

History and Potential of Artificial Intelligence for the Environmental Sciences

Philippe Tissot

Conrad Blucher Institute

Interim Director & Associate Research Professor

Texas A&M University-Corpus Christi

American Meteorological Society AI Committee

Acknowledgments

Sue Haupt (NCAR), William Moninger (NCAR), Amy McGovern (OU), Andre Van der Westhuysen (NOAA), Vladimir Krasnopolski (NOAA), AMS AI Committee Members, Students and Faculty at CBI and TAMUCC (present, past)



Topics for Discussion

- Conrad Blucher Institute
- History of Artificial Intelligence & Machine Learning
 - Broadly
 - For Environmental Sciences
 - Through the Lens of the AMS AI Committee Activities 1985 -
- ML Methods Applied to Environmental Cases 2000's, 2010's
 - Neural Networks / Water Levels
 - Random Forests / Sea Turtle Cold Stunnings
 - Deep Learning (SDAE) / Lightning Predictions
 - Deep Learning (3D Conv) / Coastal Fog
- Physics? Changes & Constants in AI

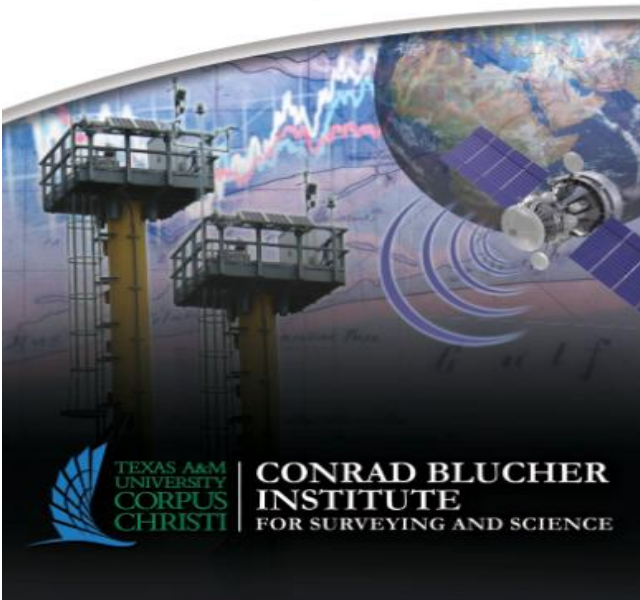
Conrad Blucher Institute for Surveying and Science



Learning From
The Past...



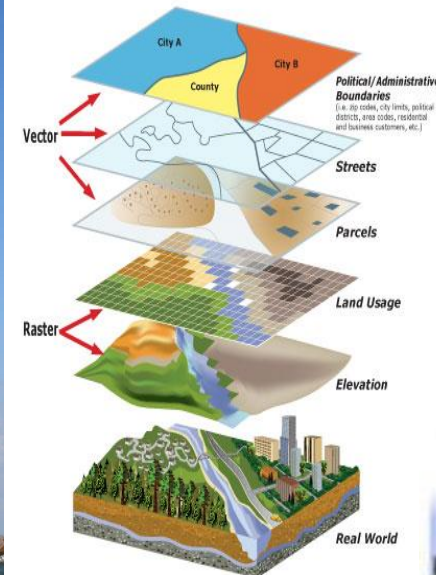
...Surveying
The Future



Labs/Units

- Operations
- Measurement Analytics Lab (MANTIS)
- **Coastal Dynamics Lab**
- Geospatial, Optimization and Analytics Lab (GOAL)
- Spatial {Query} Lab (S{Q}L)
- Texas Spatial Reference Center
- Supports BS, MS, PhD programs

