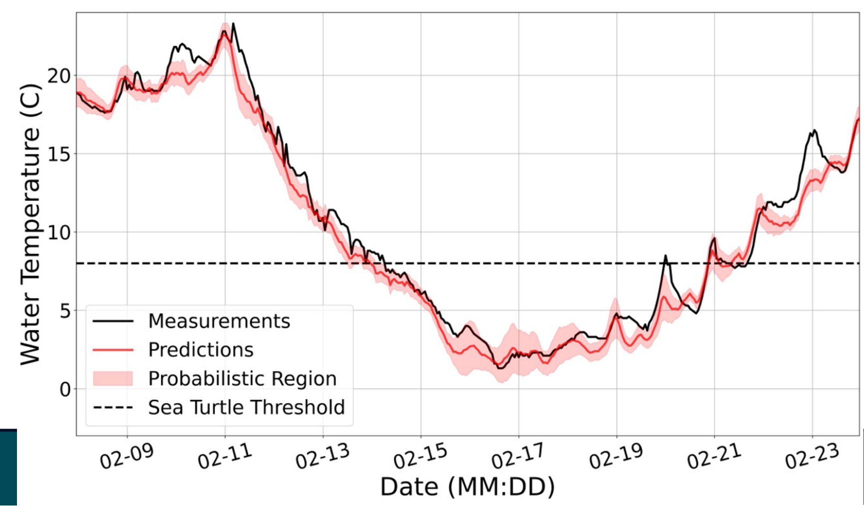
Uncertainty Quantification

- Novel approaches to estimated epistemic uncertainty for weather
  - Developed an open-source library https://github.com/ai2es/miles-guess
- Published tutorial paper on UQ for ES
- Development of novel UQ approaches for turtle cold stunnings, in-depth interviews with end-users, and operationalized new method

Evidential Deep Learning: Enhancing Predictive Uncertainty Estimation for Earth System Science Applications, Schreck et al. (2024). Artificial Intelligence for the Earth Systems. https://doi.org/10.1175/AIES-D-23-0093.1

Creating and Evaluating Uncertainty Estimates with Neural Networks for Environmental-Science Applications. Haynes et al. (2023). Artificial Intelligence for the Earth Systems. https://doi.org/10.1175/AIES-D-22-0061.1



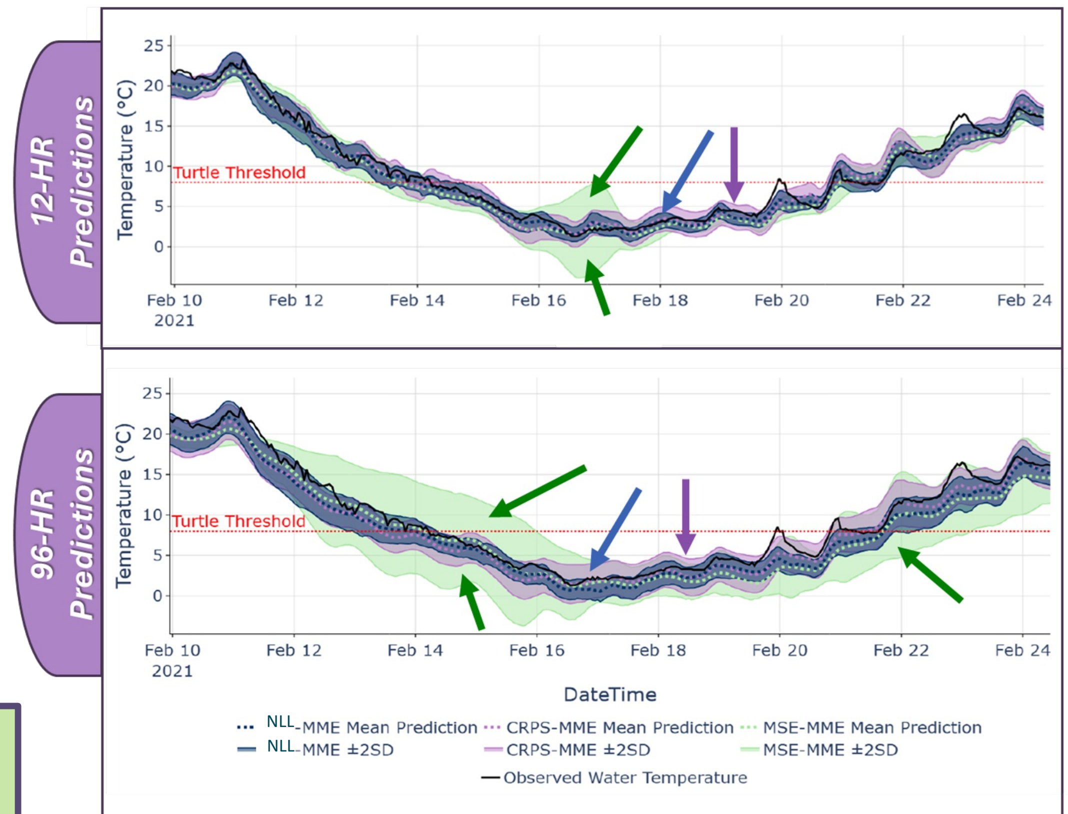


Machine Learning Uncertainty Quantification for Cold-Stunning Events

Leveraged **Multi-Model Ensemble (MME)** approaches to compare three ensemble models with **differing loss functions:**

- Mean Squared Error (MSE)
- Negative Log-Likelihood (NLL)
- Continuous Ranked Probability Score (CRPS)

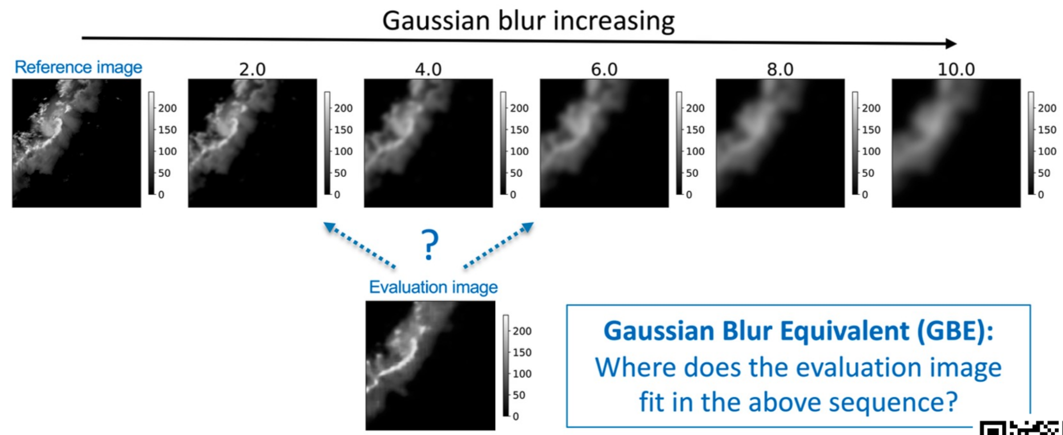
Found that **CRPS-MME** produced most calibrated uncertainty estimates for **extreme, high-impact water temperature predictions** using *nonparametric statistical analysis*



White, M. C., et. al. (Accepted). Machine Learning Uncertainty Quantification for Extreme Cold Water Events. Artificial Intelligence for the Earth Systems.
AMS talk: Wednesday 11:30 322A

Physics-inspired AI: Measuring Sharpness

- **Problem:**
    - Generative AI models can produce “sharper” forecasts than traditional DL
    - Is sharpness correlated with trust?
    - How do we meaningfully measures for “sharpness” for weather?
- **Solution:** Identify and evaluate sharpness metrics from other fields. Development of novel Gaussian blur equivalence tool for uniform interpretation of metrics.



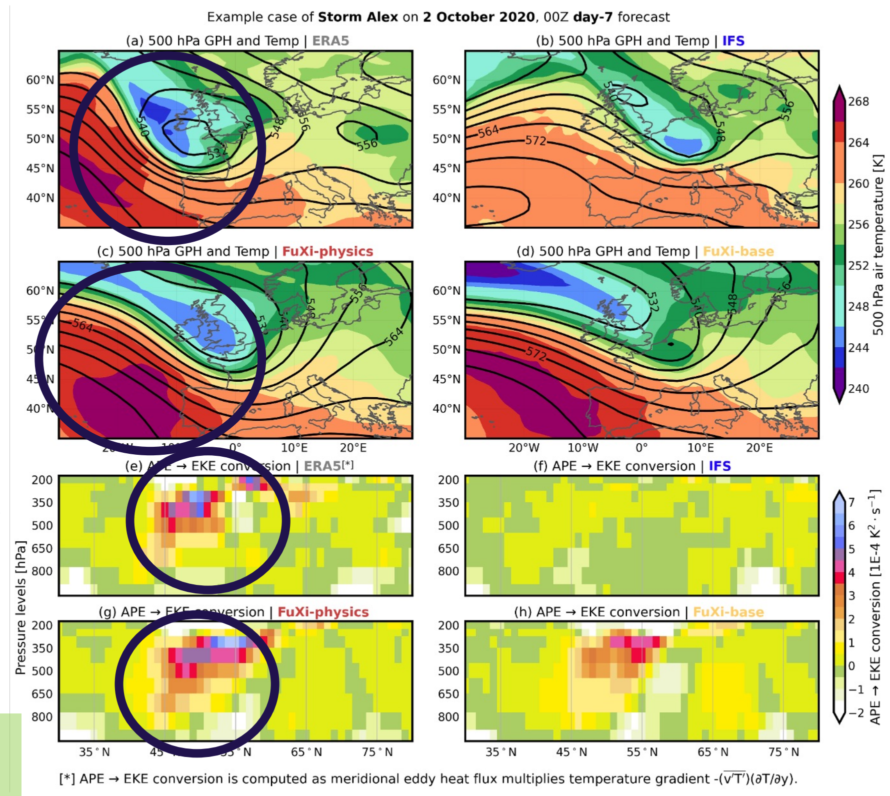
Ebert-Uphoff, I., Ver Hoef, L., Schreck, J.S., Stock, J., Molina, M.J., McGovern, A., Yu, M., Petzke, B., Hilburn, K., Hall, D.M. and Gagne, D.J., 2025. Measuring Sharpness of AI-Generated Meteorological Imagery. *Artificial Intelligence for the Earth Systems*. https://doi.org/10.1175/AIES-D-24-0083.1

CREDIT: Combining AI and Physics for More Accurate and Realistic Forecasts

CREDIT: Open foundational research platform for AI Earth System Prediction developed at NSF NCAR.

Problem: AI NWP models don't follow physical laws, resulting in artifacts and instabilities.

Solution: Add global physics constraints during training and inference. Improves precip and cyclone structure, especially after day 4.



