Environmental Applications of AI & the AI2ES National AI Institute

Philippe Tissot

Conrad Blucher Institute Chair for Coastal Artificial Intelligence, Texas A&M University-Corpus Christi

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

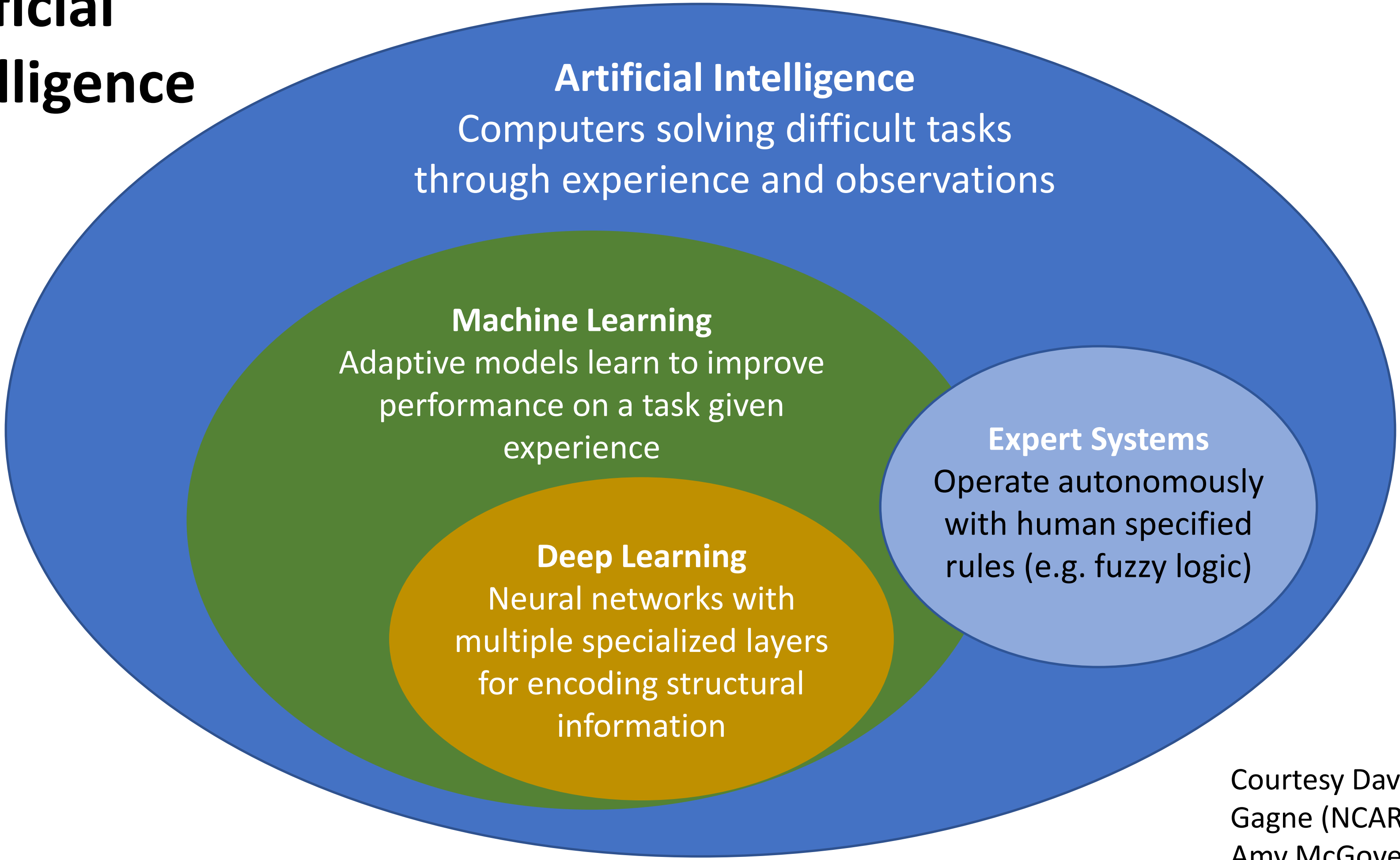
Friends & Partners IN AVIATION WEATHER

FPAW Fall 2024 Meeting

TEXAS A&M UNIVERSITY CORPUS CHRISTI | CONRAD BLUCHER INSTITUTE FOR SURVEYING AND SCIENCE

ARTIFICIAL INTELLIGENCE · ENVIRONMENTAL SCIENCE · RISK COMMUNICATION

Artificial Intelligence



Courtesy David John Gagne (NCAR) & Amy McGovern (OU)

History of AI/ML

40’s: Similar concepts envisioned by Vannevar Bush after World War II, “As We May Think”, the Memex

50’s: Ideas spurred by Alan Turing “can machines think?”, “Computing Machinery and Intelligence” and Claude Shannon (Theseus electromechanical mouse) in the 1950s

1955: “Artificial Intelligence” term coined by John McCarthy (academic summer school)

Ups and downs : **50’s-mid 70s ↗ mid 70’s-mid 80’s ↘ mid 80’s-mid 90’s ↗ 2000’s ↘ 2010’s ↗ ↗ ↗**

In the environmental sciences start at least in the 80’s likely early 70’s

Needs: - a lot of data! e.g. atmospheric sciences are a good “beachhead” for AI
- a nonlinear system

The 1956 AI Summer School

School AI Topics:

- Automatic Computers
- How Can a Computer be Programmed to Use a Language
- Neuron Nets
- Theory of the Size of Calculation
- Self-Improvement
- Abstractions
- Randomness & Creativity

A PROPOSAL FOR THE
DARTMOUTH SUMMER RESEARCH PROJECT
ON ARTIFICIAL INTELLIGENCE

J. McCarthy, Dartmouth College
M. L. Minsky, Harvard University
N. Rochester, I.B.M. Corporation
C.E. Shannon, Bell Telephone Laboratories

August 31, 1955

http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf

Early Foci:

- Simulate, understand the human brain, relationship between humans and machines, robotics, …

But AI for Environmental Sciences:

- Different focus
- Study & prediction of nonlinear systems

AMS AI Workshop and Short Courses: 1985 – New Orleans 2025 .....

Boulder 1987: AIRES II

meeting review

Summary Report on the Second Workshop on Artificial Intelligence Research in the Environmental Sciences (AIRES), 15–17 September 1987, Boulder, Colorado

Rosemary Dyer[1] and William Moninger,[2]

Meeting Convenors

- **Goals:**
  - Forum for ongoing AI work in environmental sciences & promising directions
  - Give newcomers survey of state of the art
- **Other info:**
  - 80 participants
  - Meteorology, hydrology, environmental protection, and uses of intelligent data base
  - Emphasis on expert systems & their inference engines
  - One mention of neural nets (K. Young, univ. Arizona)

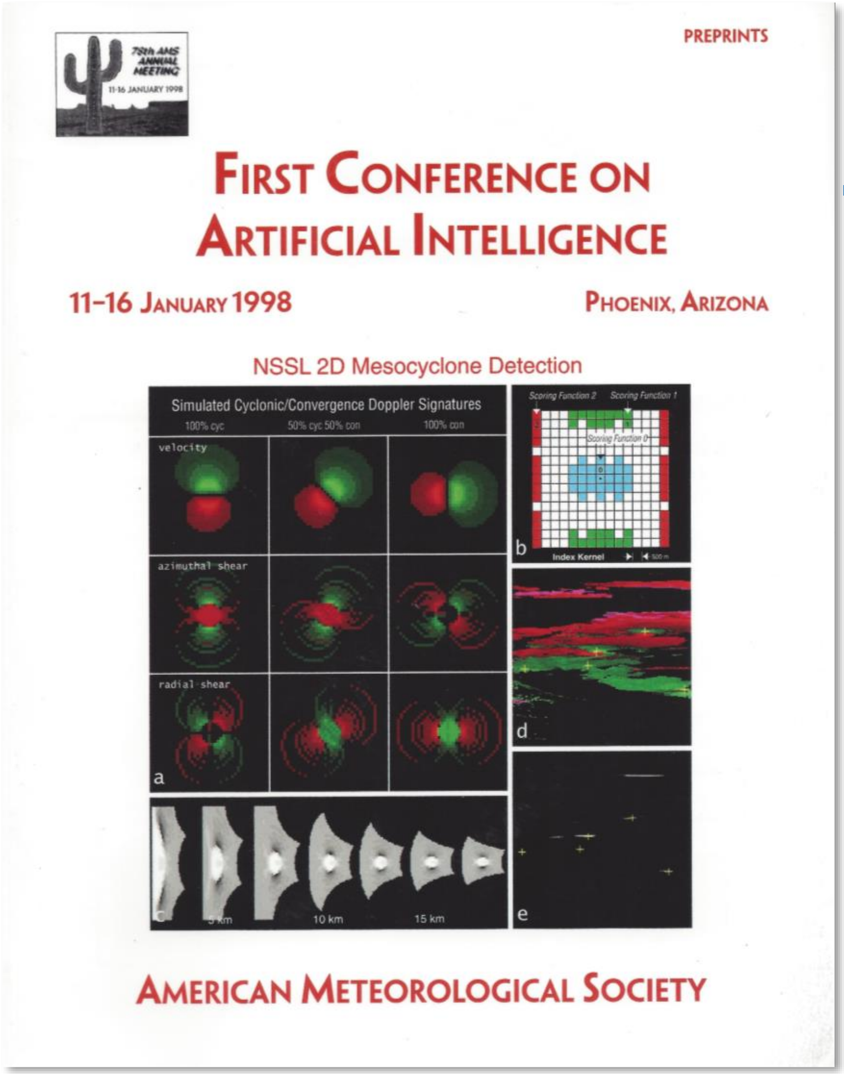
Bulletin American Meteorological Society

TABLE 1. Past and current AI work in environmental science as of January 1988.

