Machine Learning for Coastal Fog Predictions and the AI2ES National AI Institute

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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.

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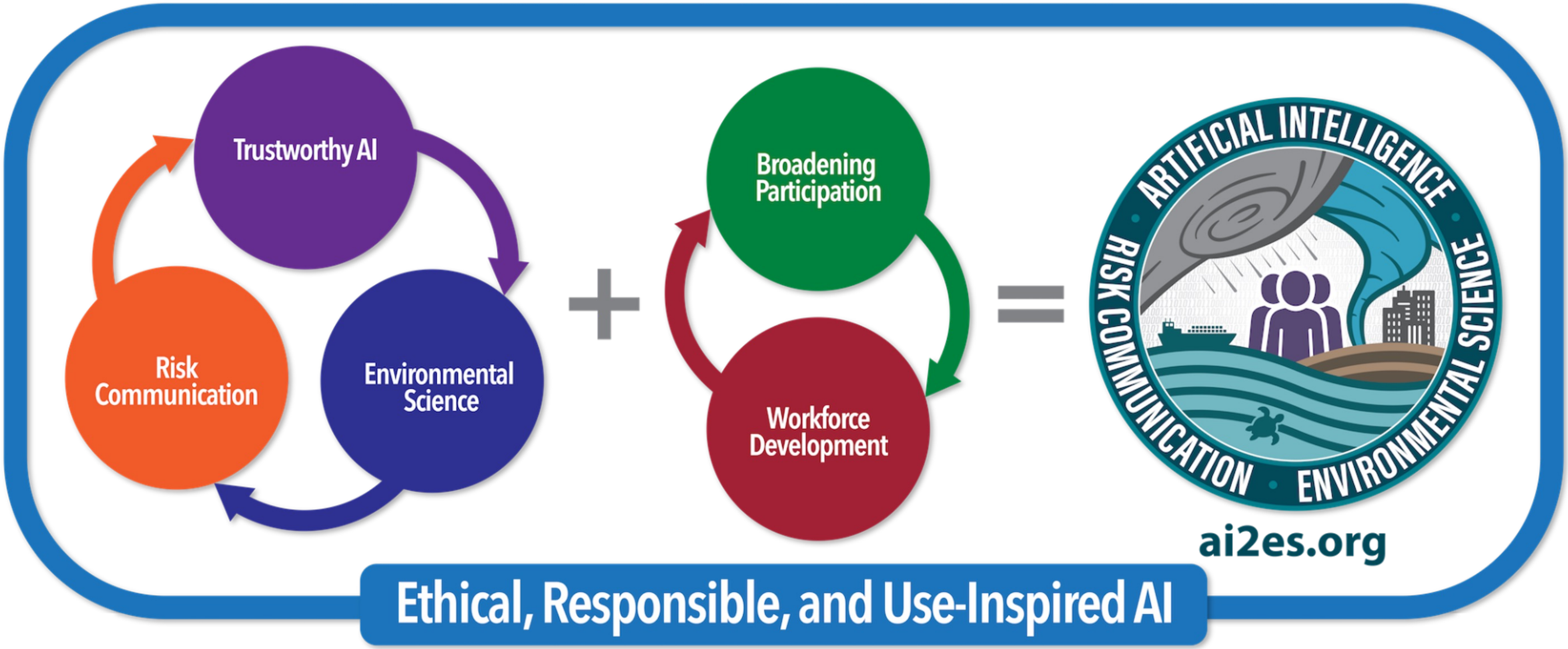
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Risk Communication
Environmental Science
Broadening Participation
Workforce Development
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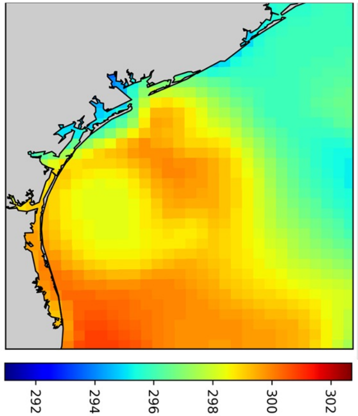
Coastal AI: Predictions, Stakeholders and Trust
The power of Artificial Intelligence (AI) to predict and better understand events at the intersection of Atmosphere-Ocean-Land
Atmosphere
Ocean
Land
Photo: Jon Brandt©
HIGH WATER
Inundations
Coastal Fog
Sea Turtle Conservation

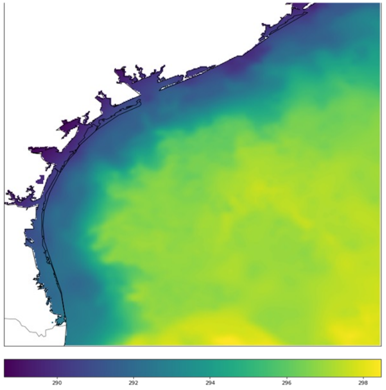
Coastal Fog Predictions: FogNet

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

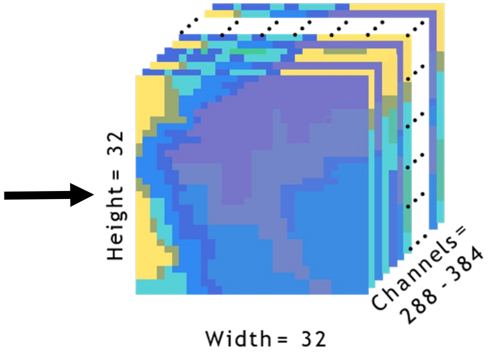
Corpus Christi is the 3rd largest port in the nation (tonnage) and like many other ports incurs significant fog delays - better predictions would lead to more efficient operations.