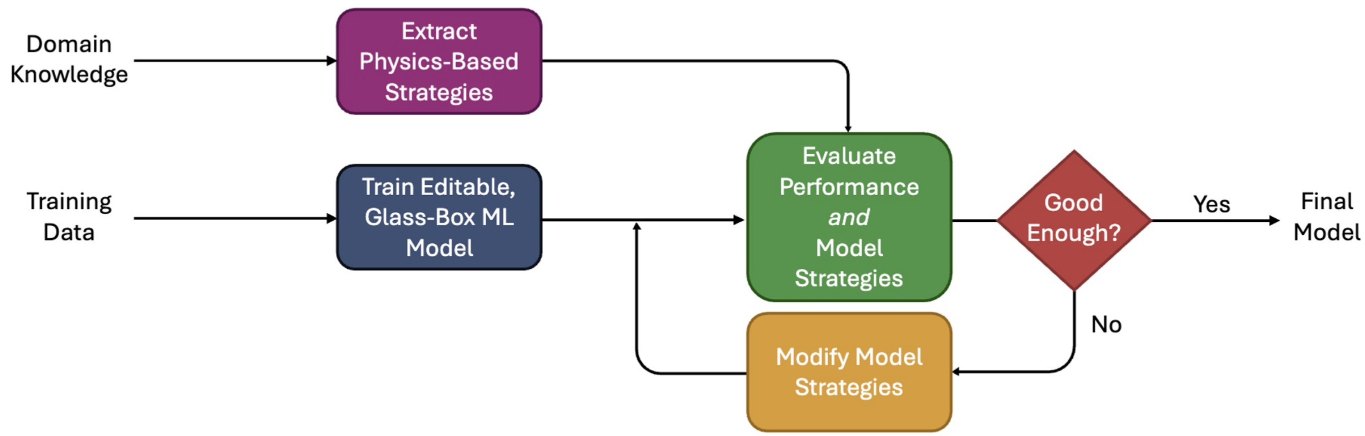
Case study showing stronger horizontal and vertical gradients in physics-constrained AIWP model.

Sha's talk on Wed. 2:45 in 330A:
"Improving AI Weather Prediction Models Using Global Mass and Energy Conservation Schemes"

Sha, Y., Schreck, J. S., Chapman, W., & Gagne, D. J. (2025). Investigating the use of terrain-following coordinates in AI-driven precipitation forecasts. Geophysical Research Letters.https://doi.org/10.1029/2025GL118478

Physics-based AI

- Goal: Develop AI models that **emulate strategies a human would use**
- Methods: use feature engineering + ML models for which we can visualize and tune strategies



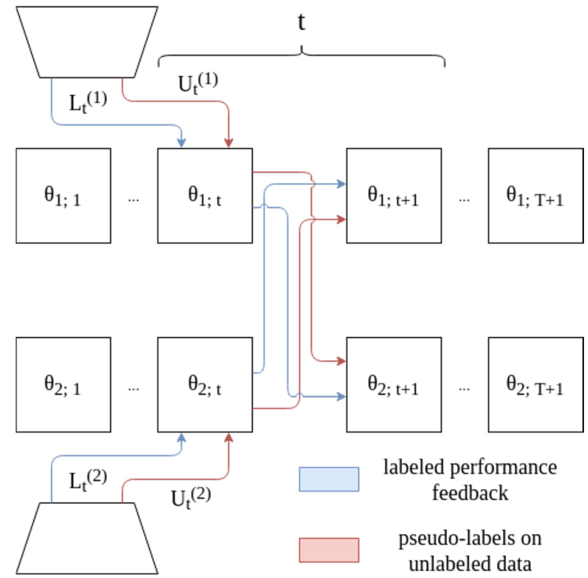
Mitchell, N., Ver Hoef, L., Ebert-Uphoff, I., Moen, K., Hilburn, K., Lee, Y, and Kind, E.J.. (2025), **Knowledge-Guided Machine Learning: Illustrating the use of Explainable Boosting Machines to Identify Overshooting Tops in Satellite Imagery** (in review at AIES).
Pre-print: https://arxiv.org/abs/2507.03183

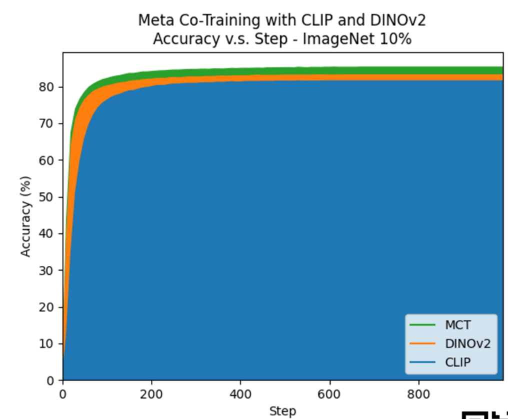
Robust AI

Semi-Supervised Learning Contributions

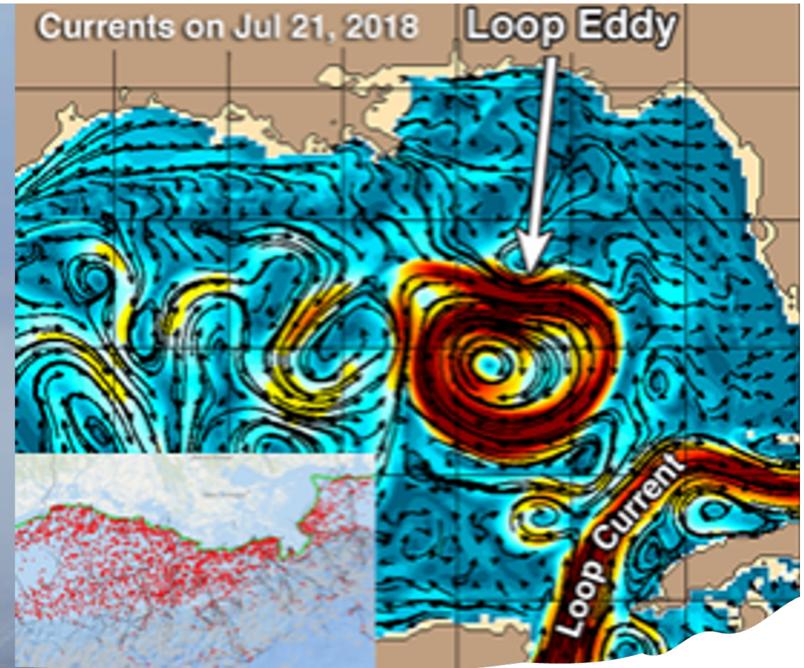
- **Meta Co-Training (European Conference on AI 2025; Rothenberger & Diochnos)**
    - Novel method for multi-view learning that advances how models learn from limited labeled data.
    - Establishes new **State-of-the-Art accuracy** classification in several image datasets used for few-shot classification tasks.
    - Two follow-up papers on this work currently under submission.

- **Review on Pseudo-Labeling (accepted in Journal of AI Research, 2025; Rothenberger et al.)**
    - Taxonomy of semi-supervised and unsupervised learning techniques used for pseudo-labeling.





Use Inspired: Coastal Oceanography

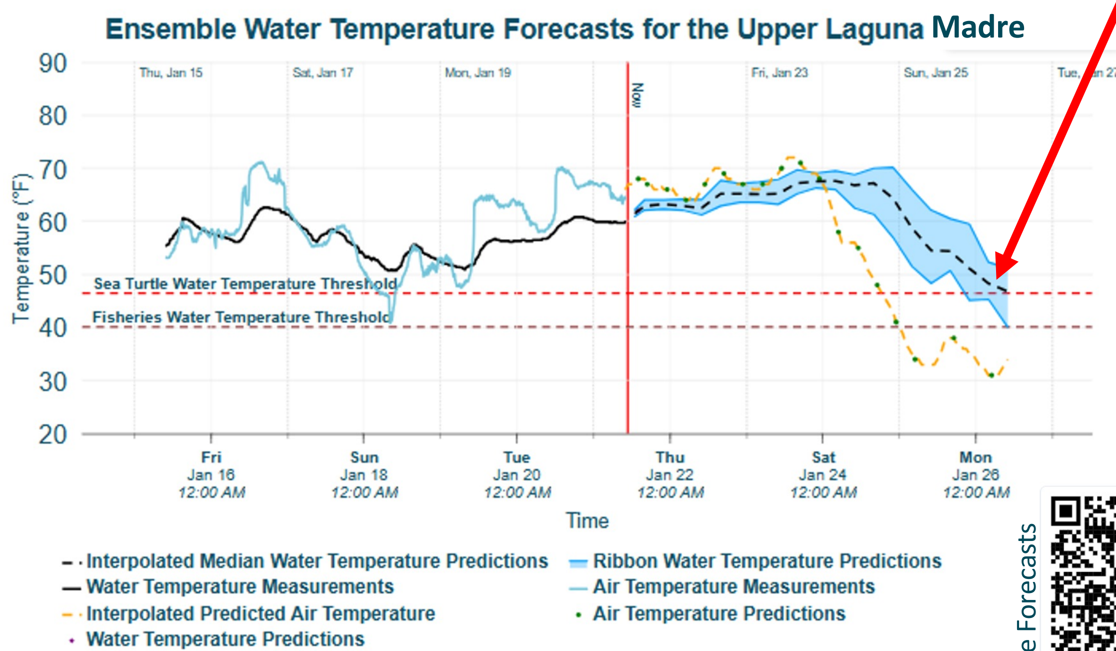


Use-Inspired Operational ML Cold-Stunning Predictions with UQ

Predictions for this Monday morning

Conducted interviews with coastal users to assess (1) how they make decisions using ML predictions and (2) how they interpret different representations of water temperature information (deterministic versus probabilistic)

Qualitative findings will inform advancements to new predictive water temperature visualizations and communication of new uncertainty information for users



Live Forecasts

Developed full UQ method for ML cold stunning predictions, attend **Miranda White**'s Wednesday 11:30 AM, J10B.4 Talk, room 322A "AI machine learning uncertainty quantification for cold-stunning events" and other talks from team

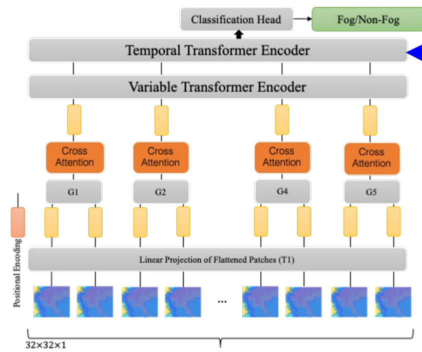
Use-Inspired Physics Based ML Models For Fog Predictions

Created deep learning models to predict fog/visibility based on sea surface temperatures and HRRR predictions

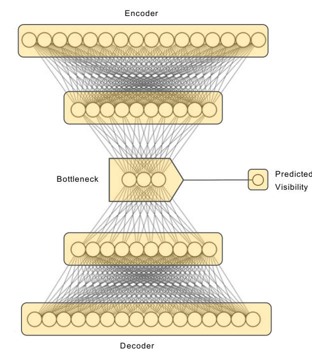
3D-CNN (FogNet), Transformer (FogNet V2) & VAE Fog Predictions for prototype operational model

Physics guided architecture (3D CNN) and/or features selection (VAE)

Lesson: models with the most embedded Physics outperformed all other models

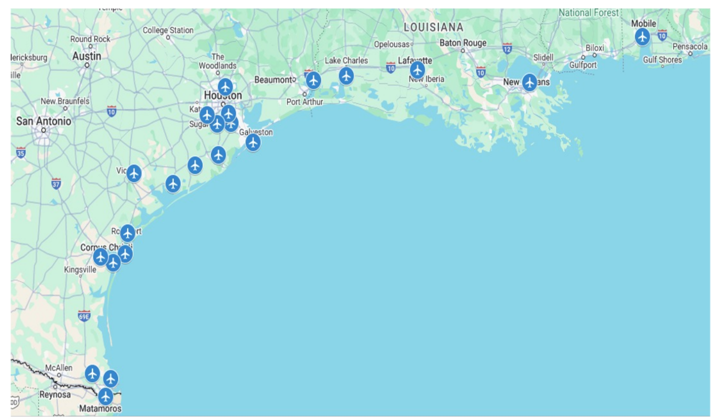


High performance Research Models



Related single model for the full northwest Gulf for operational prototype

Live Site



Kamangir, H., Collins, W., Tissot, P., King, S. A., Dinh, H., Durham, N., & Rizzo, J. (2021). FogNet: A Multiscale 3D CNN with Double-Branch Dense Block and Attention Mechanism for Fog Prediction. *Machine Learning with Applications,* 5, 100038. https://doi.org/10.1016/j.mlwa.2021.100038.