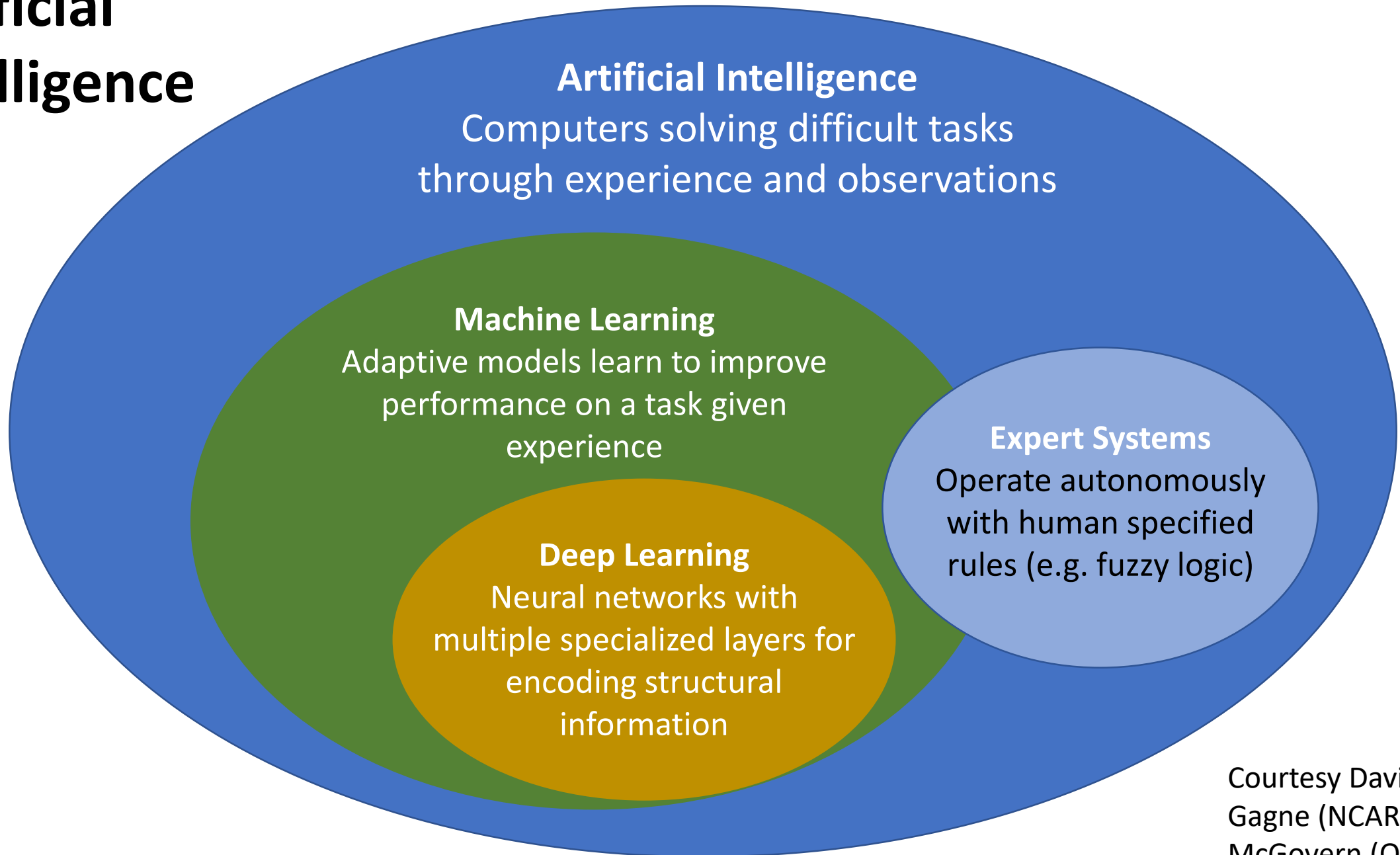
} Coastal
AI



What is Artificial Intelligence?

- **From Wikipedia**
- In [computer science](#), artificial intelligence (AI), sometimes called machine intelligence, is [intelligence](#) demonstrated by [machines](#), in contrast to the natural intelligence displayed by humans.
- Leading AI textbooks define the field as the study of "[intelligent agents](#)": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals.
- Colloquially, the term "artificial intelligence" is often used to describe machines (or computers) that mimic "cognitive" functions that humans associate with the [human mind](#), such as "learning" and "problem solving"

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

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

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>

AMS AI Workshop and Short Courses: 1985 – Boston 2020

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 Dyer¹ 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.