- **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

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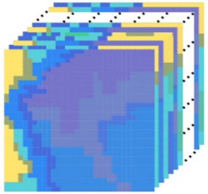
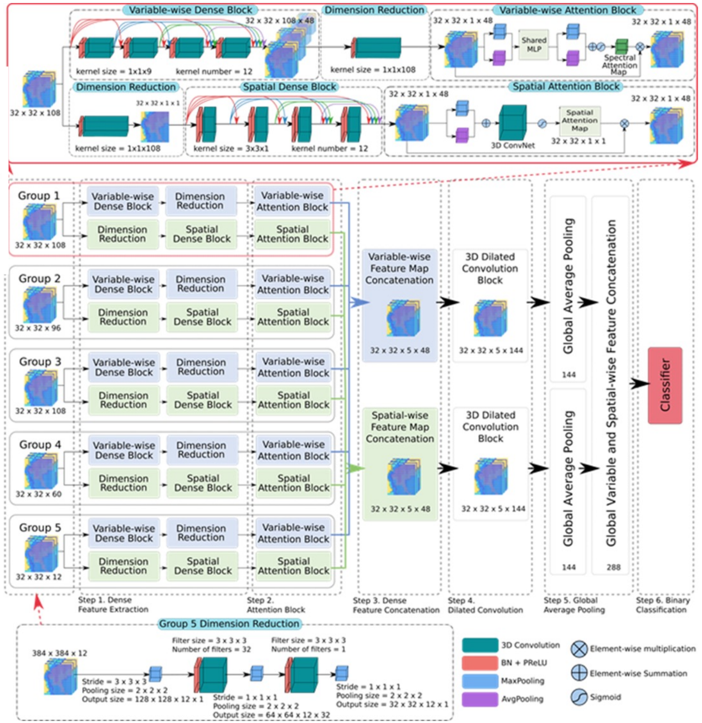
FogNet Architecture & Performance

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

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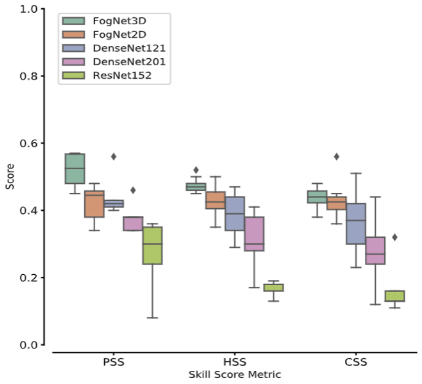
Kamangir, H., Collins, W., Tissot, P., King, S. A., Dinh, H. T. H., Durham, N., & Rizzo, J. (2021). FogNet: A multiscale 3D CNN with double-branch dense block and attention mechanism for fog prediction. *Machine Learning with Applications*, **5**, 100038.

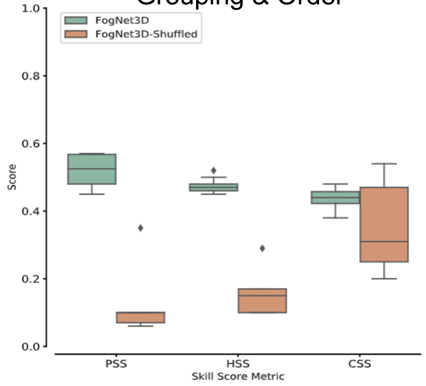
FogNet: Architecture - Variable Importance - XAI

- 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?

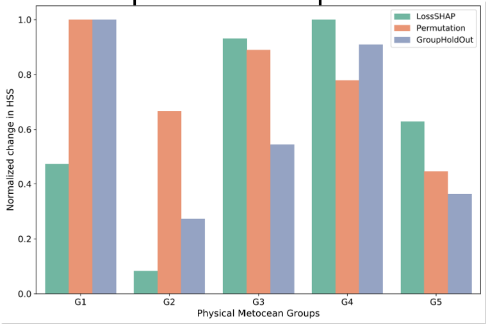
3D-CNN vs 2D Alternatives



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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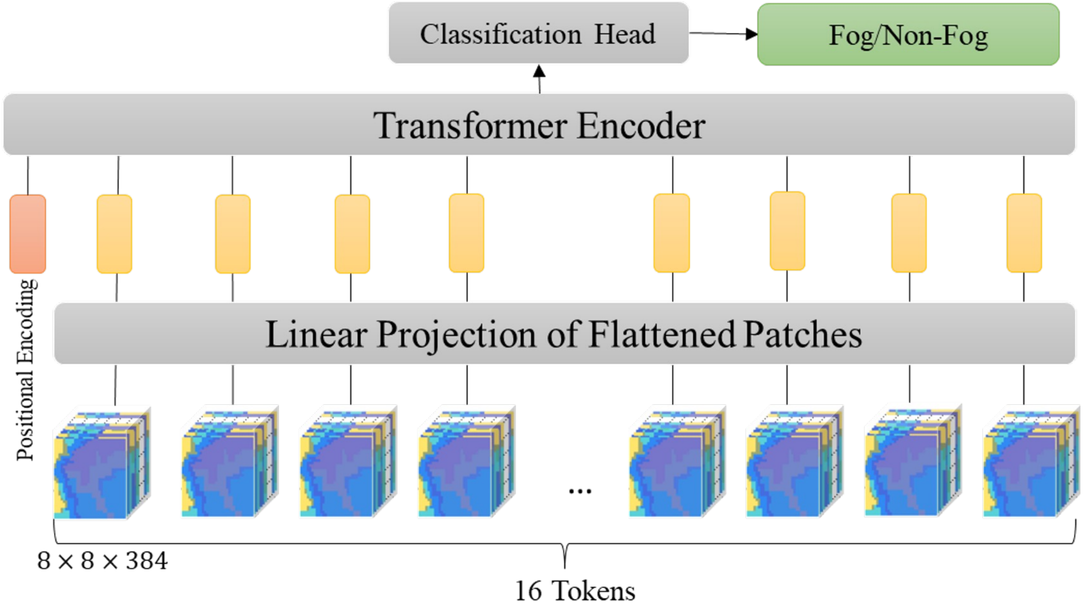
Self-Attention vs CNNs for FogNet V2 Architecture