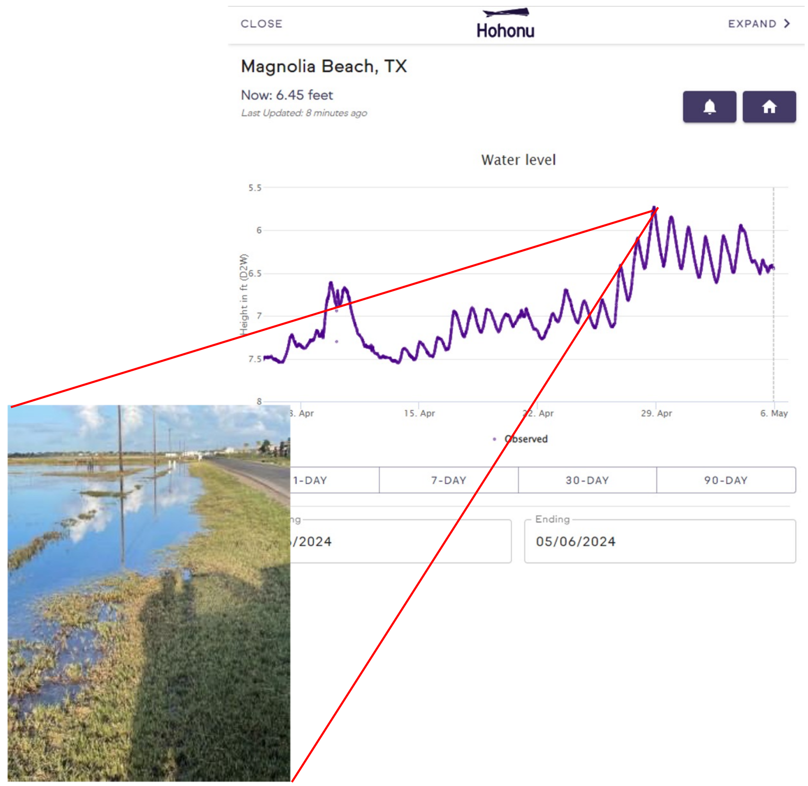
Kamangir, H., Krell, E., Collins, W., King, S. A., & Tissot, P.E. (2022). Importance of 3D Convolution and Physics-based Feature Grouping in Atmospheric Predictions. *Environmental Modelling & Software,* 154, 105424, https://doi.org/10.1016/j.envsoft.2022.105424.

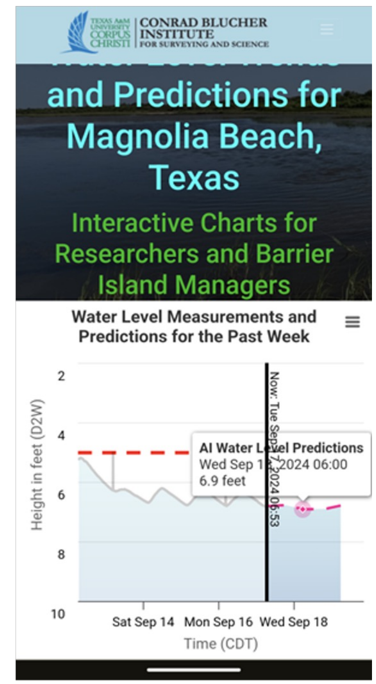
Use-Inspired ML Coastal Flooding Predictions

Developed and implemented deep learning methods to predict water levels at tide gauges along the Texas coast

Worked with stakeholders to deploy low-cost water level sensors at coastal inundation hot spots

Developed and implemented a ML method to predict water levels at location with short time series while taking advantage of the state and federal backbone of tide gauges





Vicens-Miquel, M.; Tissot, P.; Medrano, F. A. Exploring Deep Learning Methods for Short-Term Tide Gauge Water Level Predictions. Water 2024, 16(20), 2886. https://doi.org/10.3390/w16202886

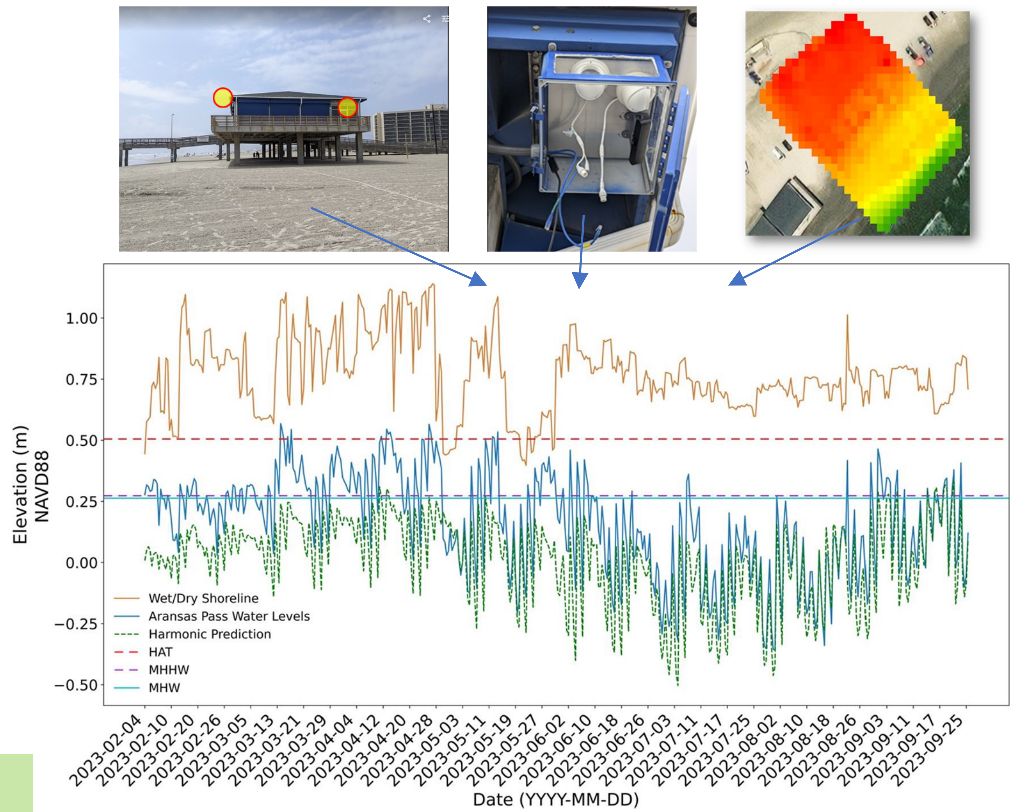
Camera Based Measurements of Total Water Levels

Developed a camera and ground survey based method to track the height of the maximum coastal inundation on a beach or **total water levels**

Demonstrated that tidal datums are not a good indicator of coastal flooding for the microtidal Texas coast

Identified the relative drivers of coastal inundation, in particular wave period, for the Texas coast

Developed and implemented a total water level predictive ML model

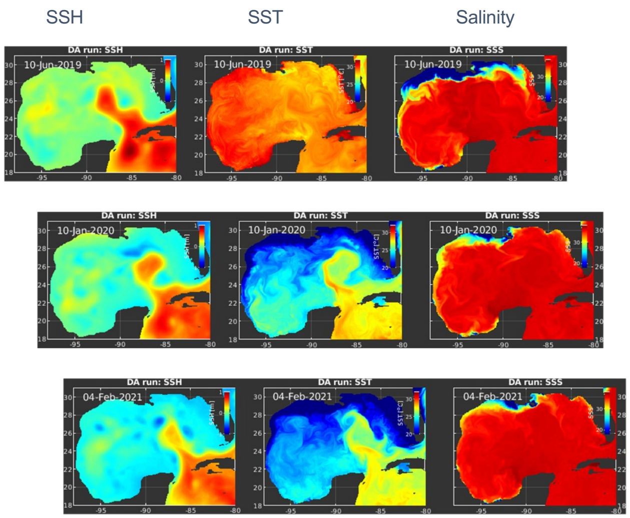


Vicens-Miquel, M., et al. "Machine-Learning Predictions for Total Water Levels on a Sandy Beach." Journal of Coastal Research 41.1 (2025): 57-72. DOI: 10.2112/JCOASTRES-D-24-00016.1

Vicens-Miquel, M.; Williams, D.; Tissot, P.E. (2024). Analysis of Sandy Beach Morphology Changes from a High Spatial Temporal Resolution Dataset. Journal of Coastal Research. https://doi.org/10.2112/JCOASTRES-D-24-00007.1

Coastal Oceanography - Offshore

- Developed **OceanNet** for mesoscale ocean circulation predictions of the Loop Current and the Gulf Stream systems
- Developed **OceanWaveNet** based on ensemble learning approach for ocean surface wave forecasting
- Developed **Simultaneous emulation and downscaling** with physically consistent deep learning-based regional ocean emulators
- Developed **Generative Lagrangian data assimilation** for ocean dynamics under extreme sparsity



Chattopadhyay, A., M. Gray, T. Wu, A. B. Lowe, R. He (2024), OceanNet: A principled neural operator-based digital twin for regional oceans, *Scientific Reports*, 14, 21181 (2024) doi: 10.1038/s41598-024-72145-0