AI Systems Number	Subject Matter
22	Environmental forecasting
3	Weather diagnosis
6	Automated pattern recognition
9	Assistance to operational users of environmental data
5	Assistance to environmental researchers
1	Tutor for meteorology students
15	Hazard response, short and long term
8	Hydrology and crop management
Supporting Studies	
5	Investigations of cognitive processes of environmental forecasters

NOTE: For a detailed list of each of these systems and studies, contact William R. Moninger, NOAA/Environmental Research Laboratories, NOAA, R/E2, 325 Broadway, Boulder, CO 80303.

https://journals.ametsoc.org/doi/pdf/10.1175/1520-0477-69.5.508



AMS AI Conferences
1998 -2025

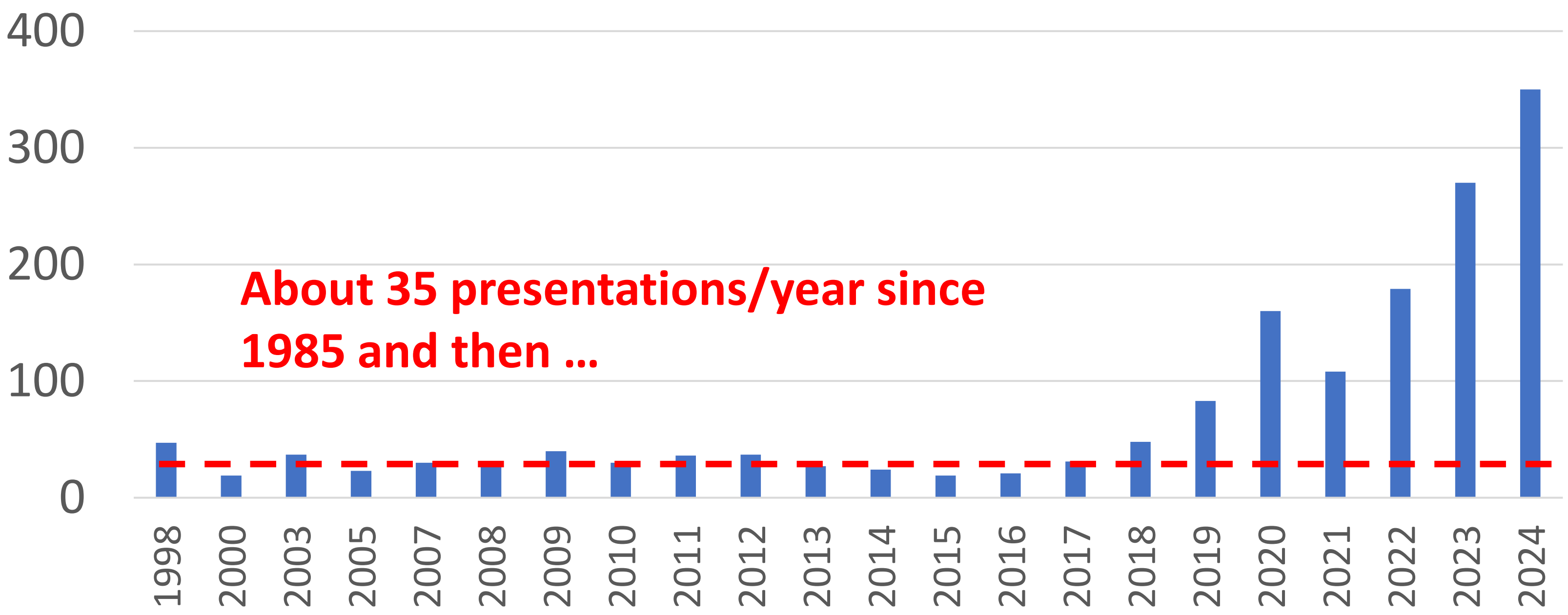
1998: 8 Sessions – 47 Presentations

- Artificial Neural Nets for Precipitation Forecasts
- Artificial Neural Nets for Satellite Retrieval and Pattern Recognition
- Climate Classification and Prediction
- Decision Aids and Natural Language Systems
- Image Processing
- Poster
- The Human Element in Forecasting
- Intelligent Statistics (joint with PROB/STAT)

Including:
"Neural Networks as a Generic Tool for Satellite Retrieval Algorithm Development and for Direct Assimilation of Satellite Data into Numerical Models", ***V.M. Krasnopolsky***

Impact of AI in Environmental Sciences:

of presentations at the American Meteorological Society (AMS) AI Applications to Environmental Sciences Conferences (24th in New Orleans Jan. 12-16, 2025)



ai2es.org

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, directly improving climate resiliency.

ai2es.org

@ai2enviro

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

AI2ES Senior Leadership Team

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

John Allen, Central Michigan University

Ann Bostrom, University of Washington

Phillip Davis, Del Mar College

Imme Ebert-Uphoff, Colorado State University

Julie Demuth, National Center for Atmospheric Research

David John Gagne, National Center for Atmospheric Research

Ruoying He, North Carolina State University

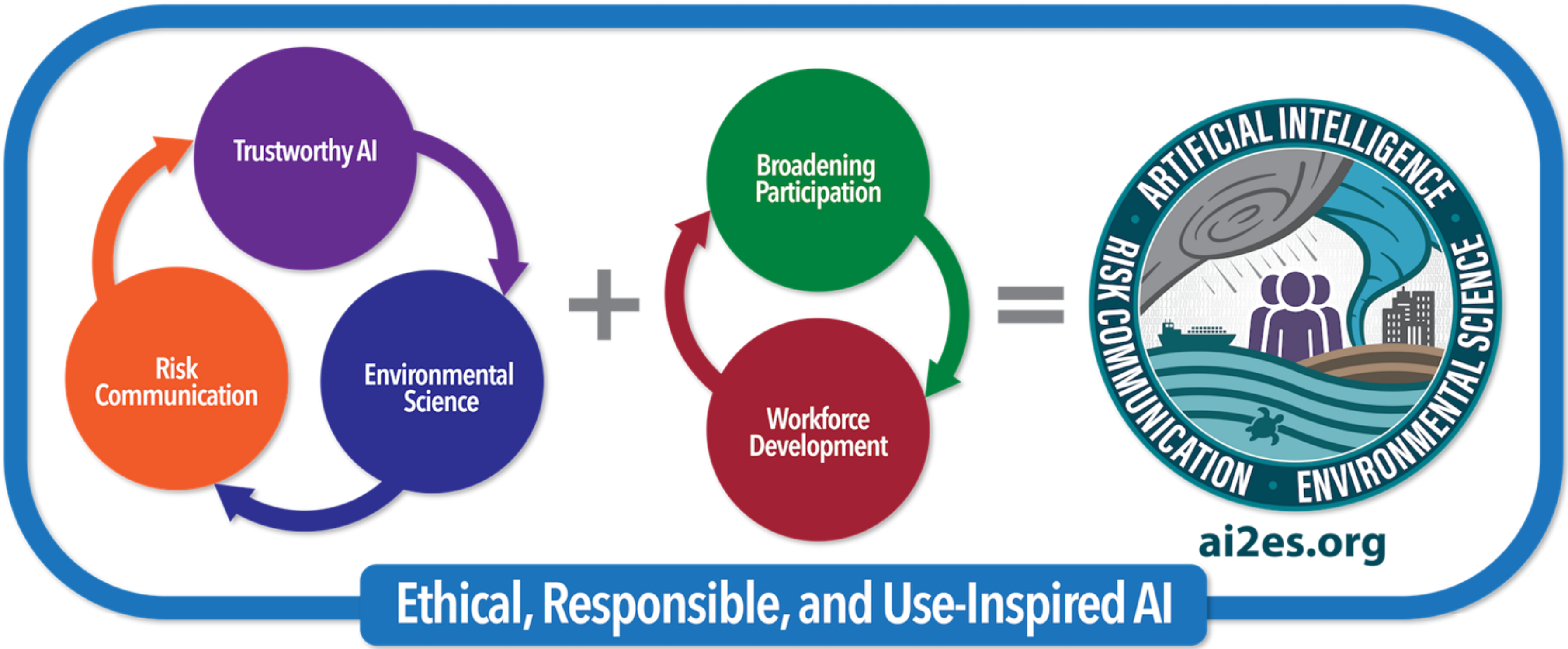
Nathan Snook, University of Oklahoma

Jebb Stewart, National Oceanic and Atmospheric Administration, advisor

Philippe Tissot, Texas A&M University, Corpus Christi

Christopher Thorncroft, University of Albany

John Williams, The Weather Company, IBM



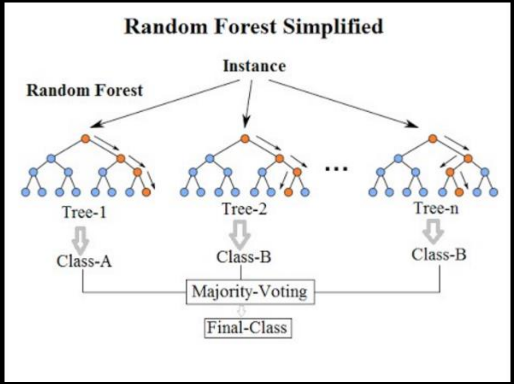
Advocating for convergent efforts for the development of AI environmental models:

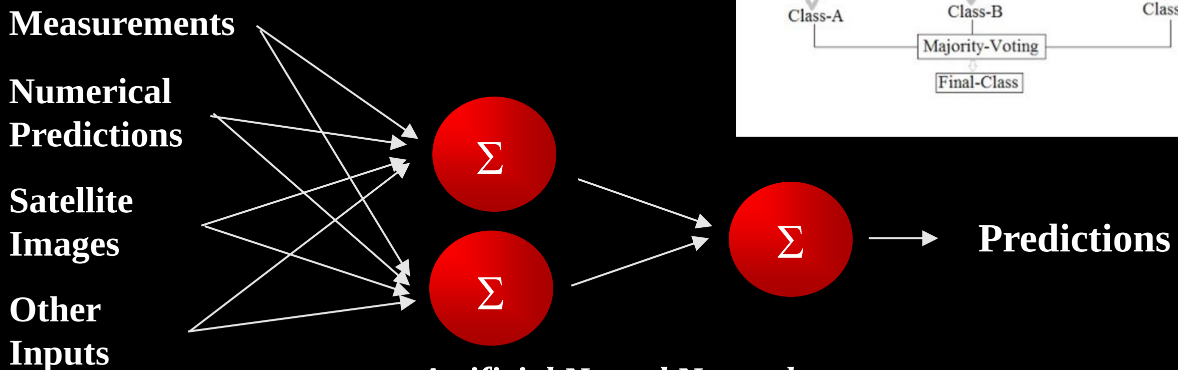
McGovern, A., Demuth, J., Bostrom, A., Wirz, C. D., Tissot, P. E., Cains, M. G., & Musgrave, K. D. (2024). The value of convergence research for developing trustworthy AI for weather, climate, and ocean hazards. npj Natural Hazards, 1(1), 13.
https://doi.org/10.1038/s44304-024-00014-x


Coastal AI: Predictions, Stakeholders and Trust
The power of Artificial Intelligence (AI) to predict and better understand events at the intersection of Atmosphere-Ocean-Land
Atmosphere
Ocean
Land
Photo: Jon Brandt©
HIGH WATER
Inundations
Coastal Fog
Sea Turtle Conservation

Examples of AI Methods for Environmental Applications

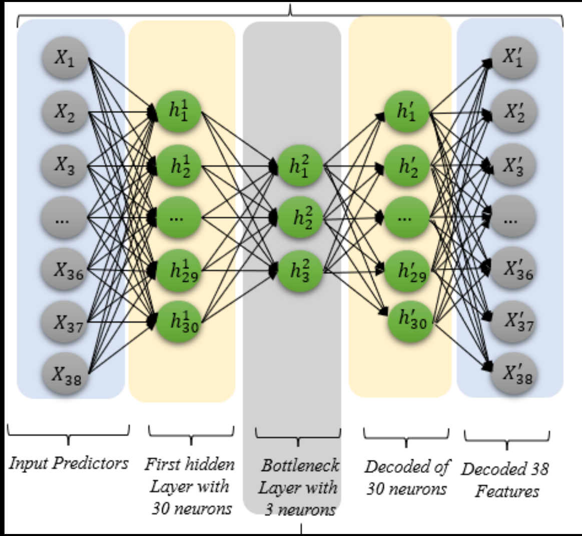
Operational neural networks for water level, temperature and current predictions, Random Forest for model interpretation





Artificial Neural Network

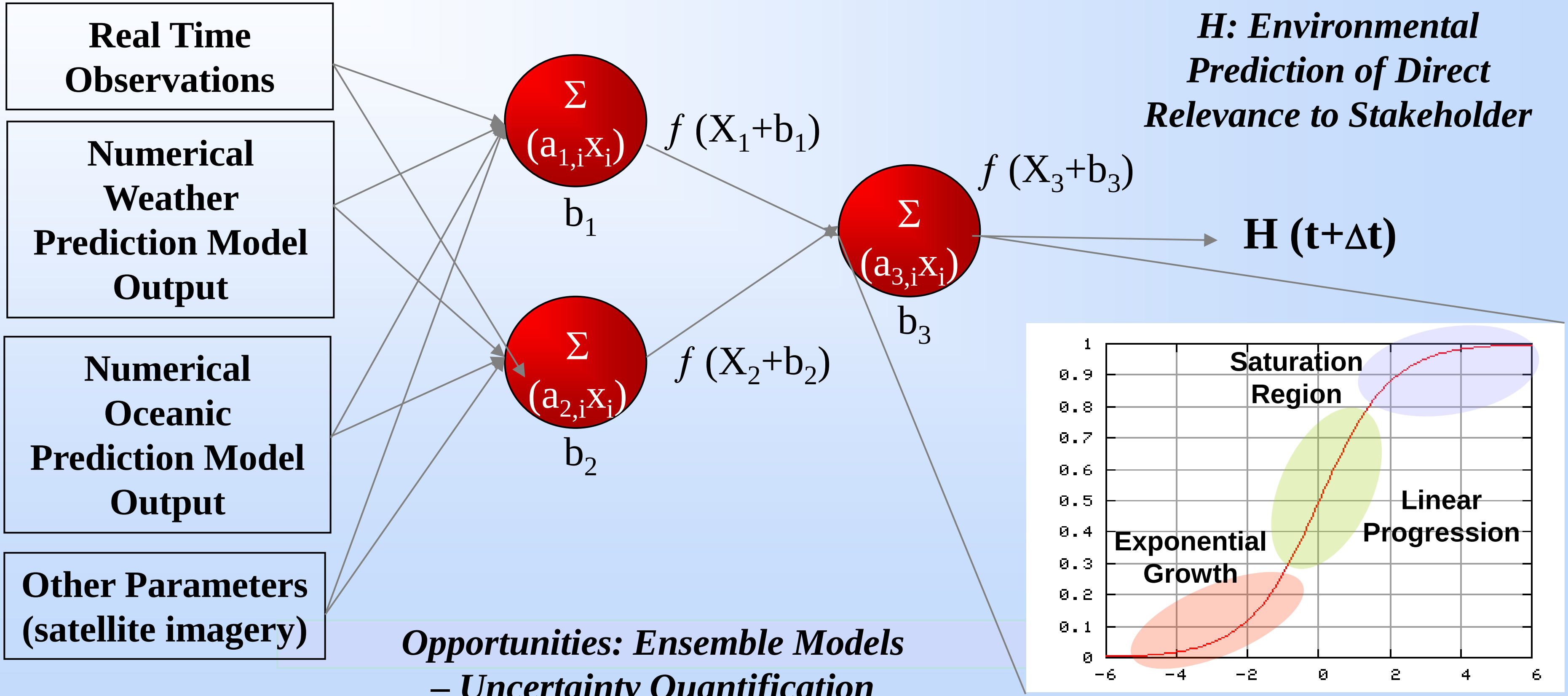
Autoencoder to predict lightning



Cox, D. T., Tissot, P.E. and Michaud P. (2002). Water Level Observations and Short-Term Predictions Including Meteorological Events for Entrance of Galveston Bay, Texas. Journal of Waterway, Port, Coastal and Ocean Engineering, 128-1, 21-29. doi: 10.1061/(ASCE)0733-950X(2002)128:1(21).

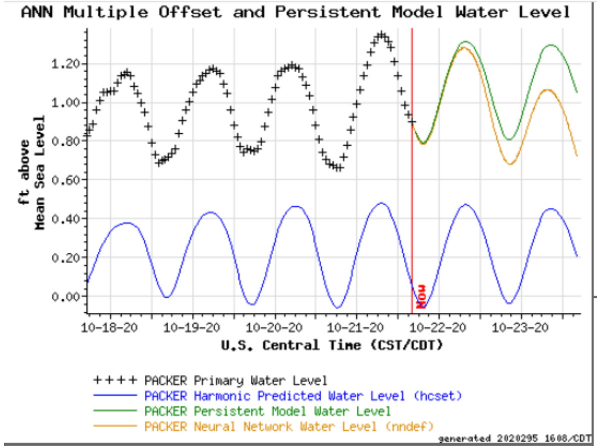
Kamangir, H., Collins, W., Tissot, P. & King, S. (2019). A Deep Learning Model to Predict Thunderstorms within 400 km2 South Texas Domains" . Meteorological Applications, in review.