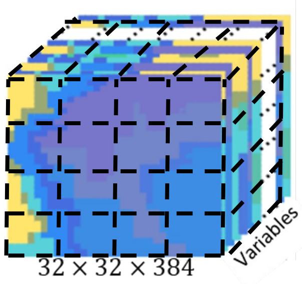
- Self-attention's receptive field is always full image vs fixed size neighborhood grid for CNNs
- Self-attention is a sample-specific feature learning using dynamic filters vs fixed filters used by CNNs
- There is no limitation in terms of input data structure for self-attention models to learn the inter-correlation between inputs and targets
- Self-attention models provide intrinsic global and local explainability by returning the attention scores

Multi-view self-attention

A) Vanilla Vision Tokenizing

- Vision Transformer based Tokenizing: tokenizing each cube $[X \in R]^{(H\times W\times C)}$ which H and W are 32 and C is 384 variables into 16 non-overlapping patches with size of $P^{(8\times 8\times 384)}$
- In overall, there are 17 tokens
- This model will learn the inter-correlation between patches with all variables in depth.





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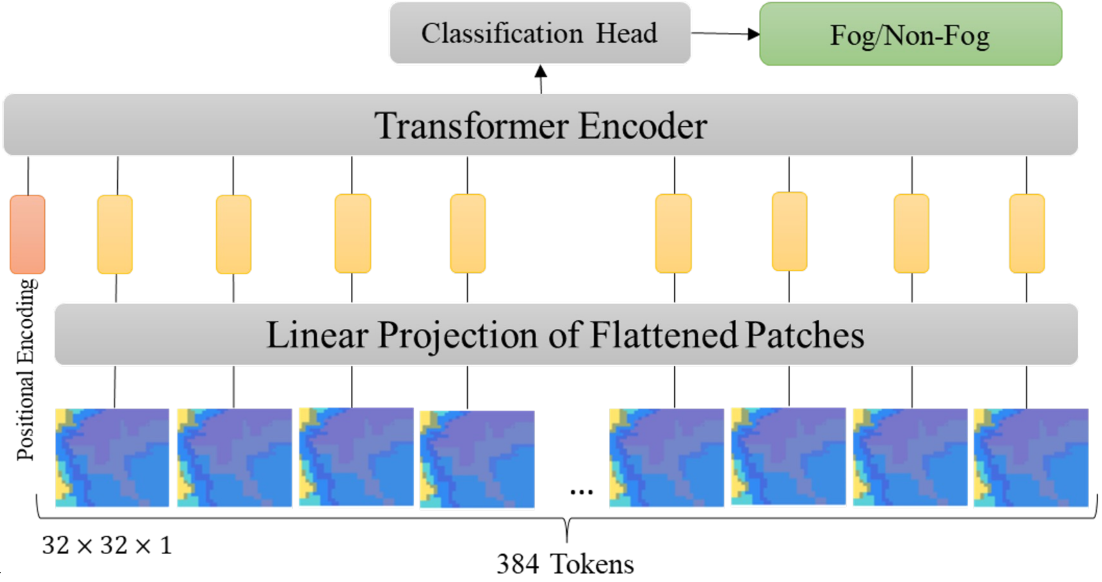
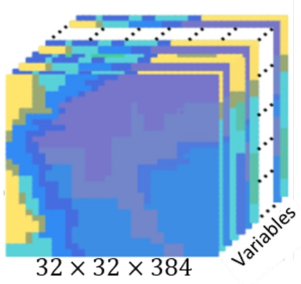
Multi-view self-attention

B) Uniform Variable Tokenization (UVT)

- Tokenizing each variable as a token with size of 32 by 32
- In overall, there are 384 tokens of 32 x 32 + 1 positional token
- This model will learn the inter-correlation with and within each variable