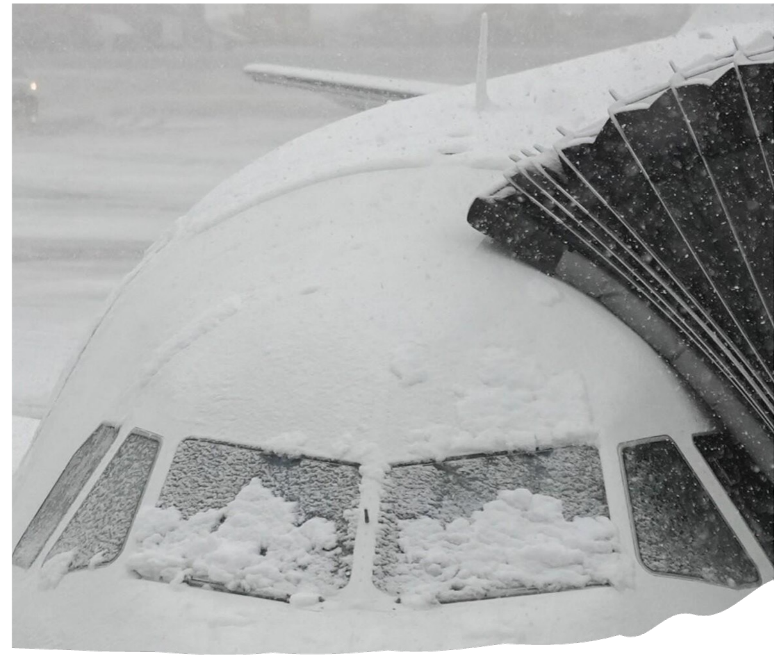
Chaichitehrani*, N., R. He, and M. N. Allahdadi (2024) Forecasting ocean waves off the U.S. East Coast using an ensemble learning approach. *Artificial Intelligence for the Earth Systems*. doi: 10.1175/AIES-D-23-0061.1

Gray, M*. A., A. Chattopadhyay, T. Wu, A. Lowe, and R. He (2025), Long-term Prediction of the Gulf Stream Meander Using OceanNet: a Principled Neural Operator-based Digital Twin, Ocean *Sciences, doi: 10.5194/os-21-1065-2025*

Lowe, A. B*., M, Gray, A. Chattopadhyay, T. Wu, R. He (2025), Long-term predictions of Loop Current Eddy evolutions using OceanNet: a Fourier neural operator-based data driven ocean emulator, *Artificial Intelligence for the Earth System*, doi: 10.1175/AIES-D-24-0039.1.

Lupin-Jimenez, L., Darman, M., Hazarika, S., Wu, T., Gray, M., He, R., Wong, A., & Chattopadhyay, A. (2025). Simultaneous emulation and downscaling with physically consistent deep learning-based regional ocean emulators. *Journal of Geophysical Research: Machine Learning and Computation*, 2(3), doi.org/10.1029/2025JH000851

Asefi, N., Lupin-Jimenez, L., Wu, T., He, R., & Chattopadhyay, A. (2025). Generative Lagrangian data assimilation for ocean dynamics under extreme sparsity. *Machine Learning: Earth*. DOI 10.1088/3049-4753/ae0b70



Use Inspired: Winter Weather

Winter weather road surface detection with NYSDOT

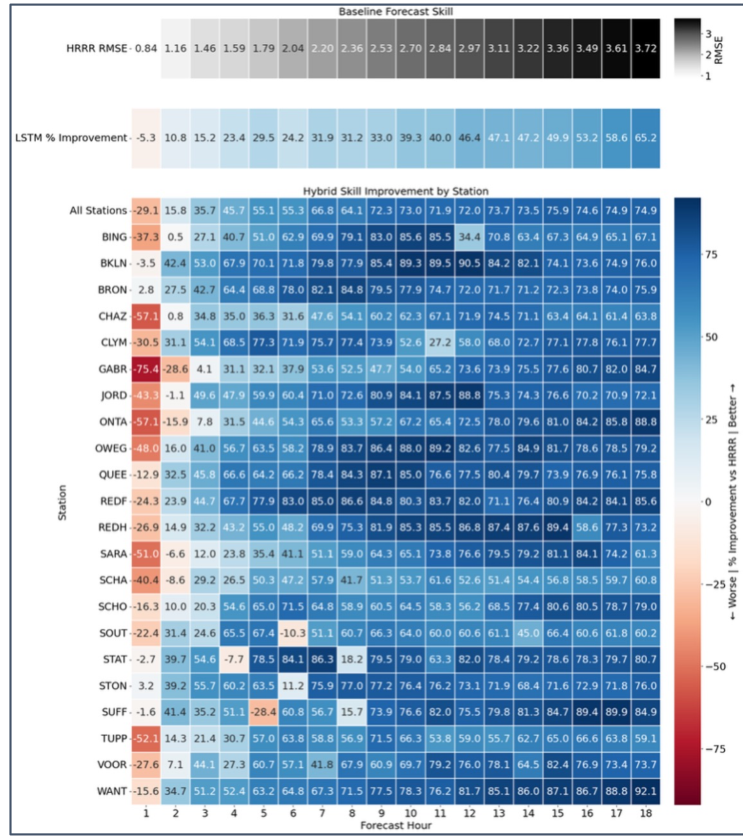
- Improved ML model employing CNN, RF, and ensembling methods
  - Paper accepted (1/17/26)
- Convergent science
  - UA-NCAR visiting week (June 2025)
  - Conducted 10 hours of interviews individually across 15 different NYSDOT end-users
- Public datasets on Zenodo
  - Updated labeling guidelines and trials with RC
  - Datasheet prepared and available

[DOT Official #8]: "In general using [AI] … that is just where the future is going, to help with some of these things, so it just makes sense. Use the tools. ***If you can use cameras to help in real time or help predict, that is where we need to be going****."*

AMS presentation Thursday, Jan 29 10:45am - A User-Centered Approach to Developing a Trustworthy AI Tool for Weather-Related Road Surface Prediction with the New York State Department of Transportation

Forecast Error Prediction for the HRRR

- Enhanced baseline LSTM skill by integrating a Vision Transformer (ViT) encoder with microwave radiometer vertical-profile inputs.
- Improved end-user decision support by quantifying predictive uncertainty with a Bayesian Neural Network (BNN) and delivering calibrated uncertainty metrics.
- Papers in Production:
    - *Predicting Forecast Errors for the HRRR using LSTM Neural Networks: A Comparative Study Using New York and Oklahoma State Mesonets*
    - *A Hybrid LSTM-ViT Architecture for Prediction HRRR forecast errors*
    - *Evaluating Deep Learning Forecast Error Modeling for High Impact Weather*



AMS presentation Monday, Jan 26 9:45am - A Hybrid LSTM-Vision Transformer Architecture for Predicting Short Term NWP Forecast Errors

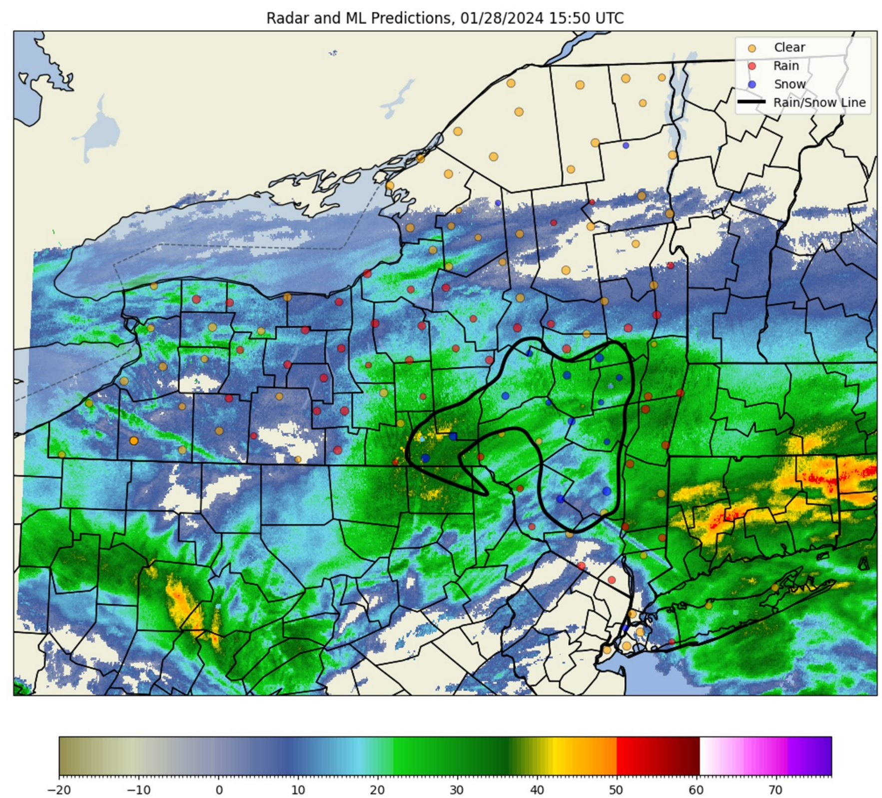
Current Weather Conditions from Mesonet Images

Goal:

- Identify and delineate rain, snow, and clear air from the mesonet cameras in real time for situational awareness

Achievements:

- Public Dataset on Zenodo
- Trustworthy Data Preparation
- ML Modeling for detection using a CNN architecture
- RF architecture for determining camera obstructions

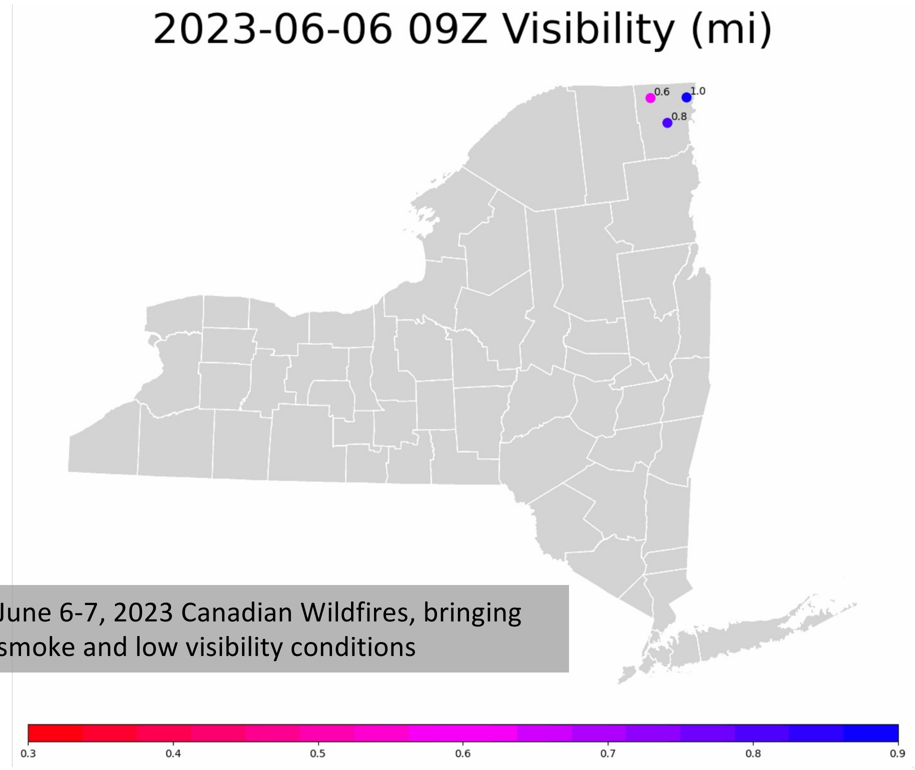


AMS presentation Monday, Jan 26 11:00am - Applications for a Machine Learning Camera Image Classifier Trained on the New York State Mesonet