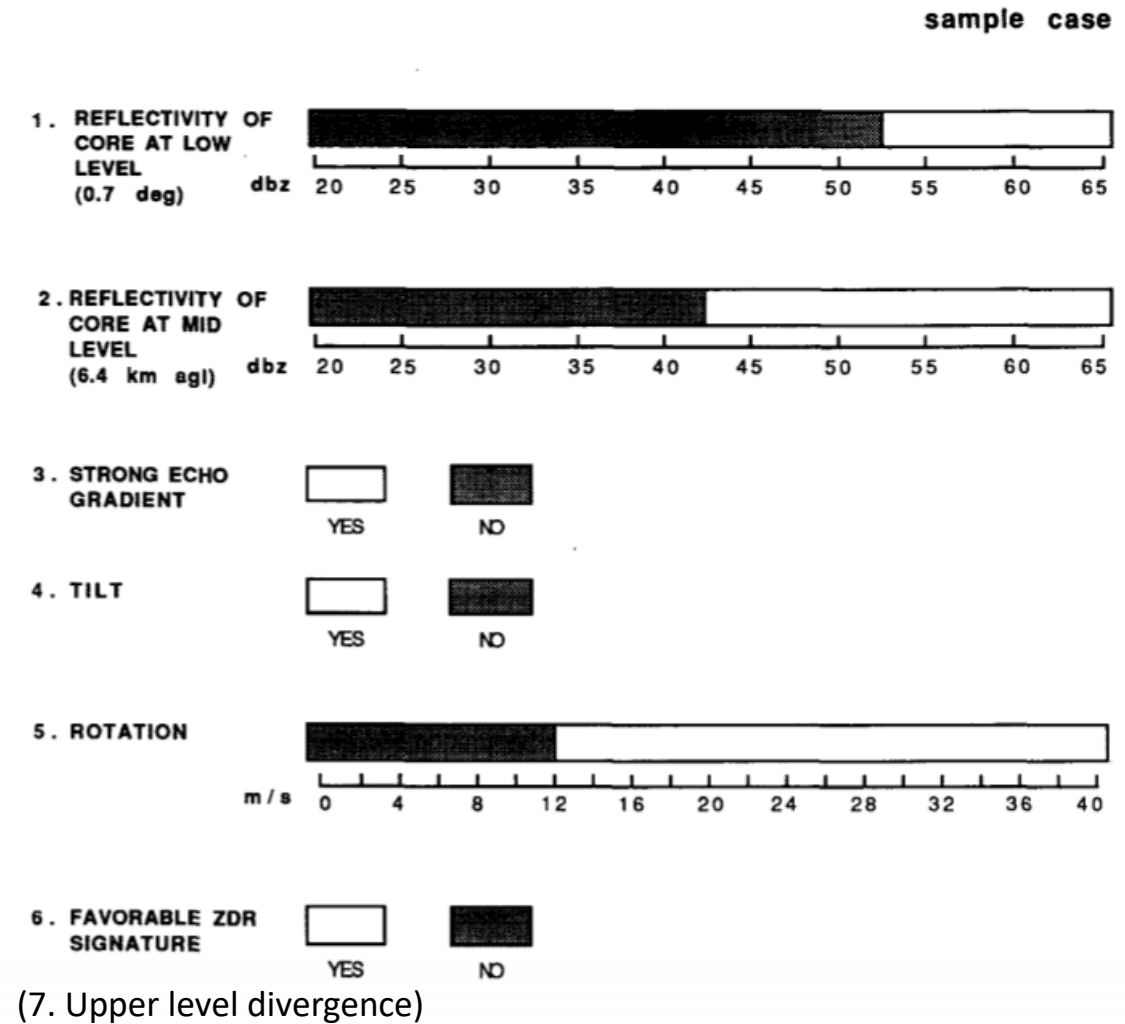
AI Systems Number	Subject Matter
22	Environmental forecasting
3	Weather diagnosis
6	Automated pattern recognition
9	Assistance to operational users of environmental data
5	Assistance to environmental researchers
1	Tutor for meteorology students
15	Hazard response, short and long term
8	Hydrology and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

Hail Forecasting: Human vs Regression vs Expert System

“The future in weather forecasting is a partnership between person and machine and an understanding of the capabilities and limitations of both is critical to make the partnership effective” [1]

- 1988 Limited Information Hail Forecasting Experiment
- Comparison
 - Expert System
 - Meteorologist
 - Weighted Sum Model



[1] [Stewart, T. R., Moninger, W. R., Brady, R. H., Merrem, F. H., Stewart, T. R., & Grassia, J. \(1989\). Analysis of expert judgment in a hail forecasting experiment. Weather and forecasting, 4\(1\), 24-34.](#)