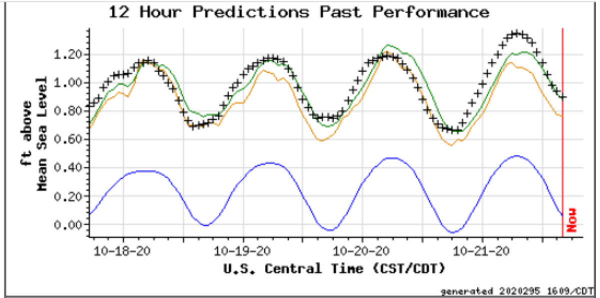
Operational Neural Network Predictions Combining Gridded Model Predictions & Real Time Measurements

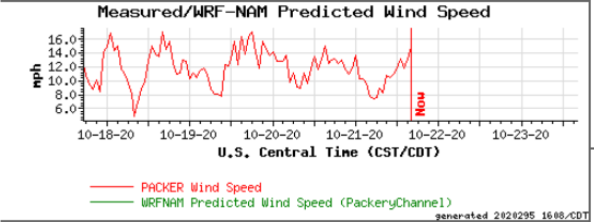


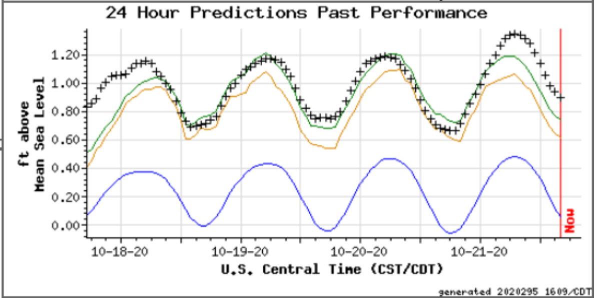
Opportunities: Ensemble Models – Uncertainty Quantification

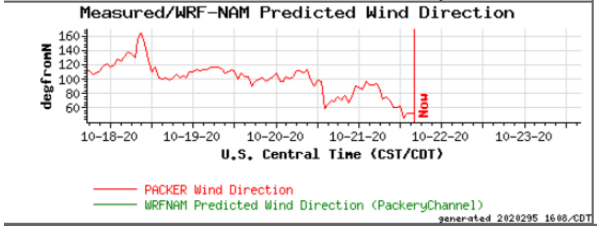
Shallow Neural Networks Operational Predictions

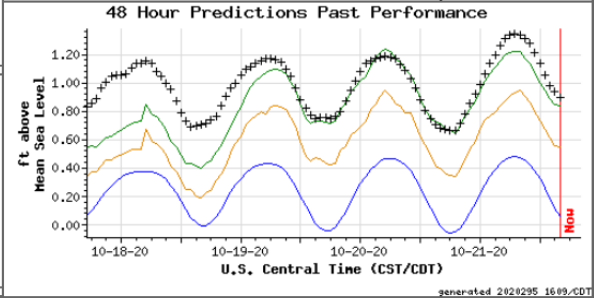












Water level predictions for Corpus Christi Bay (10/21/2020)

Trustworthiness through Real-Time Performance

Coastal Fog Predictions for Airports and Ports: Multiscale 3D CNN & Transformer Versions (research) and VAE R2O Version

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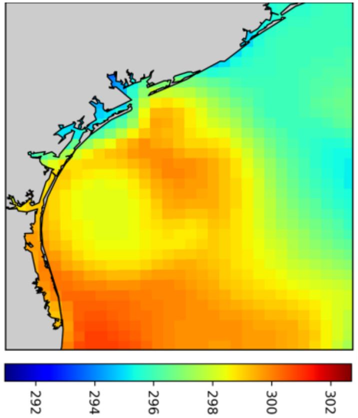
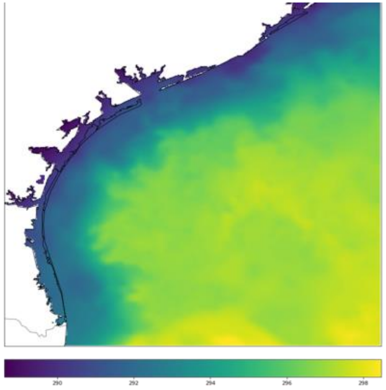
Coastal Fog Predictions: FogNet

Initial model combining numerical weather predictions and satellite imagery into 3D CNN model for binary predictions of fog visibilities below 1600, 3200, and 6400m and lead times up to 24hrs

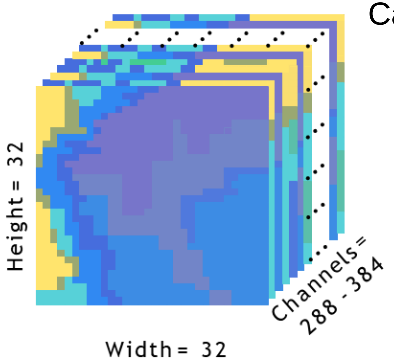
Traffic in ports and airports is temporarily interrupted due to fog. Can AI predict the timing?



- **NAM:** North American Mesoscale Surface Temperature
- Hourly Prediction Product
- 12 km Spatial Resolution



- **MUR:** Multi-Scale Ultra-High Resolution Sea Surface Temperature
- Daily Product
- 1 km Spatial Resolution



Cubes of 288-385 feature maps, depending on lead time

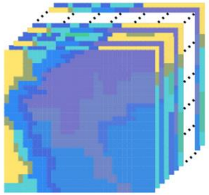
ai2es.org

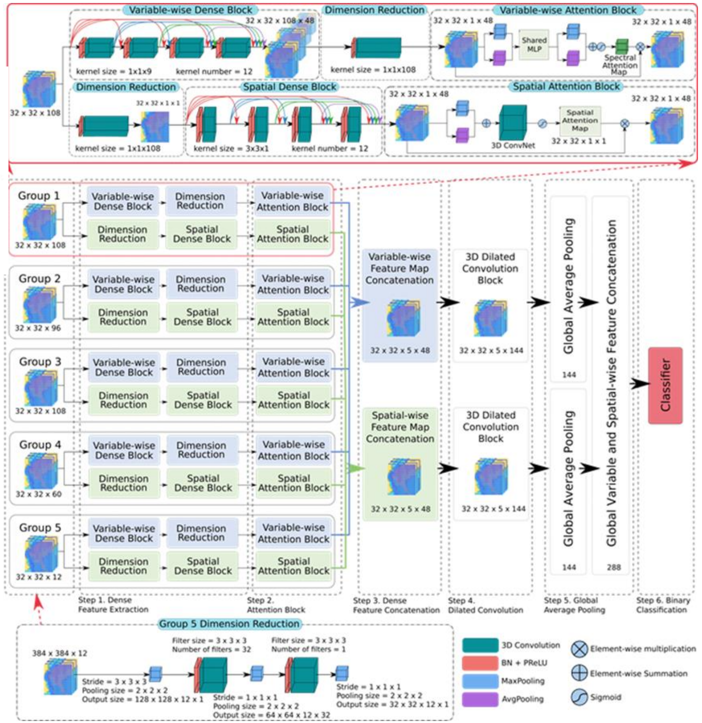
FogNet Architecture & Performance

FogNet input maps are divided into 5 groups based on physics

Groups

1. Vertical wind profile
2. Turbulence kinetic energy & humidity
3. Lower atmospheric thermodynamic profile
4. Surface atmospheric moisture & microphysics
5. Sea surface temperature





Guidance Comparisons - *24-hr lead time*						
	≤1600 m		≤3200 m		≤6400 m	
Metrics	*FogNet*	*HREF*	*FogNet*	*HREF*	*FogNet*	*HREF*
HSS	0.59	0.23	0.46	0.27	0.59	0.40
PSS	0.52	0.30	0.54	0.37	0.63	0.45
CSI	0.35	0.15	0.32	0.18	0.45	0.28

Kamangir, H., Collins, W., Tissot, P., King, S. A., Dinh, H. T. 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.