Atmospheric Visibility Estimation from Mesonet Images

Goals

- Estimate atmospheric visibility distance from camera images
- Develop techniques for training models using noisy labels
- Apply network over entire state with novel sites to provide critical visibility information to emergency managers and state agencies

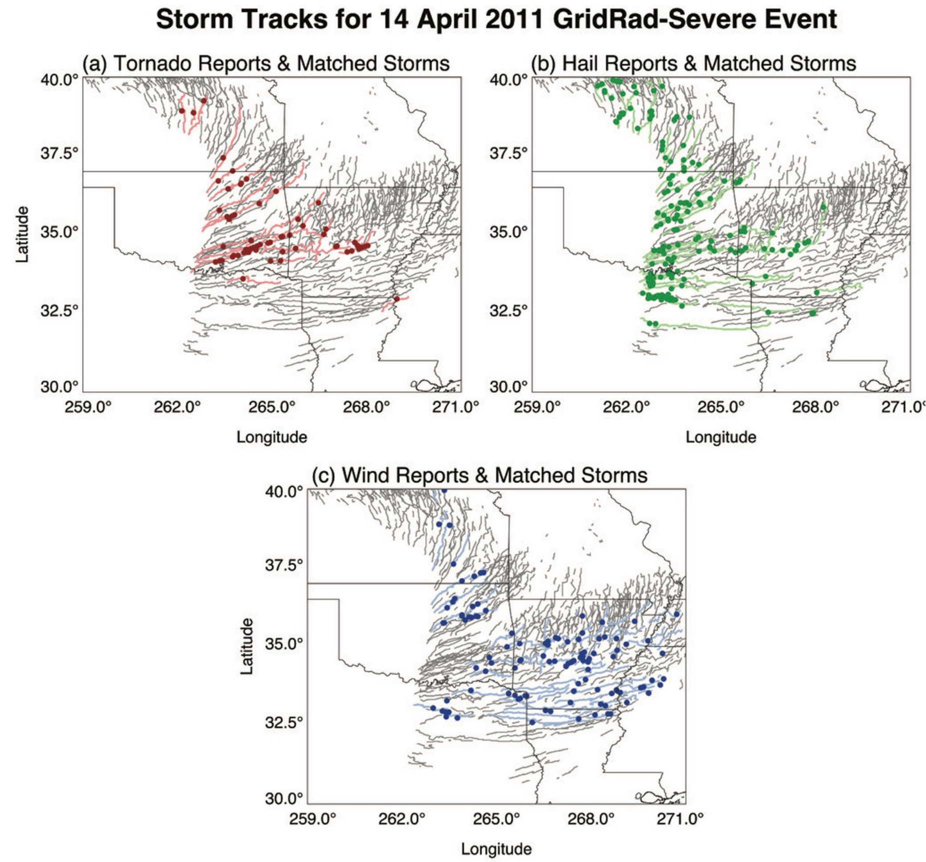


June 6-7, 2023 Canadian Wildfires, bringing smoke and low visibility conditions


Use Inspired: Convective
Weather

Convective Weather

- Developed open dataset of severe storms across CONUS (GridRad-SEVERE)
- Deep dive into nowcasting of tornadoes in mesoscale convective systems (MCSs)

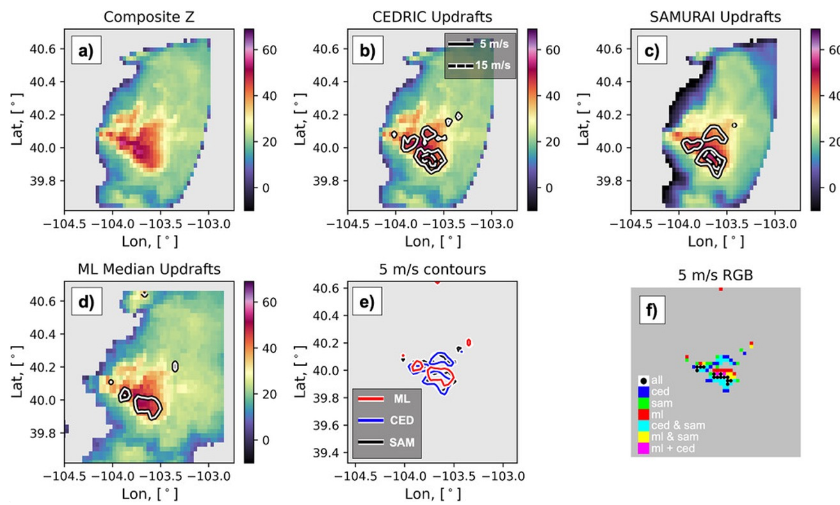


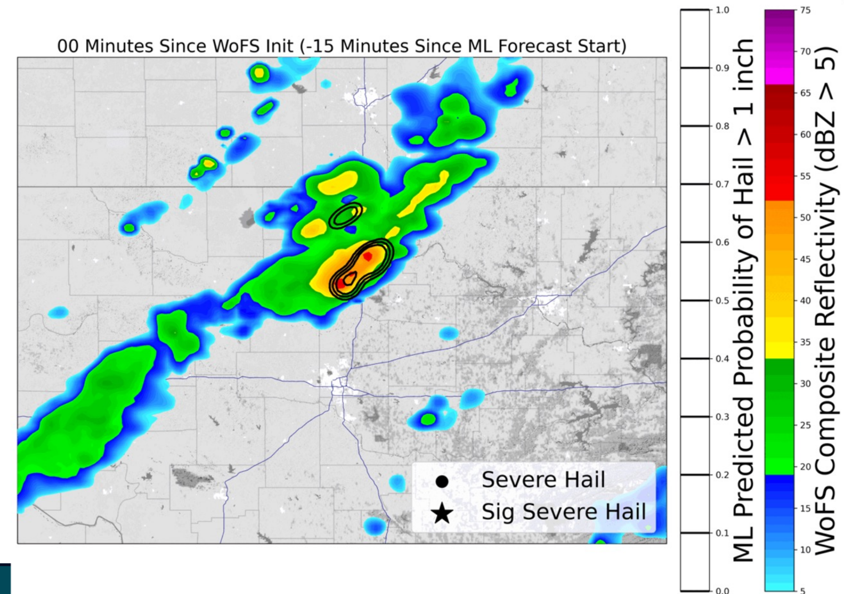
Murphy, A. M., C. R. Homeyer, and K. Q. Allen, 2023: Development and Investigation of GridRad-Severe, a Multiyear Severe Event Radar Dataset. Mon. Wea. Rev., 151, 2257–2277, https://doi.org/10.1175/MWR-D-23-0017.1.

Murphy, A. M., and C. R. Homeyer, 2023: Comparison of Radar-Observed Tornadic and Nontornadic MCS Cells Using Probability-Matched Means. J. Appl. Meteor. Climatol., 62, 1371–1388, https://doi.org/10.1175/JAMC-D-23-0070.1.

Convective Weather

- Developed real-time approach to estimating updraft distribution from radar
- Demonstrated improved hail nowcasting combining NWP and observations





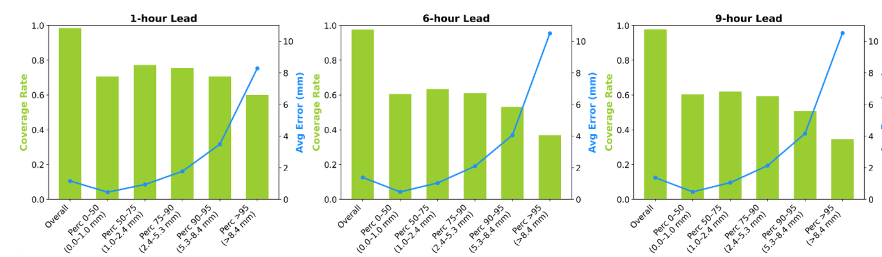
Chase, R. J., A. McGovern, C. R. Homeyer, P. J. Marinescu, and C. K. Potvin, 2024: Machine Learning Estimation of Maximum Vertical Velocity from Radar. Artif. Intell. Earth Syst., 3, 230095, https://doi.org/10.1175/AIES-D-23-0095.1.

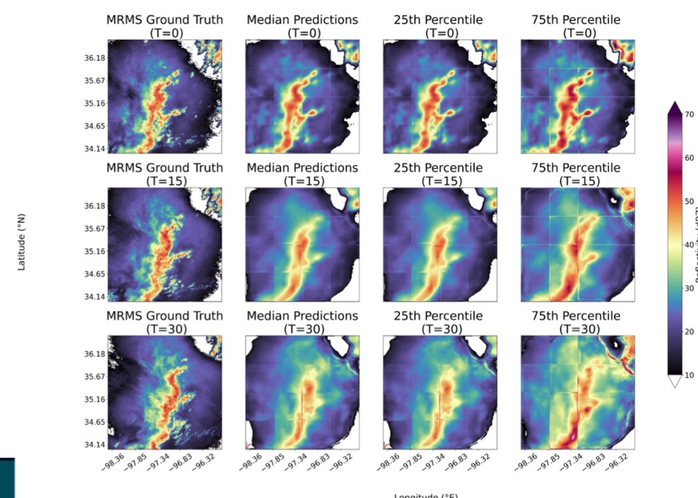
Schmidt, T. G., and Coauthors, 2024: Gridded Severe Hail Nowcasting Using 3D U-Nets, Lightning Observations, and the Warn-on-Forecast System. Artif. Intell. Earth Syst., 3, 240026, https://doi.org/10.1175/AIES-D-24-0026.1.