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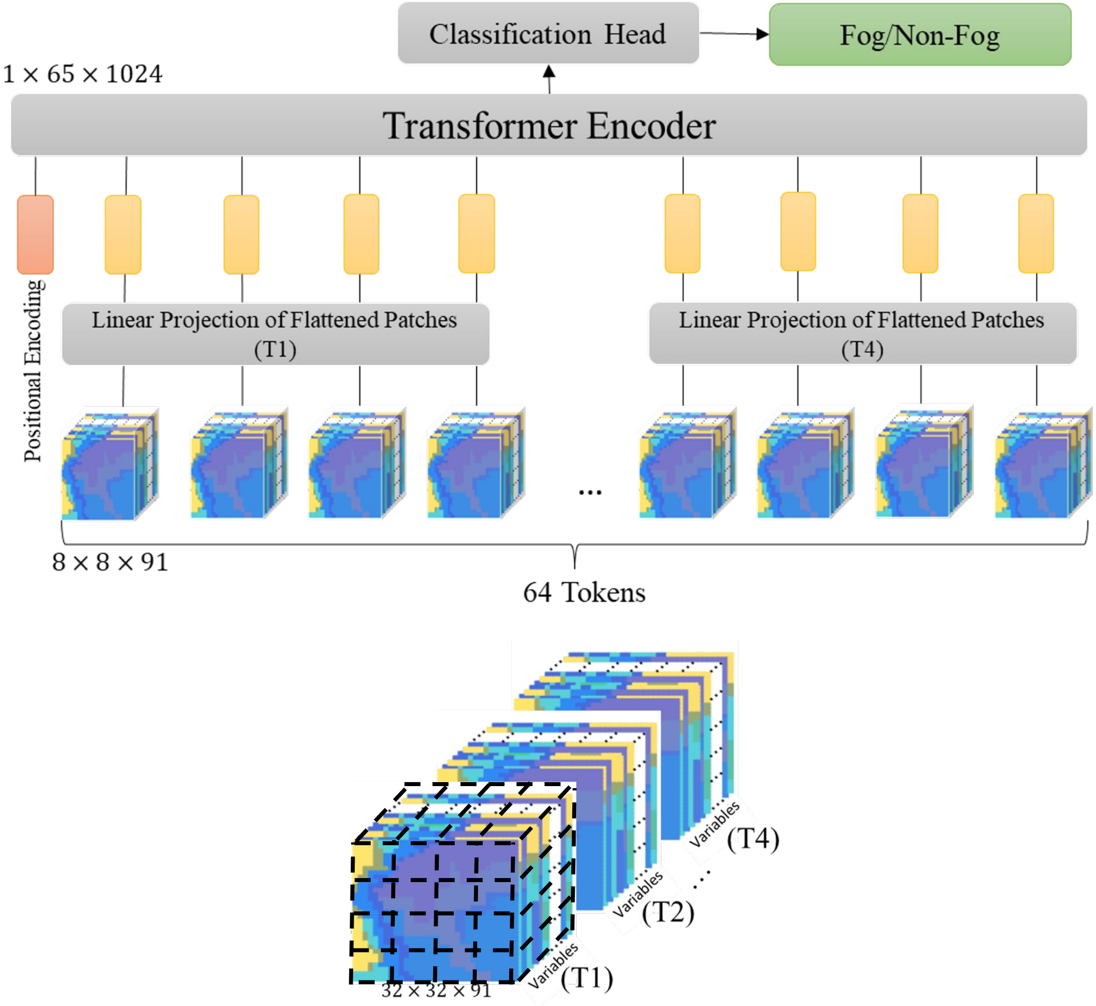
Multi-view self-attention

C) Spatio-temporal Factorized Self-Attention (STFSA)

- Tokenizing each image with 91 for each time with size of 8 by 8, then concatenate the temporal tokens for encoder.
- In overall, there are 65 tokens
- This model will first learn the inter-correlation within and among each patch for every time-step, followed by the temporal correlation.



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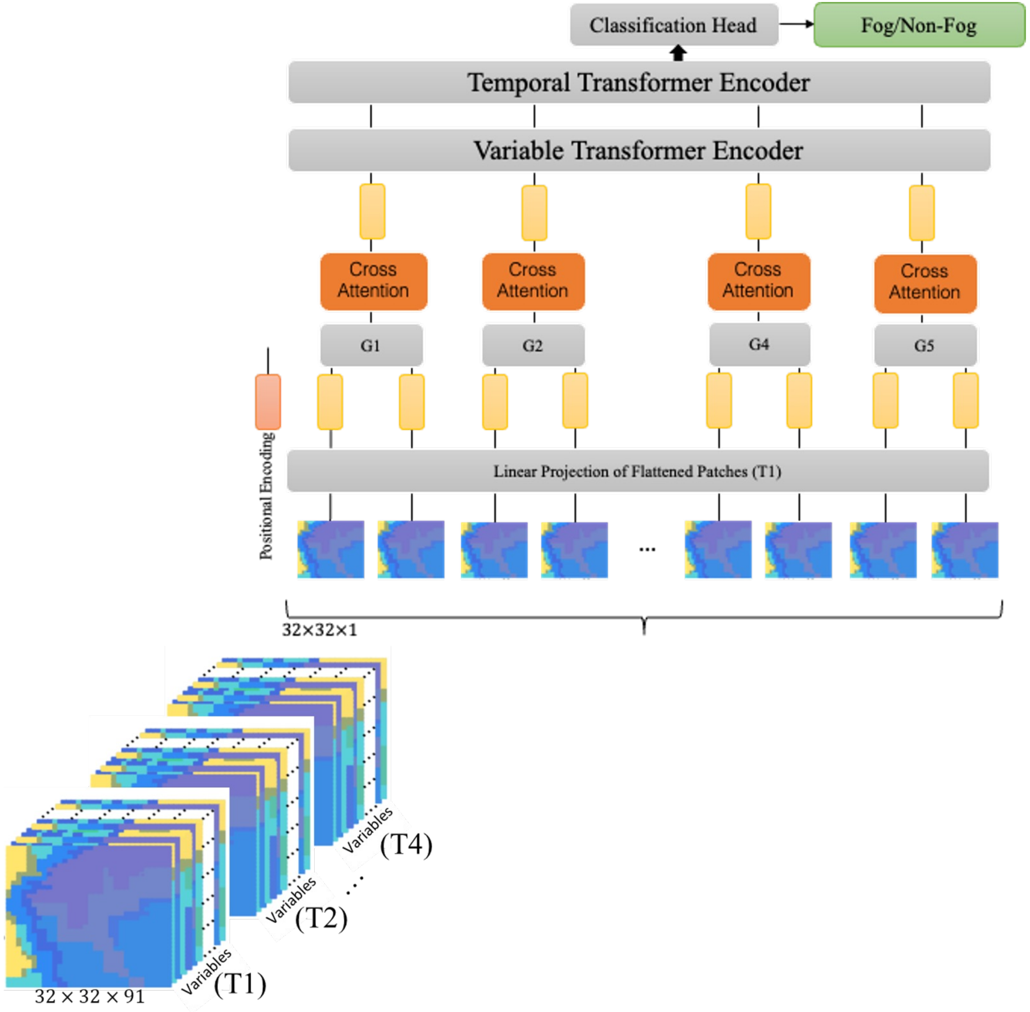
Multi-view self-attention