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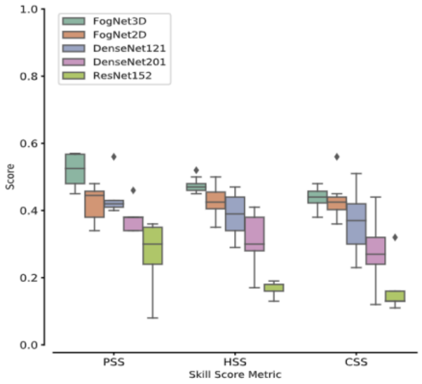
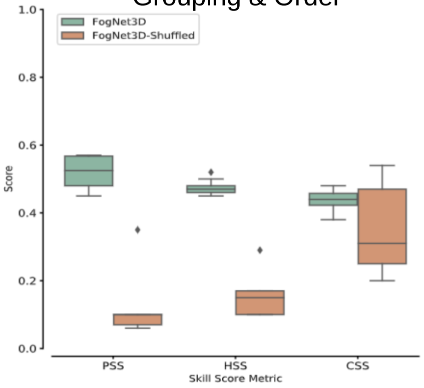
FogNet: Architecture & Variable Importance (XAI)

- 3D CNN, grouping & ordering of feature maps all lead to performance improvements
- XAI provides guidance for future model development
- Helpful to explain/establish trust with stakeholders?

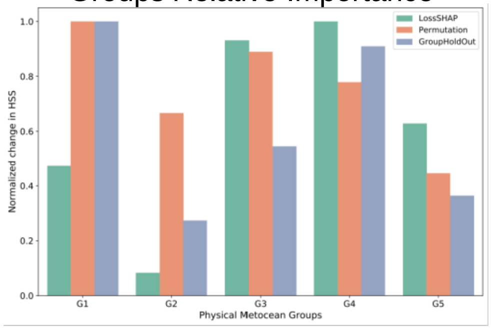
3D-CNN vs 2D Alternatives



Importance of Physics-based Grouping & Order



Groups Relative Importance



Location Importance

G5: TMP - SST, t1

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 Modeling & Software*, **154**, 105424. https://doi.org/10.1016/j.envsoft.2022.105424.

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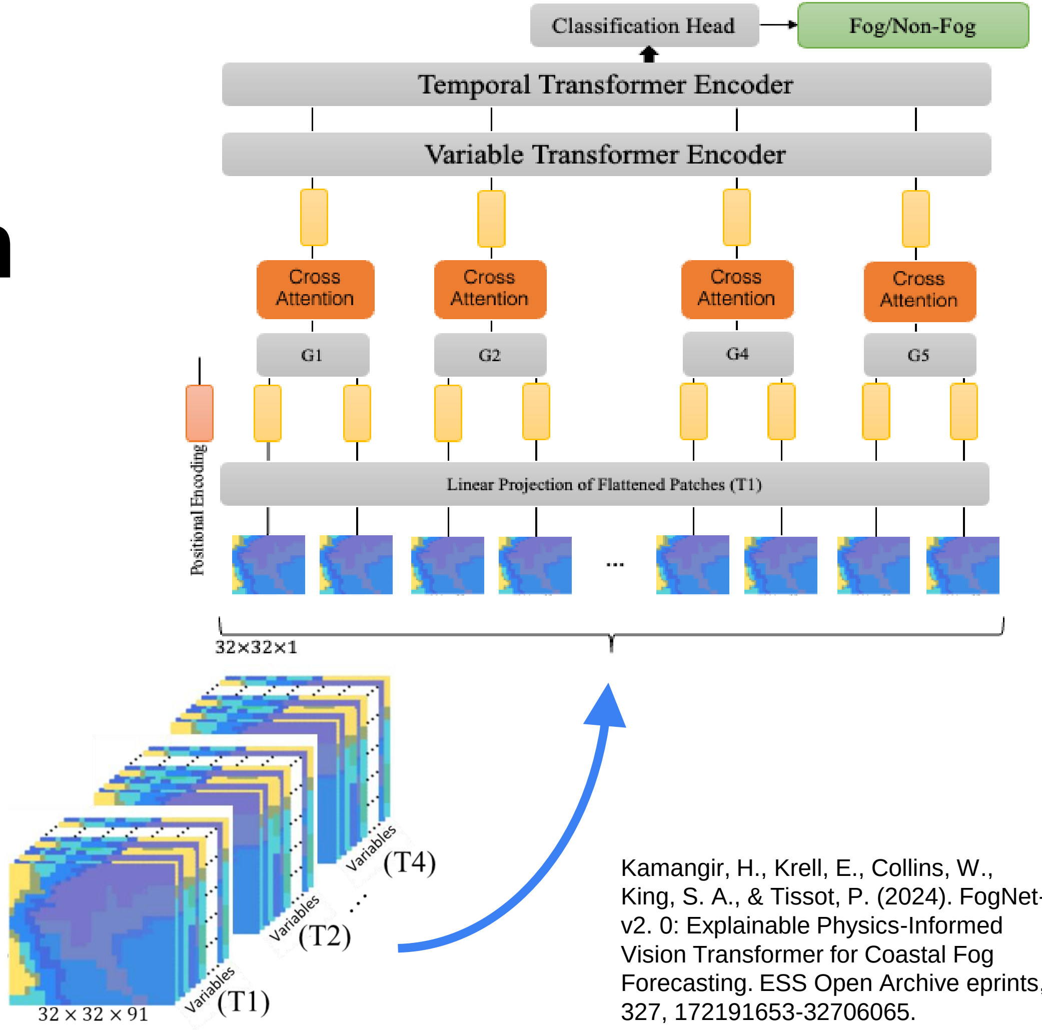
Multi-view self-attention Version

Physical-grouped Spatio-temporal Factorized Self-Attention (STFSA) Version

- 384 tokens
- Using cross-attention and variable aggregation within each group to accelerate training time
- This model will first learn the spatial inter-correlation within each variable, then by cross attention and aggregation on variable-wise basis within each group. It will then discern the temporal correlation within time-spets.



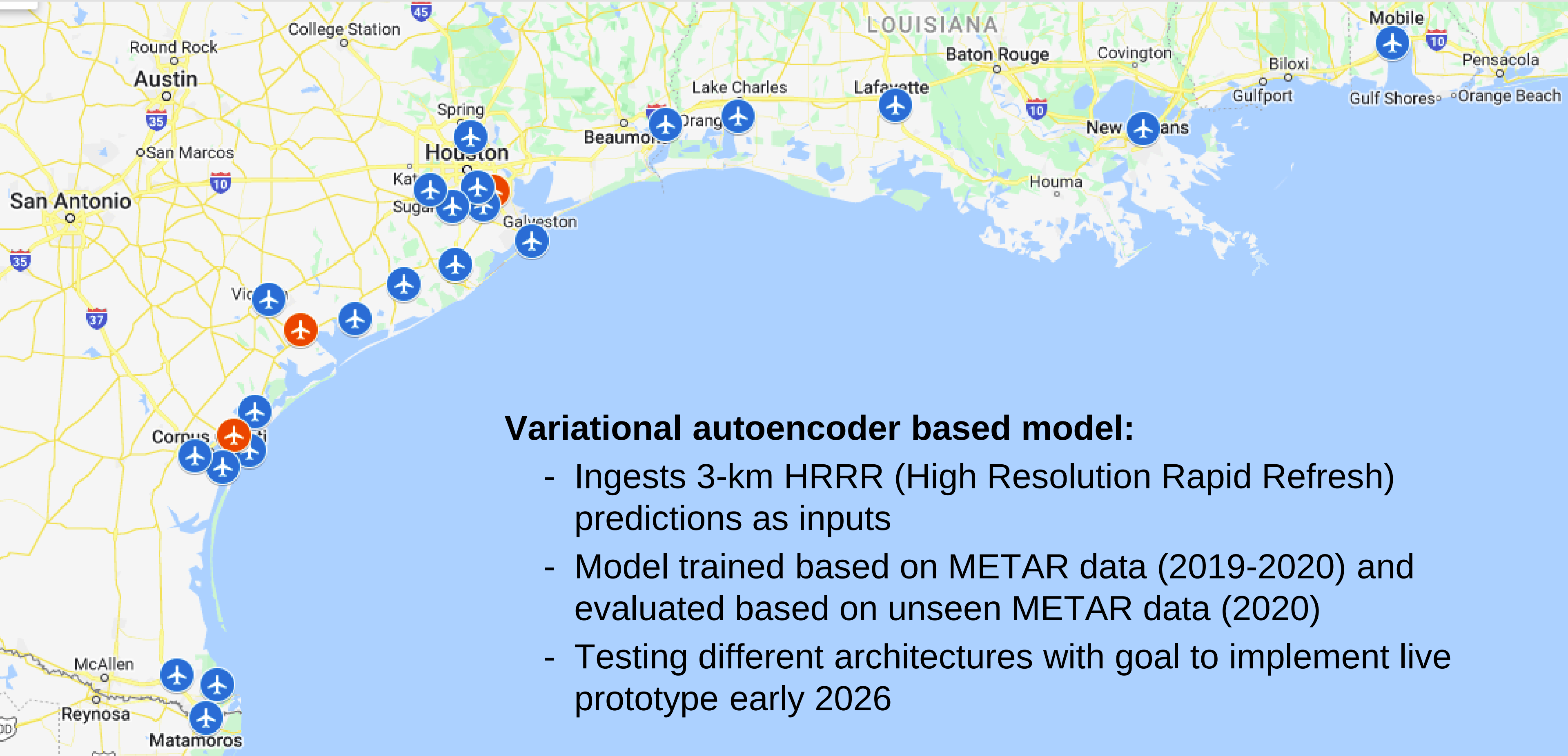
Kamangir, H., Krell, E., Collins, W., King, S. A., & Tissot, P. (2024). FogNet-v2. 0: Explainable Physics-Informed Vision Transformer for Coastal Fog Forecasting. ESS Open Archive eprints, 327, 172191653-32706065.