Convective Weather

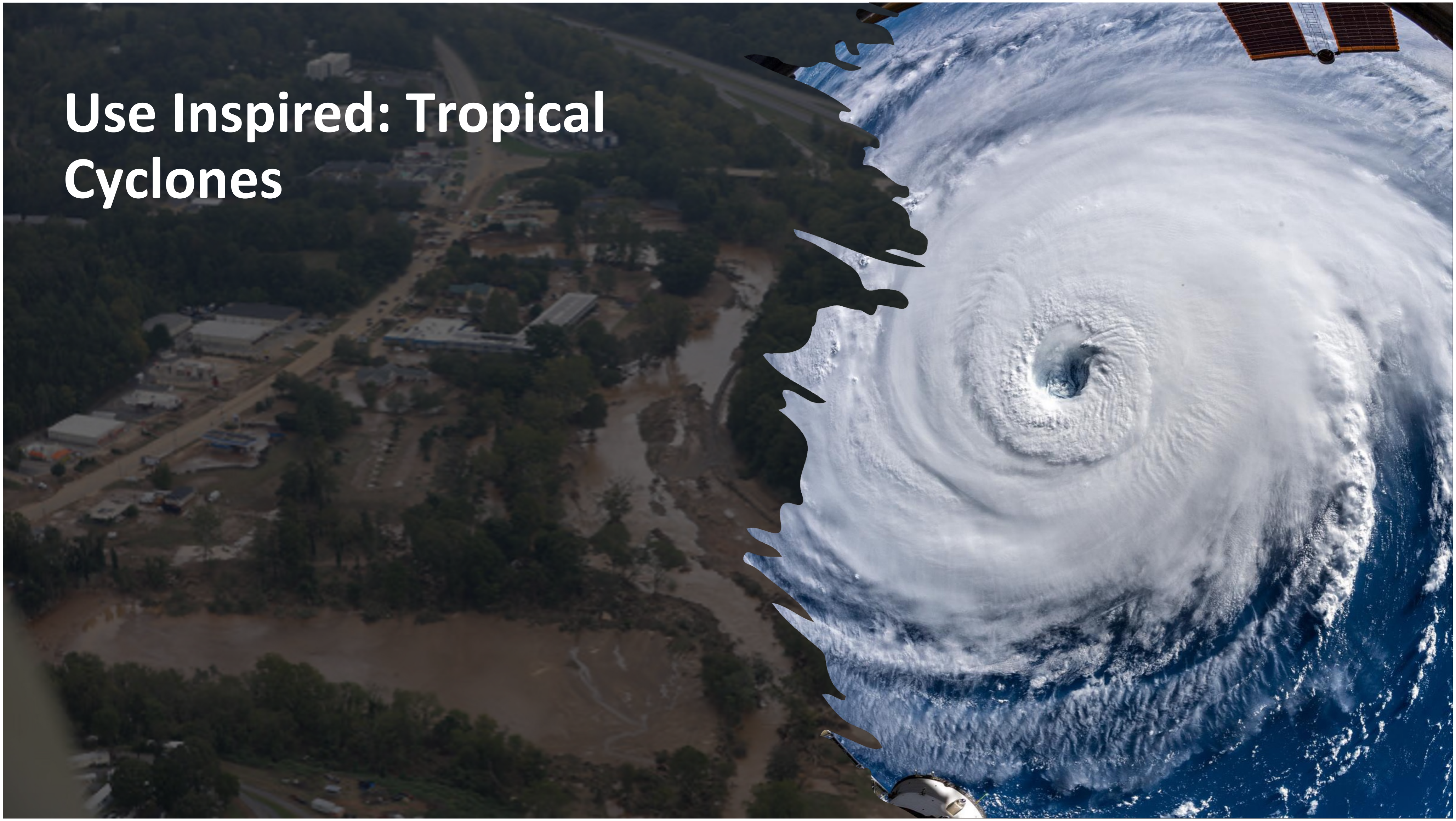
- Published a review paper on convective prediction with AI
- Demonstrated real-time predictions for convection initiation and hazards
- Collaboration at OU on observation based flash flood nowcasting
- With ExpandAI:
    - CONUS high-resolution rainfall prediction with UQ
    - Radar nowcasting for tornadic storms

Talk: A Diffusion-Based Framework for 1-km Spatial Resolution Precipitation Forecasting over CONUS, Wed 5:15pm 330A
Talk: AI-MLP: Severe Weather Probabilities from Global AI Weather Models, Wed 11am 362C
Poster: Deep Learning for Probabilistic Nowcasting of Radar Reflectivity in Tornadic Storms, Monday 3pm, Poster 155
Poster: Short-Range Forecasting of Flash Flood Warnings with Observation-Based Deep Learning AI, Monday 3pm, Poster 158



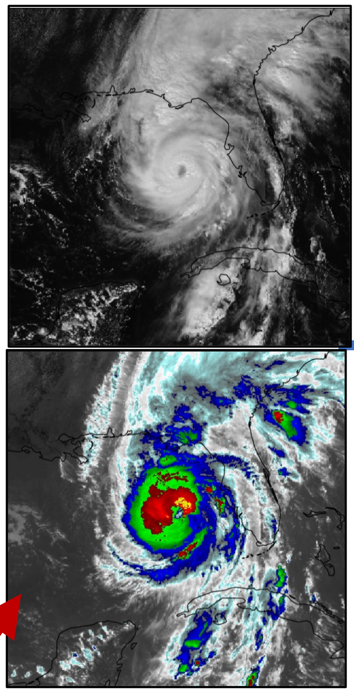


McGovern, A., R. J. Chase, M. Flora, D. J. Gagne, R. Lagerquist, C. K. Potvin, N. Snook, and E. Loken, 2023: A Review of Machine Learning for Convective Weather. Artif. Intell. Earth Syst., 2, e220077, https://doi.org/10.1175/AIES-D-22-0077.1.


Use Inspired: Tropical
Cyclones

TCs – *Synthetic* Passive Microwave (SPM) Imagery

Input: Geostationary Satellite Imagery



TC convective structure NOT visible

ML Models

- Fully-Connected NN (ANN)
- U-Net Convolutional NN (CNN)
- Score-Based Diffusion (EDM)

Loss Functions

Traditional:
- Mean Absolute Error (MAE)
- Mean Square Error (MSE)

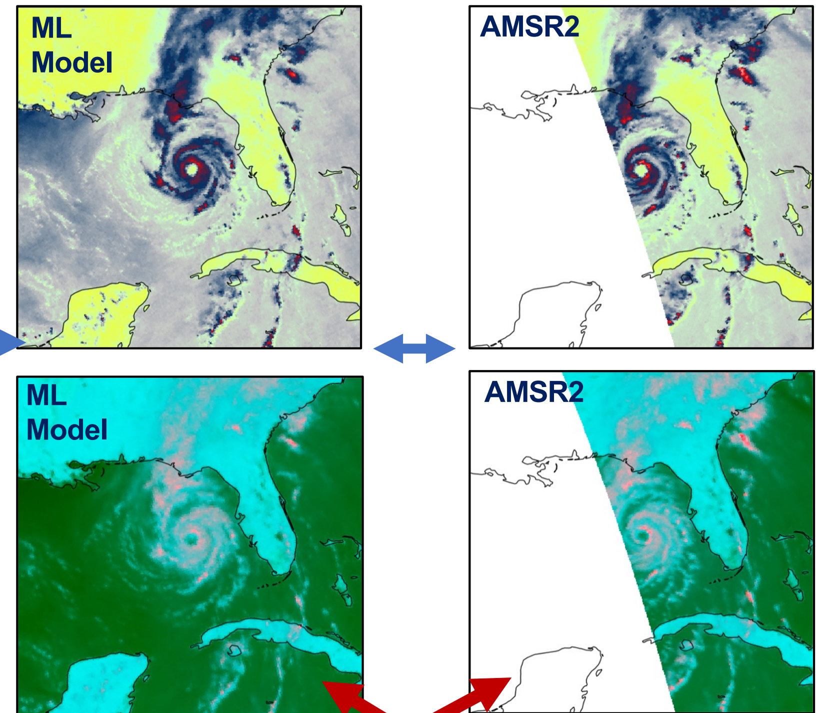
Physically Inspired:
- Weighted MAE & MSE

Uncertainty-Estimating
- Parametric Distributions (normal, sinh-arcsinh)
- Ensemble Predictions (CRPS)

Images from Major Hurricane Helene (AL09 2024).

Output: *Synthetic* Microwave Imagery

Observed Passive Microwave Imagery



TC convective structure visible

TCs – Real-time *Synthetic* Microwave Imagery

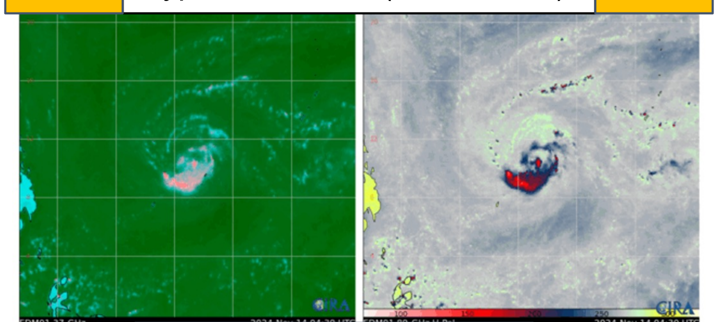
Real time predictions **every 10 minutes**

Predictions are **TC-following**
- 4-km Mercator
- 37- and 89- GHz

Diffusion model and **NN consensus** produced from eight individual U-Nets

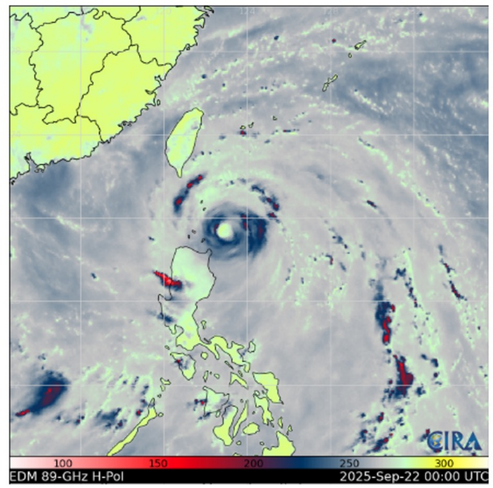
Images on [TC-Realtime](), a CIRA website containing a variety of satellite and model products for TC forecasting

37 GHz | Typhoon Man-Yi (WP25 2024) | 89 GHz



AI-generated, real-time

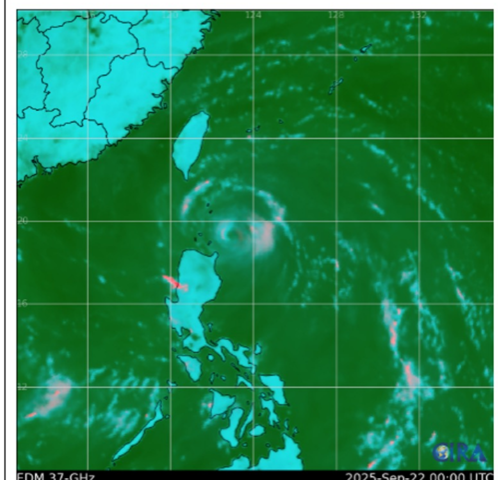
Synthetic Passive Microwave 89 GHz Imagery (Diffusion)



Loop | Latest Image | Archive | About
Time of This Image: 2025-09-22 00:00

Typhoon Ragasa

Synthetic Passive Microwave 37 GHz Imagery (Diffusion)



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WP24 2025

Live Site

Credit: Kathy Haynes, CIRA

TCs - Science Discovery with SPM

Applied PCA to synthetic passive microwave (SPM) imagery.

Goal: learn about TC evolution from AI-generated dataset.