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

- 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.



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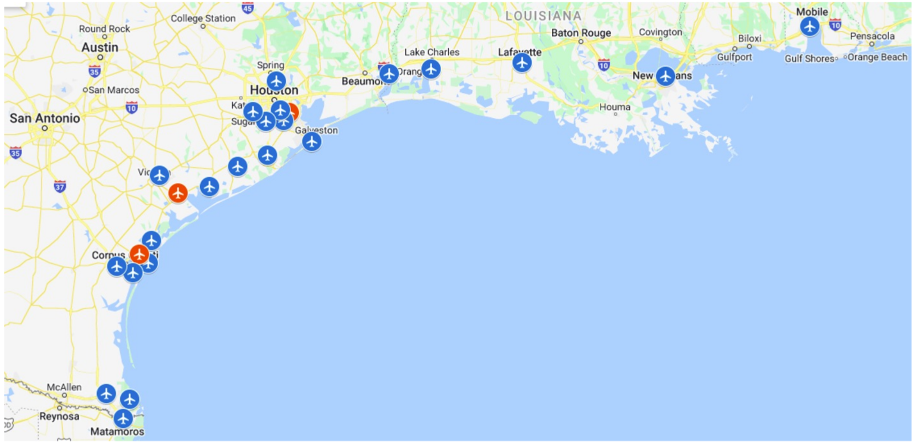
Performance Comparison

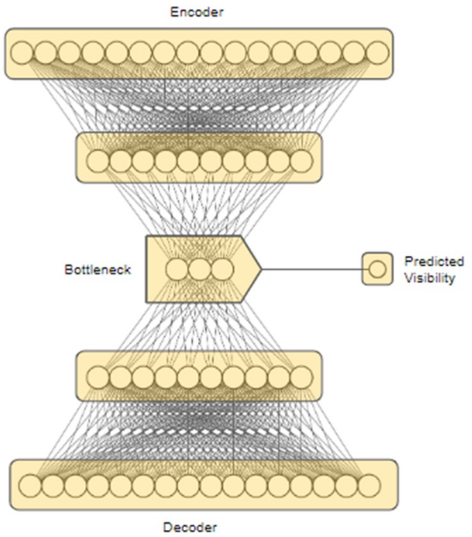
- Evaluation models for years 2018-2020 as unseen test dataset
- Evaluate 3 different self-attention models and compare with FogNet benchmark based on 8 metrics including 4 skill metrics such as CSI, PSS, HSS and CSS

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**

Additional R2O VAE Model Development



- FogNet has complex architecture and inputs
- XAI pointed to importance of local inputs
- Design and test VAE for visibility predictions
- Decisions based in part on R2O in collaboration with IBM & NWS



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

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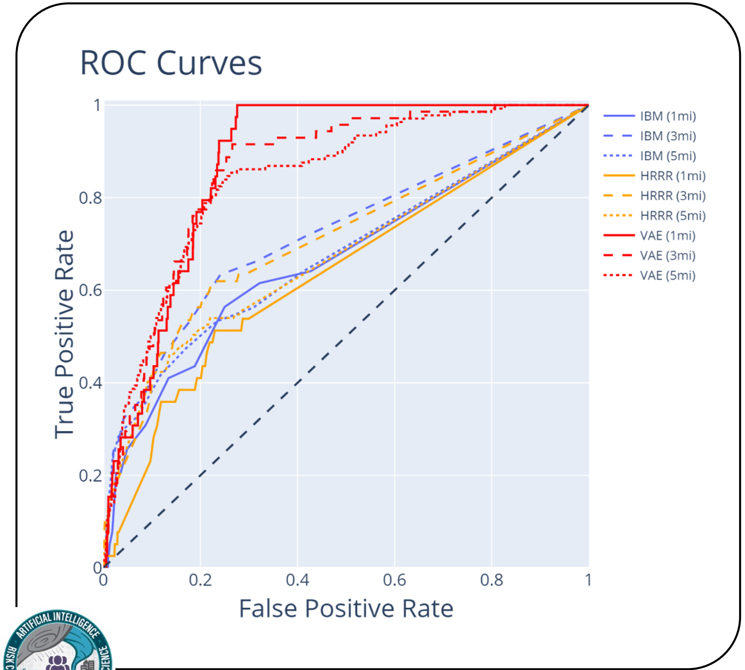
Results: Comparison with IBM and HRRR at 1, 3, 5 miles Using unseen testing data from 2020



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NWS Forecaster perceptions of new AI guidance for coastal fog prediction

Research questions

- How do forecasters **perceive AI/ML and its use in forecasting**, in general?
- How important, and in what ways, are **explanations about how the AI/ML guidance works based on XAI techniques** and **verifies** for forecasters' assessments of the new guidance trustworthiness?
- How do forecasters rate **the importance of background and the XAI/verification** information for their **trust and use of new guidance**?