Performance Comparison

- Evaluation models for years 2018-2020 as unseen test dataset
- Evaluate 3 different self-attention models and compare with FogNet benchmark based on 8 metrics including 4 skill metrics such as CSI, PSS, HSS and CSS

Model	POD	F	FAR	CSI	PSS	HSS	ORSS	CSS
FogNet	0.54	0.02	0.50	**0.35**	0.52	0.50	0.97	0.48
VVT	**0.65**	0.03	0.62	0.31	0.62	0.46	0.96	0.36
UVT	0.60	0.02	0.65	0.29	**0.55**	0.44	0.96	0.28
STFSA	0.50	**0.01**	0.47	0.34	0.48	0.50	0.97	0.51
PGSTFSA	0.50	**0.01**	**0.45**	**0.35**	0.48	**0.51**	0.97	**0.53**

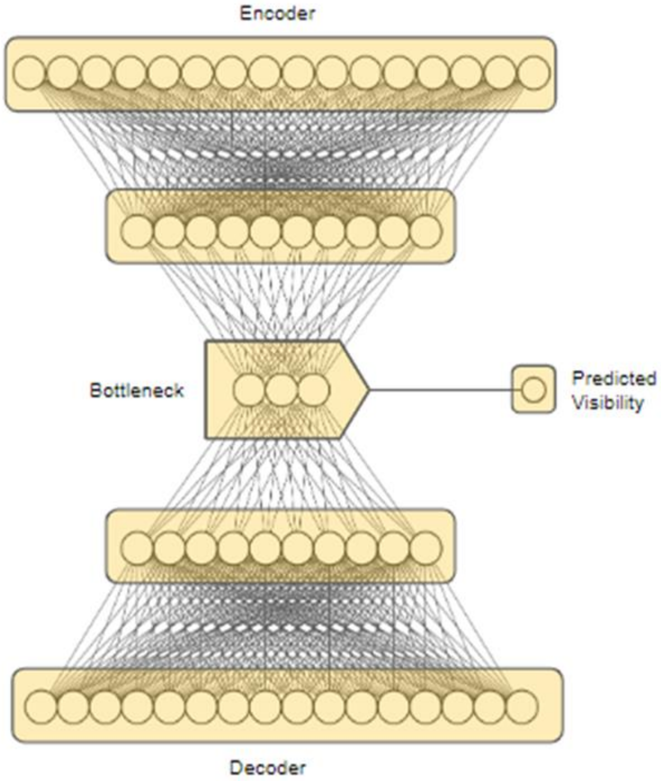
Operational VAE Version for Gulf of Mexico Coastal Airports



Variational autoencoder based model:

- Ingests 3-km HRRR (High Resolution Rapid Refresh) predictions as inputs
- Model trained based on METAR data (2019-2020) and evaluated based on unseen METAR data (2020)
- Testing different architectures with goal to implement live prototype early 2026

Operational VAE Version for Gulf of Mexico Coastal Airports



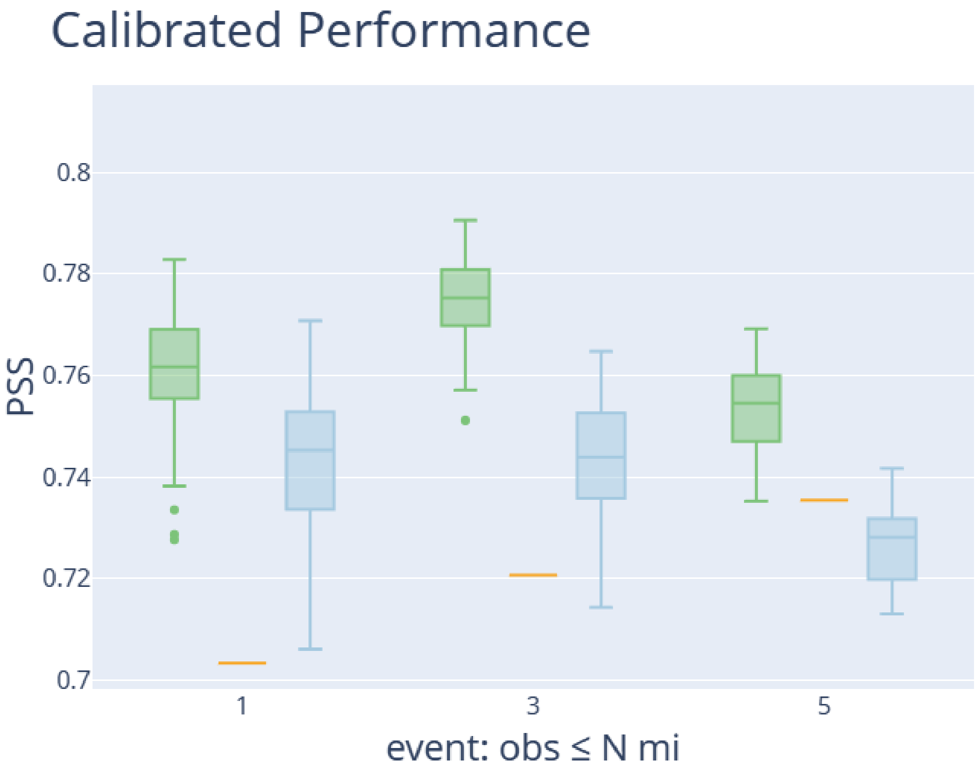
Model trained with AdamW algorithm (faster than SGD)

- RMSE decoder loss
- Cross entropy classifier loss
  - Weight of low visibility cases varied from 1 to 80

Hyperparameters tuned with Tree-structured Parzen Estimator (default sampler from Optuna library) to maximize POD and minimize FAR .

- Example architecture:
  - Learning rate 8.62e-5, L2 regularization 5.27e-5
  - Fog weighted by multiple of 26
  - 4388 with 45% dropout
  - 1097 ELU
  - 713 ELU
  - 381 ELU
  - 149 ELU
  - 3 ELU
  - 2 Sigmoid classifiers

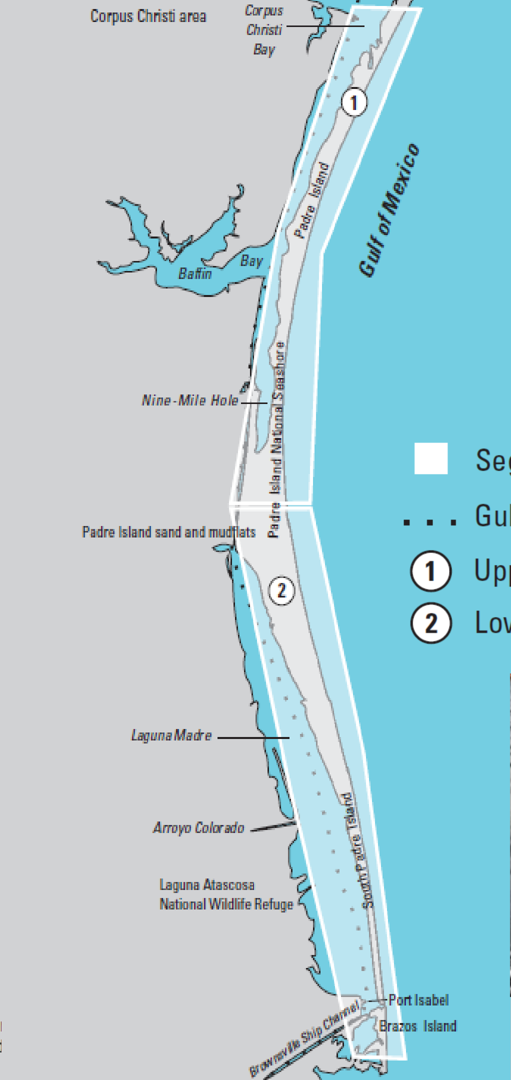
Results: Comparison with HRRR at 1, 3, 5 miles using unseen testing data from 2020 for 24 hour predictions



- Domain expert selected model features model

- Model based on all HRRR features available

- HRRR model with threshold established on same data



Cold-Stunned Sea Turtles (NPS, 2018)

Dead fish found along shores of Port Aransas (Neesy Tompkin, 2018)

Cold-Stunning Events in Laguna Madre, TX

Laguna Madre

Cools rapidly during strong cold fronts

Causes hypothermic stunning to marine life

✓ ***≈ 8°C (46.6 °F) = Sea Turtle Cold-Stunning Threshold***
(Shaver et al., 2017)

From 1980 – 2015:

- ≈ 8100 stranded sea turtles recorded
  - ≈ 55% due to hypothermic stunning (Shaver et al., 2017)