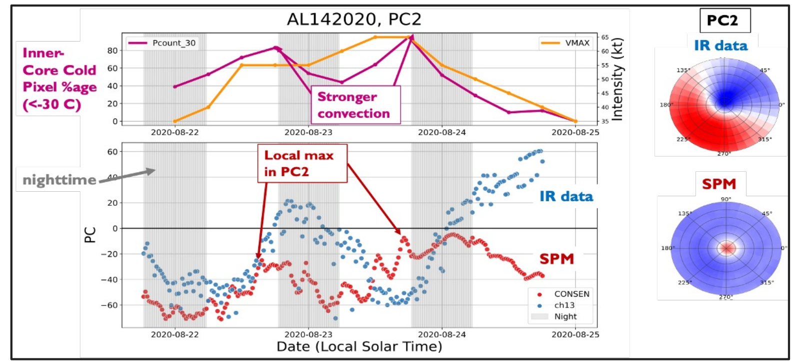
- Histogram and PDF analyses show SPM imagery is closely aligned with observed microwave imagery (not geostationary)
- Principal component analysis shows SPM imagery exhibits distinct spatiotemporal variability from geostationary
- SPM images demonstrate temporal consistency for individual storms

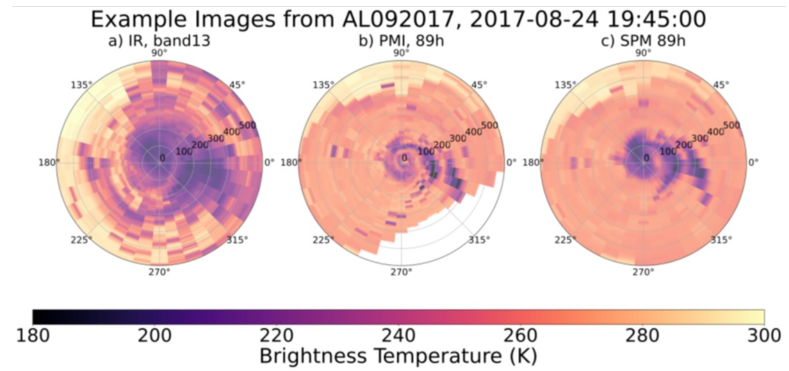
Related NSF Award: IIS-2509835

NSF AI-Ready Testbed for Tropical Cyclones - Planning the extension of NOAA's Hurricane and Ocean Testbed (HOT)

(CIRA, NCAR, NOAA/NHC)

https://www.cira.colostate.edu/ml/nsf-ai-ready-tc/



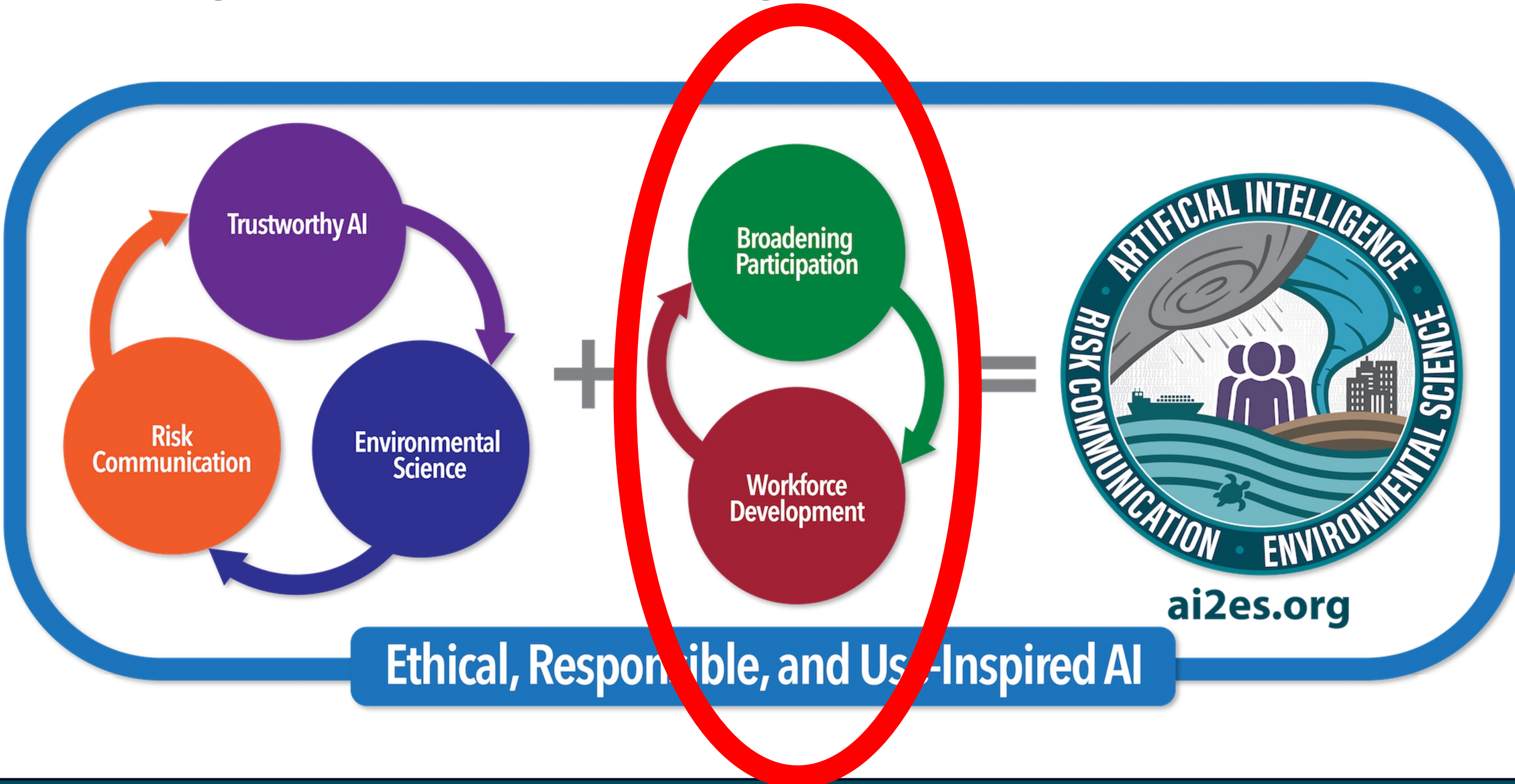


Credit: Marie McGraw, CIRA

COLORADO STATE UNIVERSITY

CIRA Connecting Models and Observations

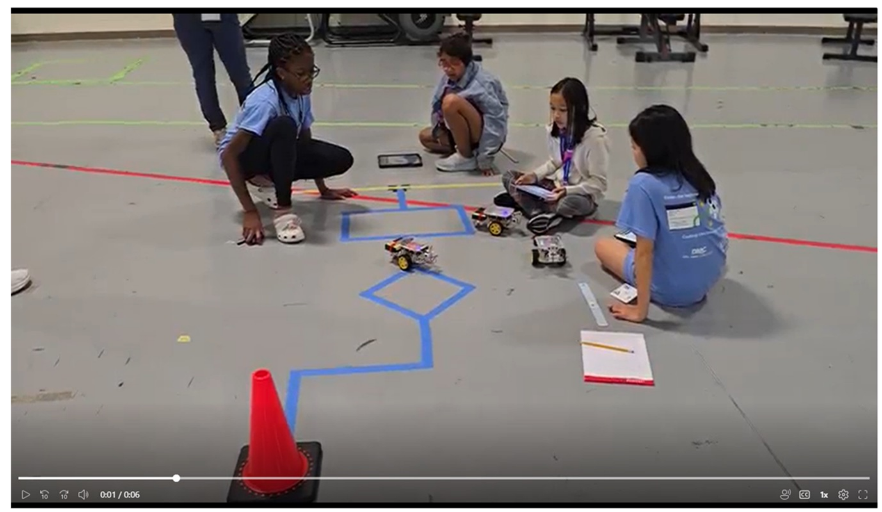
AI2ES Key Contributions By Area



AI for Weather Workforce Development : K-12

Del Mar College

- CODE_IT camp
  - Middle and high school students
  - Fun hands on learning!
  - Presentations from undergraduate researchers as part of AI2ES wide meeting
  - Q&A between campers and undergraduate researchers: school, science, careers, and life as a student
- Training middle school and high-school teachers on AI to take back to their schools



AI for Weather Workforce Development

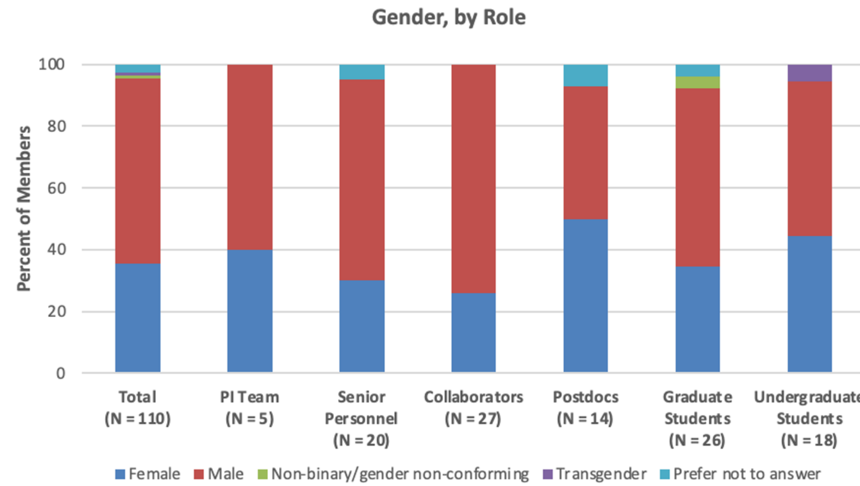
University and College Education

- Developed one of the first community college AI occupational skills award
  - Multiple cohorts have graduated and either taken this to their workforce or transferred to a 4 year college or university
- AI2ES has trained 83 undergraduates
- AI2ES created a strong pipeline to jobs for students who would not have considered these jobs before
  - Synergy across institutions
  - Knowledge transfer to industry

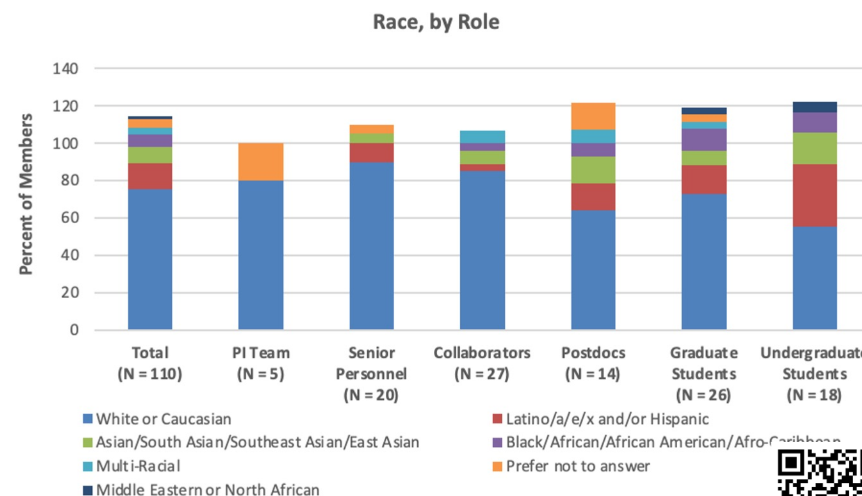
AI for Weather Workforce Development

AI2ES has trained a diverse workforce (race, gender, LGBTQIA+, level of experience, first-generation students, and socioeconomic status)