Methods

- Leveraged the **interview protocol developed for the severe interviews** and the **interview guide that was co-developed among the RC-Coastal teams during Y2** to conduct structured interviews
- **Completed 13 structured interviews** with National Weather Service Forecasters from the Eastern, Southern, Western, and Alaskan Regions

Spin-up information for AI/ML fog guidance

- AI/ML guidance, called FogNet, is being developed using a 3D convolutional neural net (3D-CNN) to predict coastal fog and mist. It does not predict rain or smog.
- The fog guidance is generated using the North American Mesoscale (NAM) and sea surface temperatures (SST) measured by the NASA Multiscale Ultra-high Resolution (MUR) dataset.
- The fog guidance predicts the probability of fog/mist at visibilities ≤ 1600 meters (1 mile) and converts these to categorical fog/no fog predictions. Predictions are made at lead-times of 6, 12, and 24 hours.
- Below is a real-world example of the fog guidance for 2 different cases (Jan 15, 2020 and Mar 11, 2020) for the Mustang Beach Airport in Port Aransas, TX. Imagine you were forecasting for fog on this day in the area and you had this guidance available to you.

FogNet: Fog prediction (Jan. 15, 2020)		
Mustang Beach Airport	**Initialized:** 6z Jan 15 **Valid:** 6z Jan 15 - 6z Jan 16	
	≤1600 m (1 mile)	
Valid time (lead time)	Prediction	Probability
12z Jan 15 (6h)	Fog	0.92
18z Jan 15 (12h)	Fog	0.64
6z Jan 16 (24h)	Fog	0.77

FogNet: Fog prediction (Mar. 11, 2020)		
Mustang Beach Airport	**Initialized:** 12z Mar 11 **Valid:** 12z Mar 11 - 12z Mar 12	
	≤1600 m (1 mile)	
Valid time (lead time)	Prediction	Probability
18z Mar 11 (6h)	Fog	0.80
0z Mar 12 (12h)	No Fog	0.14
12z Mar 12 (24h)	No Fog	0.10

Note: All information on subsequent slides is for one case only.

Student Pipeline & Expansion

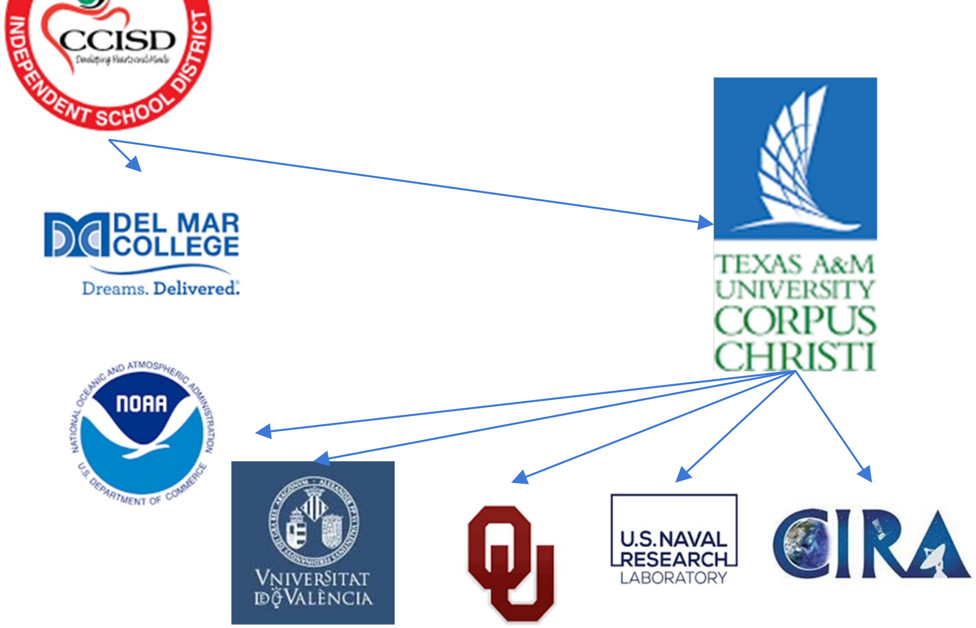
Model: Close collaboration between Community College, University, all AI2ES partners to broaden participation for big AI workforce need including:

- New GeoAI Community College academic program
- Involve many undergraduates from Community College (10 so far) and universities (19 so far) in AI research
- Also 9 graduate students funded to date
- Organize internship opportunities with AI2ES partners and others

Pipeline is working but need to export/scale up

Expand AI NSF Project FIU with AI2ES: FIU (56,000+ students) has similar demographics to TAMUCC and proposal includes a collaboration with Miami Dade Community College (55K students, 70% Hispanic/Latino)

Start with middle and high schools and broader outreach



Future AI Specialists and Leaders!