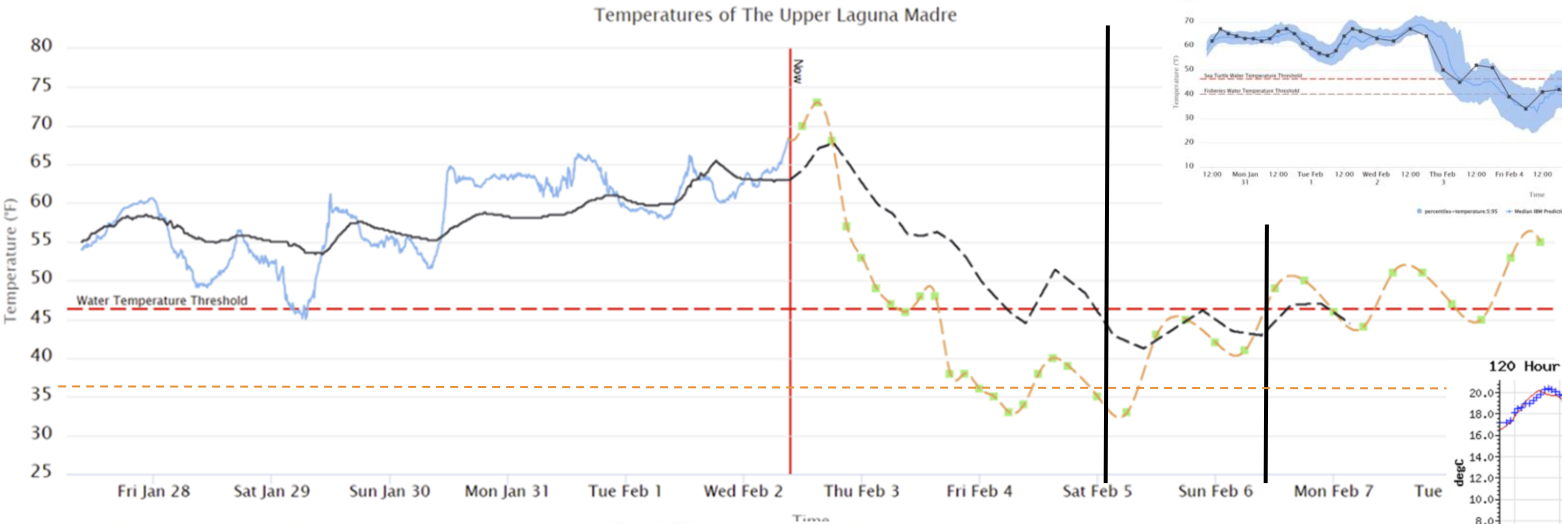
2021 winter:

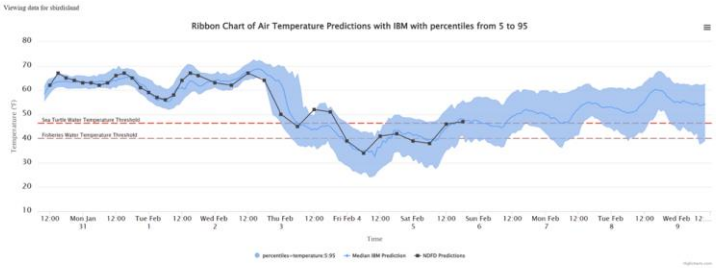
- 13,418 cold-stunned turtles reported

142,000 fish mortalities in 1997 (Shaver et al., 2017)

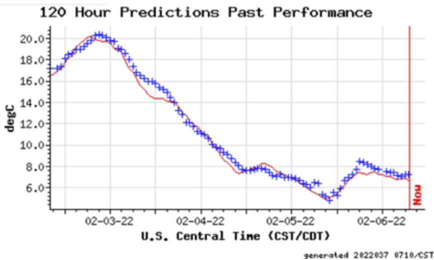
Sea Turtle and Fisheries Cold Stunning Predictions

.. request for a voluntary interruption of navigation and all coastal engineering type activities in the Laguna Madre will start 00:01AM Saturday morning (Feb. 5th) and end Sunday 12 PM (Feb. 6th) local time. This will affect traffic and coastal works through the Laguna Madre from south of the JFK Bridge in Corpus Christi (MM 551 WHL) to Port Isabel, TX (MM 661 WHL).”

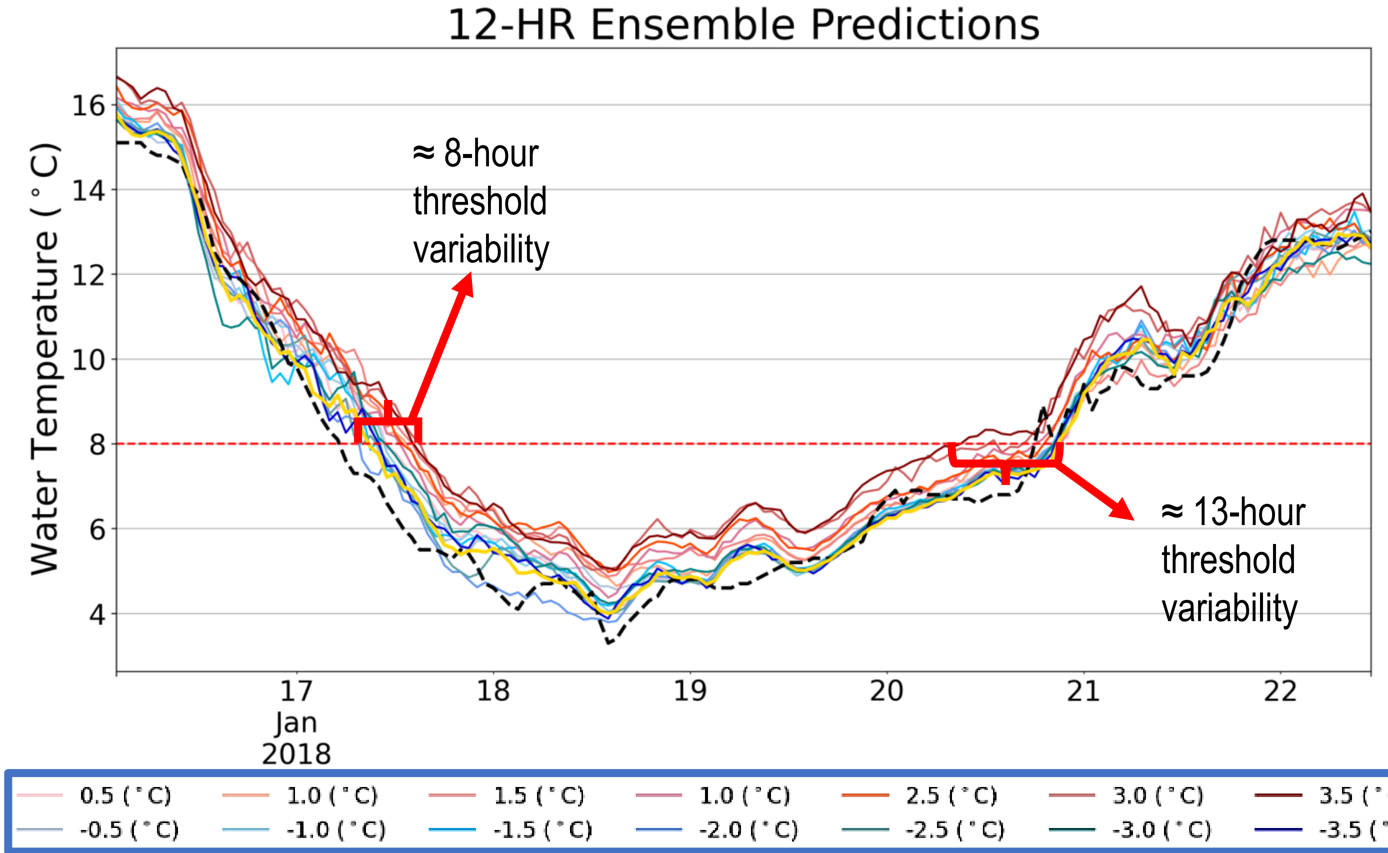




Start and stop of navigation interruption



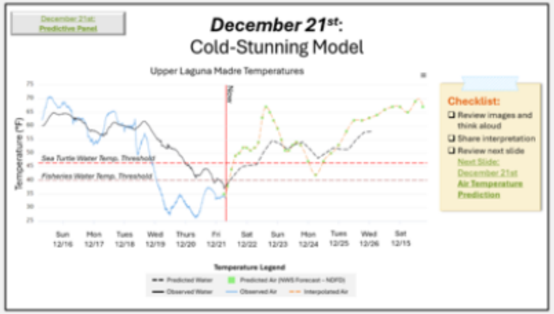
Next Step: Ensemble Model Predictions

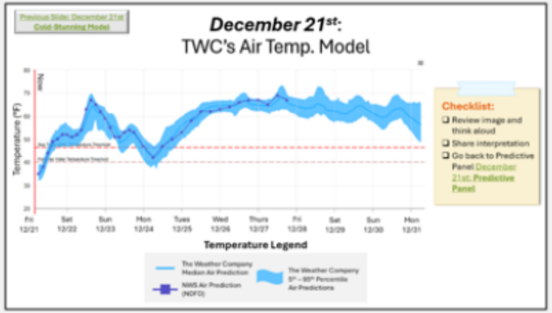


White, M., et al. (2023, January 8-12). *AI Ensemble Predictions for Cold Stunning Events in the Shallow Laguna Madre* [Conference presentation]. The 22nd Conference on Artificial Intelligence for Environmental Science, 103nd Annual Meeting of the American Meteorological Society Annual Meeting, Denver, CO, United States. https://ams.confex.com/ams/103ANNUAL/meetingapp.cgi/Paper/418860