- HRI has measured diversity in race and gender
- Discovery Day at DMC brings in 700+ middle and high schools for STEM awareness
- Spanish language outreach through news interviews and MyRadar
- ExpandAI funded in Y4 with SDSU/UCI and FIU



*Totals come from survey results

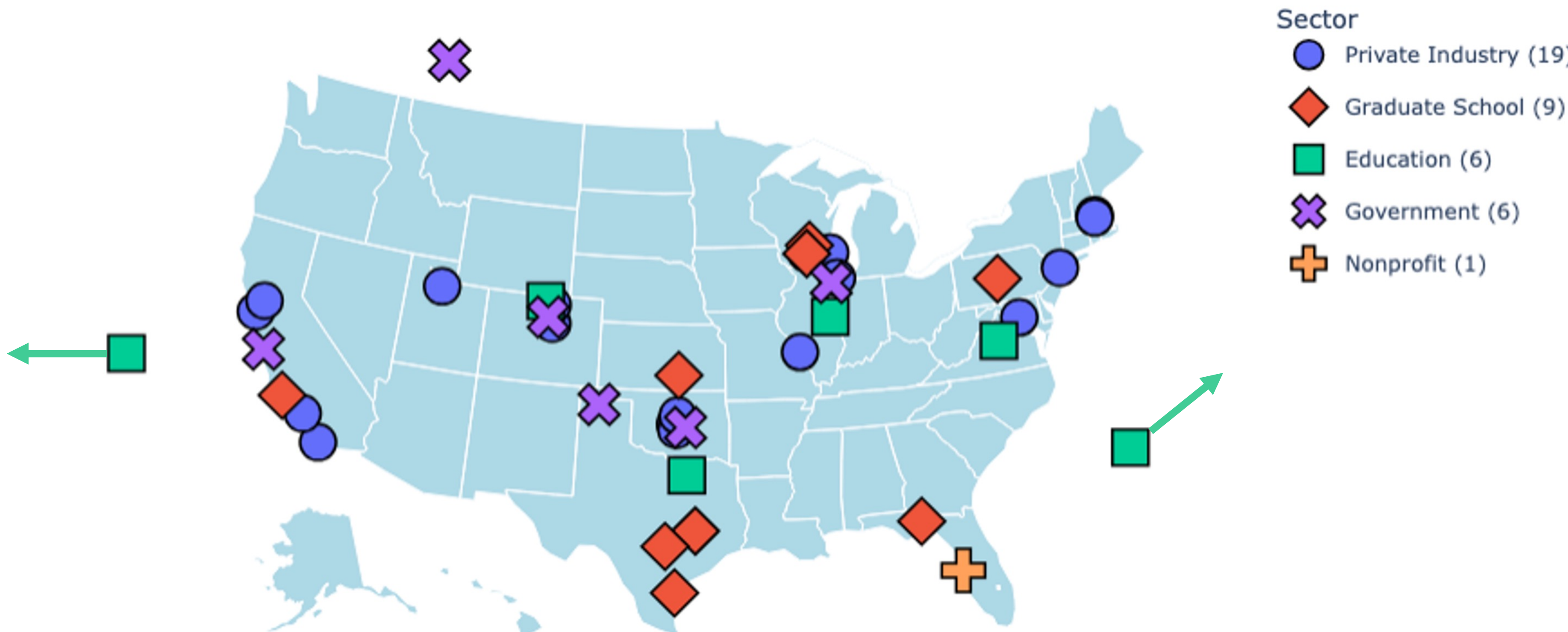


*Members were allowed to select more than one race/ethnicity, so percents may add up to more than

AI for Weather Workforce Development: Postdocs

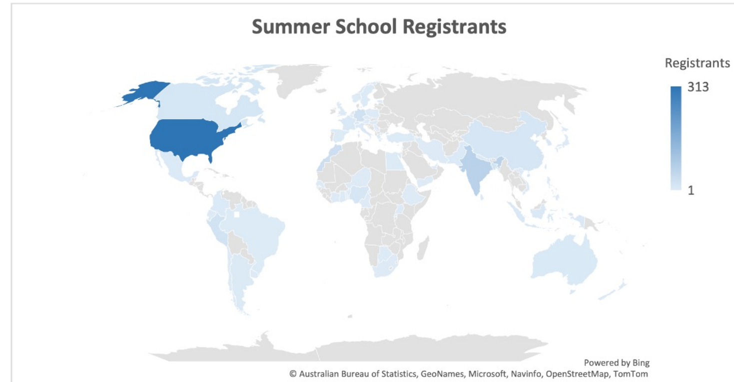
- Provided full or partial support for 23 postdoctoral scholars and worked with several affiliated ones
- Learning from each other and others in AI2ES about research approaches and concepts outside of their disciplinary specialties – and applying them in some cases!

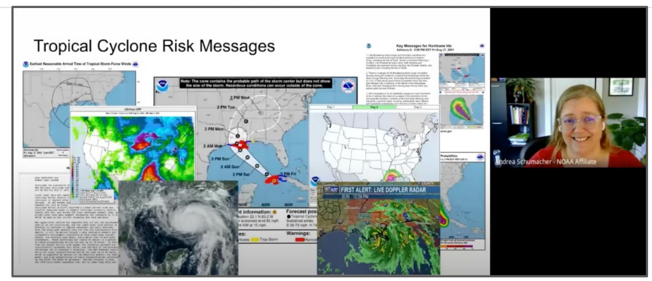
Where have AI2ES alumni gone?



AI2ES Workforce Development: Summer Schools & Tutorials

- Summer school 2021 and 2022 build broad community for trustworthy AI in environmental sciences including an innovative Trust-a-thon
- Short courses in XAI in summer 2022 and transformers in Fall 2022
- Tutorial on risk communication in May-June 2022
- Highly cited tutorials on AI/ML for operational meteorology





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Chase, R. J., D. R. Harrison, G. M. Lackmann, and A. McGovern, 2023: A Machine Learning Tutorial for Operational Meteorology. Part II: Neural Networks and Deep Learning. Wea. Forecasting, 38, 1271–1293, https://doi.org/10.1175/WAF-D-22-0187.1.

McGovern, A., Gagne II, D. J., Wirz, C. D., Ebert-Uphoff, I., Bostrom, A., Rao, Y., Schumacher, A., Flora, M., Chase, R., Mamalakis, A., McGraw, M., Lagerquist, R., Redmon, R. J., and Peterson, T. (2023) Trustworthy Artificial Intelligence for Environmental Sciences: An Innovative Approach for Summer School. Bulletin of the American Meteorological Society. 104, E1222–E1231, https://doi.org/10.1175/BAMS-D-22-0225.1

Workforce Development is critical

- “[NSF] AI2ES gave me the skills to transition smoothly into industry where I get to leverage my new expertise in AI with the new and exciting frontier of weather forecasting with AI.”
- The communication and technical skills I learned while working for [NSF] AI2ES helped me collaborate with researchers from a wide array of expertise at Google.”

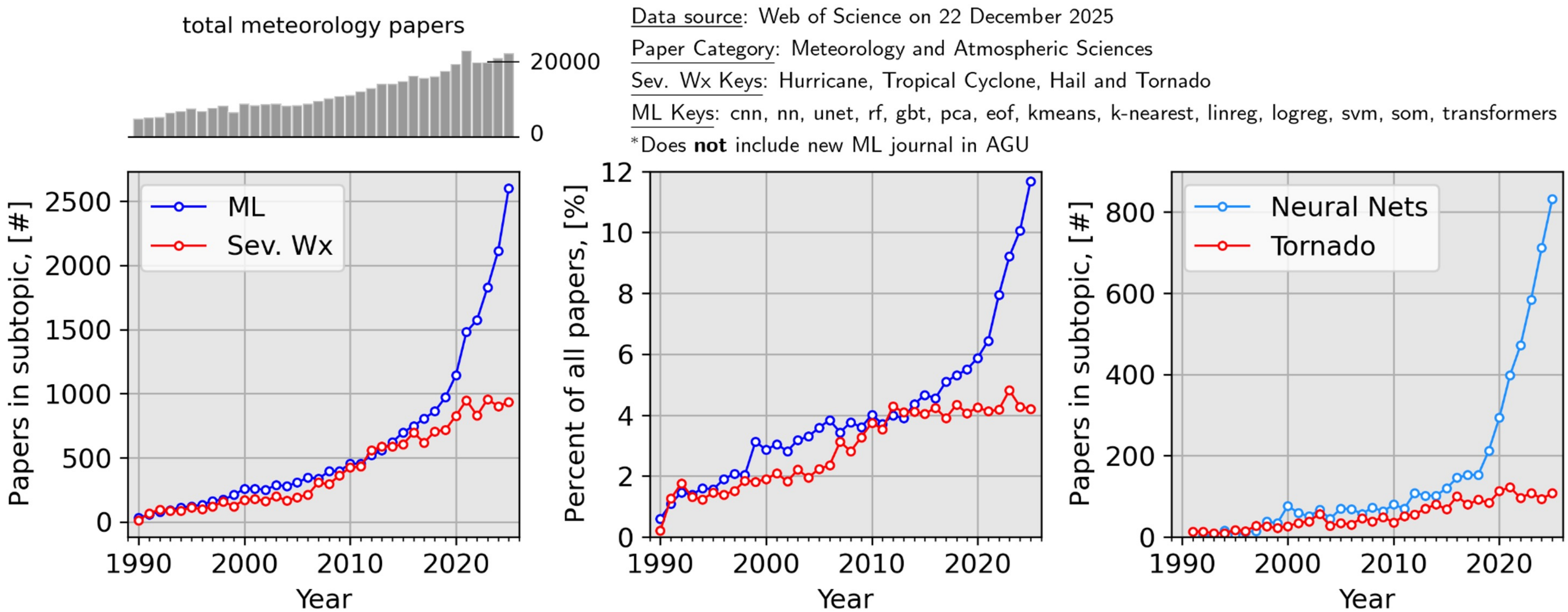
Charlotte Cabrera
Software Engineer
Google

Randy Chase
Atmospheric Data Scientist
tomorrow.io

The Future of AI2ES

- AI2ES will finish the NSF funded part of our work Aug 31, 2026
- **The novel work in trustworthy AI for weather will continue in many ways**
    - **We need to continue to fund large-scale grants to facilitate convergence research!**
- This material is based upon work supported by the National Science Foundation under Grant No. RISE-2019758
    - Related grants NOAA SDII, NSF ER2, NSF Testbed, NSF CAIG, NSF ExpandAI, and several more pending

AI for Weather is Growing Exponentially: We still need large-scale focus on trustworthy AI



Graphic from Randy Chase

Publications and AMS talks

AI2ES talks at AMS 2026

ai2es.org

amcgovern@ou.edu

AI2ES Publications