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2023 TAMUCC/DMC Student Interns (9)

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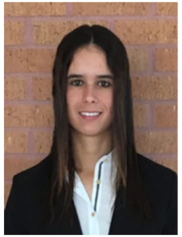
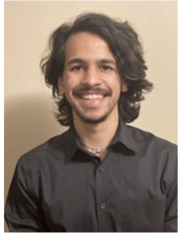


PhD (TAMUCC) Marina Vicens-Miquel: University of Valencia, Spain

PhD (TAMUCC) Evan Krell: CSU/CIRA, Fort Collins, CO

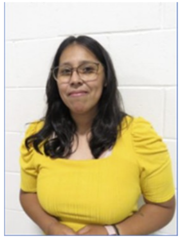


URA (DMC/TAMUCC) Hector Marrero: University of Oklahoma, Norman, OK

URA (DMC/TAMUCC) Beto Estrada: Naval Research Lab, Monterrey, CA

URA (TAMUCC) Christian Duff: NRL, Monterrey, CA

URA (TAMUCC) Savannah Stephenson: NOAA EPP/MSI Program, Washington, DC

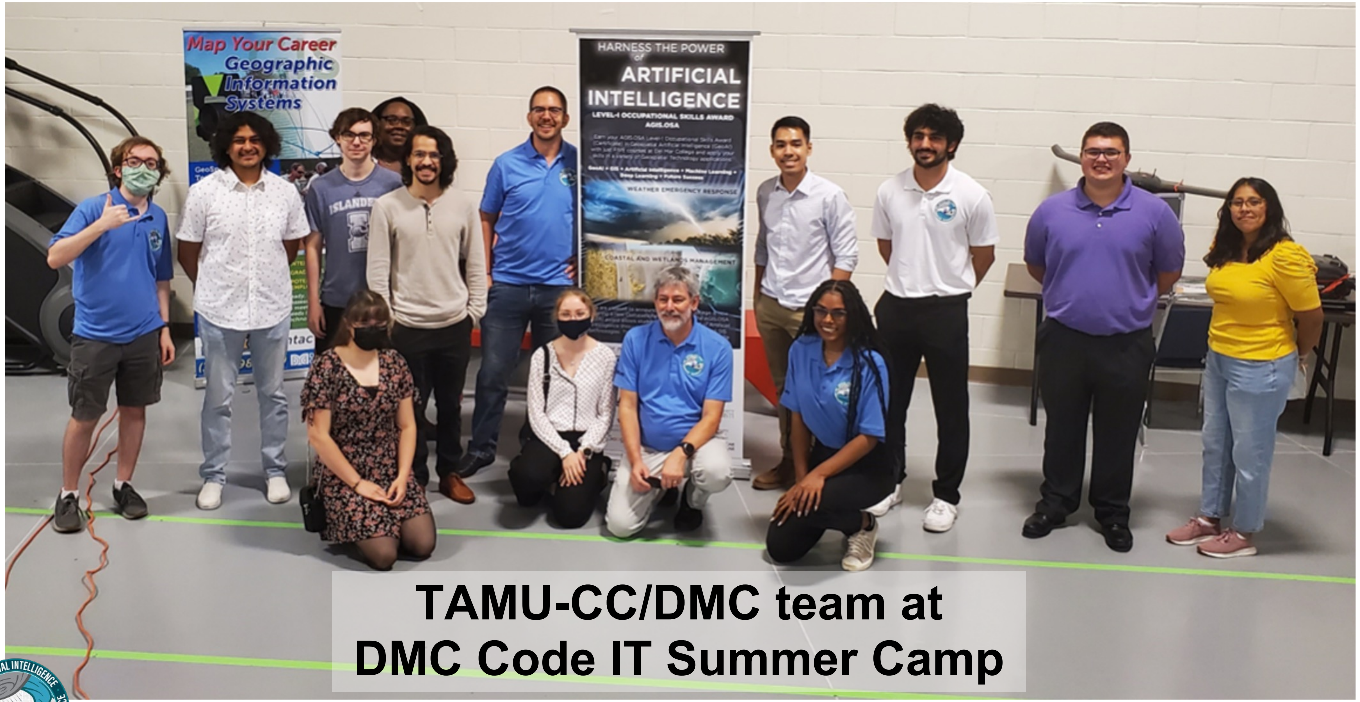


URA (DMC/TAMUCC) Ashley Marines: DOE NuPUMAS, Houston, TX, Brookhaven, NY, South Dakota

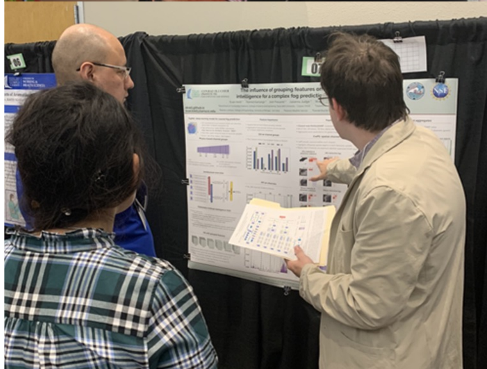
URA (DMC/TAMUC) Anointiaye Beasley and Elisa Flores both at TAMUCC REU, Corpus Christi, TX

TAMUCC 2023 Interns Cohort: 67% minority, 55% female

All TAMU-CC Students, Faculty, Staff participating in Outreach and other Events



TAMU-CC/DMC team at DMC Code IT Summer Camp



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Questions?