Test of Models with Stakeholders: Think Aloud Exercises

December 21st: Cold-Stunning Predictive Panel





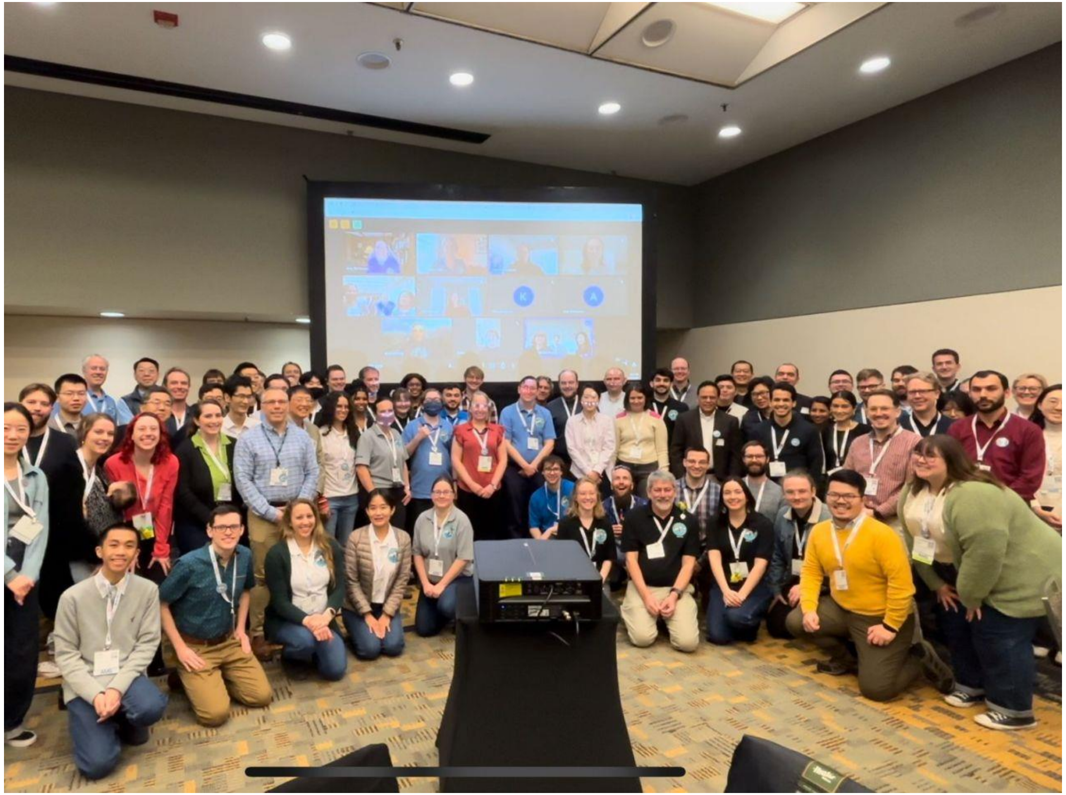
HELP Button: Previous Predictive Panel ←

Checklist:

- ❑ **Review Images:**
  - ❑ Cold-Stunning Model
  - ❑ TWC Air Temp. Model
- ❑ **Answer Questions:**
  - ❑ What is your **interpretation** of the **model outputs**?
  - ❑ What do you think is the **likelihood** of the cold-stunning threshold being crossed? ***On a scale from 0 – 10***
- ❑ **PAUSE**

Move on to Additional Water Temperature Information →

Questions/Discussion?



Philippe.tissot@tamucc.edu

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Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

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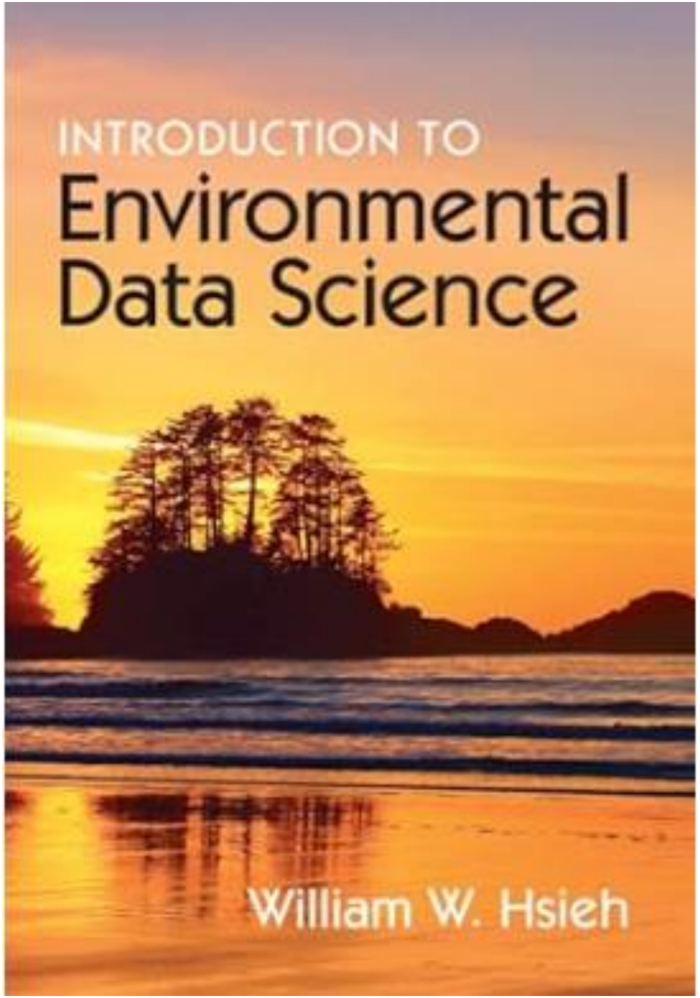

AI/ML References

[Cooperative Institute for Research in the Atmosphere (CIRA)](#)

CIRA Short Course
on
Machine Learning for Weather and Climate

Instructors:

- **Ryan Lagerquist** (CIRA Boulder *and* NOAA GSL)
  ryan.lagerquist@noaa.gov, @ralager_Wx
- **Imme Ebert-Uphoff** (CIRA Fort Collins *and* Dept. of Electrical and Comp. Eng., CSU)
  iebert@colostate.edu

FPAW FALL 2024 MEETING

Tuesday, October 29, 2024 - Thursday, October 31, 2024

FAA William J. Hughes Technical Center (WJHTC)

Atlantic City, NJ

9:55 AM – 12:05 PM	**Session 5a – AI and Aviation Weather Predictions**
9:55 AM – 10:00 AM	**Introduction:** Matt Wandishin (NOAA GSL) and John Williams (The Weather Company)
10:00 AM – 10:25 AM	**A Primer on AI Weather Models:** Randy Chase (CIRA/CSU) (r)
10:25 AM – 10:50 AM	**Kilometer-Scale Convection Allowing Model Emulation using Generative Diffusion Modeling:** Jaideep Pathak (NVIDIA)
10:50 AM – 11:15 AM	**Environmental Science Applications of AI -** Philippe Tissot, Texas A&M University - Corpus Christi and AI2ES
11:15 AM – 11:40 AM	**A New Era in Turbulence Prediction – Rapid Machine Learning Iterations and Data Validations:** Guy Zunder (Skypath) (r)
11:40 AM – 12:05 PM	**Using Machine Learning to Predict Aircraft Braking Performance in Inclement Weather:** Somil Shah (FAA)
12:05 PM – 1:00 PM	**LUNCH**
1:00 PM – 3:00 PM	**Session 5b – AI and Decision Support**
1:00 PM – 1:25 PM	**AI/ML in Aviation Weather Decision Support Systems:** Mark Veillette (MIT LL)
1:25 PM – 1:50 PM	**Establishing, Growing Use of, Trusting, and Increasing Value from AI/ML-based Weather Decision Support Services and Solutions:** John Celenza (Zipline) (remote)
1:50 PM – 2:15 PM	**An AI-Enabled TFM Prototype:** Patty McDermott and Christine Taylor (MITRE)
2:15 PM – 3:00 PM	**Panel Discussion – TBD:** All Session 3 Presenters