Photos of the AI2ES team at its Jan 2023 retreat (in a familiar location) and of the Summer 2023 NRL NREIP Interns in Monterrey

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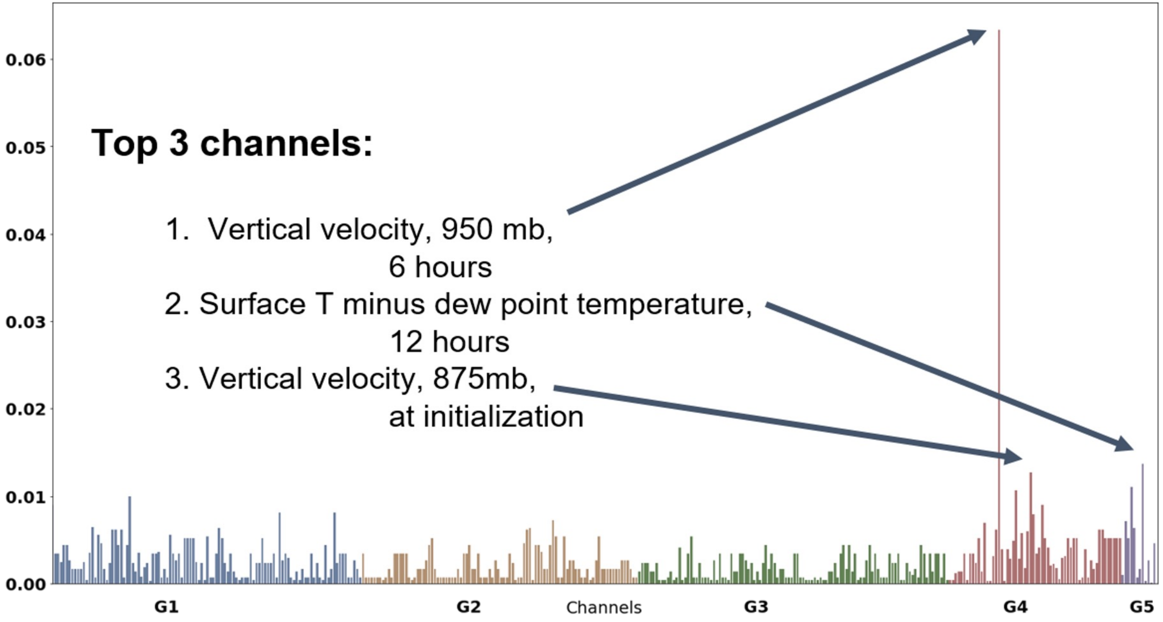
Co-developed interview instrument: XAI

- Integrated **XAI results** into the interview guide, which will provide the **first empirical evaluation** of users' perceptions of these techniques



Group 1 – Wind
Group 2 – Turbulence Kinetic Energy & Humidity
Group 3 – Lower Atmospheric Thermodynamic Profile
Group 4 – Surface Atmospheric Moisture & Microphysics
Group 5 – Sea Surface Temperature

Abstract (1)

Machine learning methods have shown to be a powerful approach to modeling coastal systems including combining the nonlinear combinations of atmosphere, ocean, and land forcings. One of the foci of the NSF AI Institute for Research on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES) is the development of ML based methods to predict visibility and onset and duration of coastal fog events. Improving such predictions is of great importance for coastal area management particularly for air and sea transportation. The reliable prediction of fog with machine learning is however challenging due to the infrequency of the target event, and the spatiotemporal and variable inter-dependency of the inputs, along with data non-stationarity. 3D CNN-based models are able to learn not only 2D spatial patterns and correlations between groups of pixels and a target but also learn spectral correlations between bands or temporal correlations between input variables. FogNet is a 3D CNN-based model taking advantage of the combination of an atmospheric numerical model output, sea surface temperature satellite imagery and derived air-sea interaction features. The input to FogNet consists of up to 384 ordered variable maps organized in five data cubes organized based on the physics of the problem (1) wind, (2) turbulence, kinetic energy and humidity, (3) lower atmospheric thermodynamic profile, (4) surface atmospheric moisture and microphysics and (5) sea surface inputs. A more granular physics grouping will also be tested. The model predicts fog and mist visibility categories below 1600m, 3200m and 6400m for 6-, 12− and 24−hr lead times with performance comparable or superior to existing operational models.

As performance continues to improve, often through the use of novel and/or more complex models, it is important to study and quantify the relative importance of the components and the inputs of these models. Along with the development of the model, explainable AI (XAI) methods were applied and adapted for FogNet. Results show that the 3D architecture indeed outperforms several 2D kernels, that the physics-based grouping of input meteorological variables leads to better performance. XAI also allowed to evaluate the benefits of different auxiliary modules, the multiscale feature learning and the parallel and separate spatial-variable-wise feature learning.

Abstract (2)

Ongoing further developments include a new version of FogNet based on a Vision-Transformer architecture. The new architecture introduces a multi-view attention method to model more explicitly nonlinearly correlated inputs and help better understand their interactions, particularly in the spatial, temporal, and variable dimensions. While the 3D CNN FogNet model and its new transformer-based architecture have shown significant improvements over present operational models, they would be challenging to implement operationally. Based on XAI results emphasizing the importance of atmospheric predictions for the target location, a Variational AutoEncoder (VAE) that would be easier to implement broadly is being developed. The model inputs are the High-Resolution Rapid Refresh (HRRR) predictions for the target location and the same calibration for 14 locations along the Texas coast.

As many organizations are working on harnessing the power of Artificial Intelligence to better predict and manage our environment, we need many more young scientists ready to contribute to this discovery and operational implementation process. AI2ES trains dozens of scientists from Community Colleges, to 4-year universities, MS, PhD and a robust cohort of Post Doctoral students. Thanks to partners at universities, national laboratories, including a Naval Research Laboratory, private industry an ecosystem is being developed to give a chance for young ML geoscientists to develop within diverse environments and be ready to tackle important and pressing challenges as part of convergent teams.