Experiment

- Interested in human processing and its limitations and comparisons
- All forecasters (7) & models provided the same information
- 75 cases per forecaster drawn from 453 Doppler radar volume scans (NOAA PROFS) → 5 categories from unlikely to severe storm predictions including hail and winds within 30 mins
- Target: in situ observations of small (14.7% $>1/4''$) and severe (5.3% $>3/4''$) hail
- Expert system: Hail prediction based on 250 rules based on the 7 cues predicting storm category 1-5 (also tornadoes and strong winds)
- Expert system development very time consuming

Performance Comparison

- Meteorologists predictions were consistent with good correlation between forecasters (typically >0.8)
- Regression analysis of meteorologists:
 - Accounting 80% to 92% of variance in meteorologists forecasts
- Correlations expert system – meteorologists
 - Any hail: 0.70 – 0.85
 - Severe hail: 0.63 – 0.79
- When models applied to other cases:
 - Regression models performance similar to respective forecasters
 - Expert system good for severe hail, low for any hail, not as good as regression
- But experiment designed with limited information, not realistic conditions



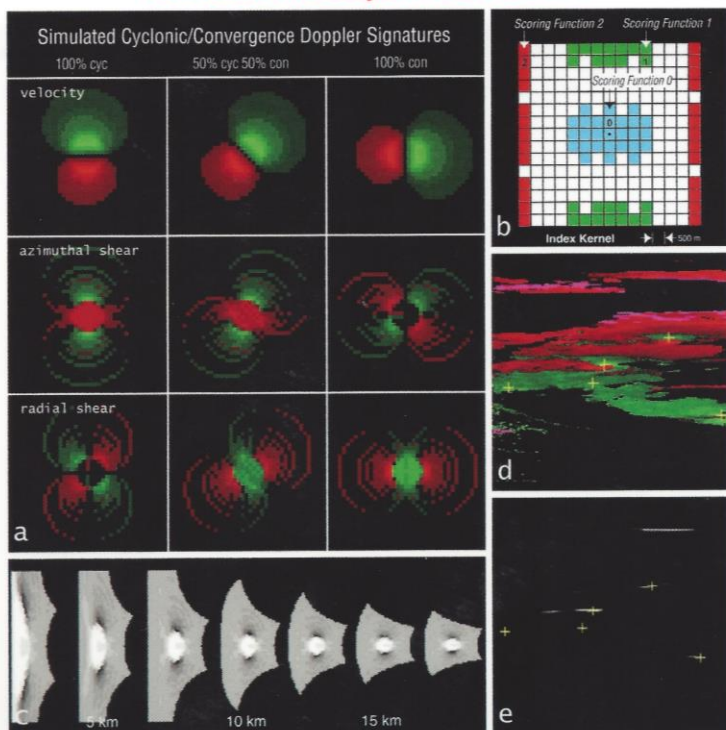
PREPRINTS

FIRST CONFERENCE ON ARTIFICIAL INTELLIGENCE

11-16 JANUARY 1998

PHOENIX, ARIZONA

NSSL 2D Mesocyclone Detection



AMERICAN METEOROLOGICAL SOCIETY

AMS AI Conferences 1998 -2020

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*

Use of AI Methods in Time

- Methods: Expert Systems, Fuzzy Logic, Neural Nets, Tree based methods, SVMs, Genetic Algorithms, Genetic Programming, Deep Learning, ...
- **1987**: Workshop, *mostly expert systems*, 1 mention of Neural Nets
- **1998** (47 presentations)
 - **Neural Nets (49%)** – Expert Systems (17%) – Fuzzy Logic (9%) – Tree Based (6%) – Other (19%)
- **2008** (32 presentations)
 - **Neural Nets (27%)** – Tree Based Methods (14%) – SVMs (13%) – Genetic Algorithms (9%) – Fuzzy Logic (5%) – Expert Systems (3%) - Other (34%)
- **2019** (101 presentations)
 - **Deep Learning (36%)** - Neural Nets (10%) – Tree Based Methods (10%) – K-Means (3%) - SVMs (2%) – Other (38%)

AI Methods at AMS AI 2020

2020 Presentations (2019)

- ***Deep Learning*** ~50% (36%)
- General Machine Learning: ~15%
- Random Forests ~10% (had other tree-based methods at 10%)
- Not Directly AI Presentations ~9%
- Multiple Machine Learning Methods ~8%
- Shallow Neural Nets ~5% (10%)

- Other methods (<3%) Self Organizing Maps, Support Vector Machines, Fuzzy Clustering, Genetic Programming

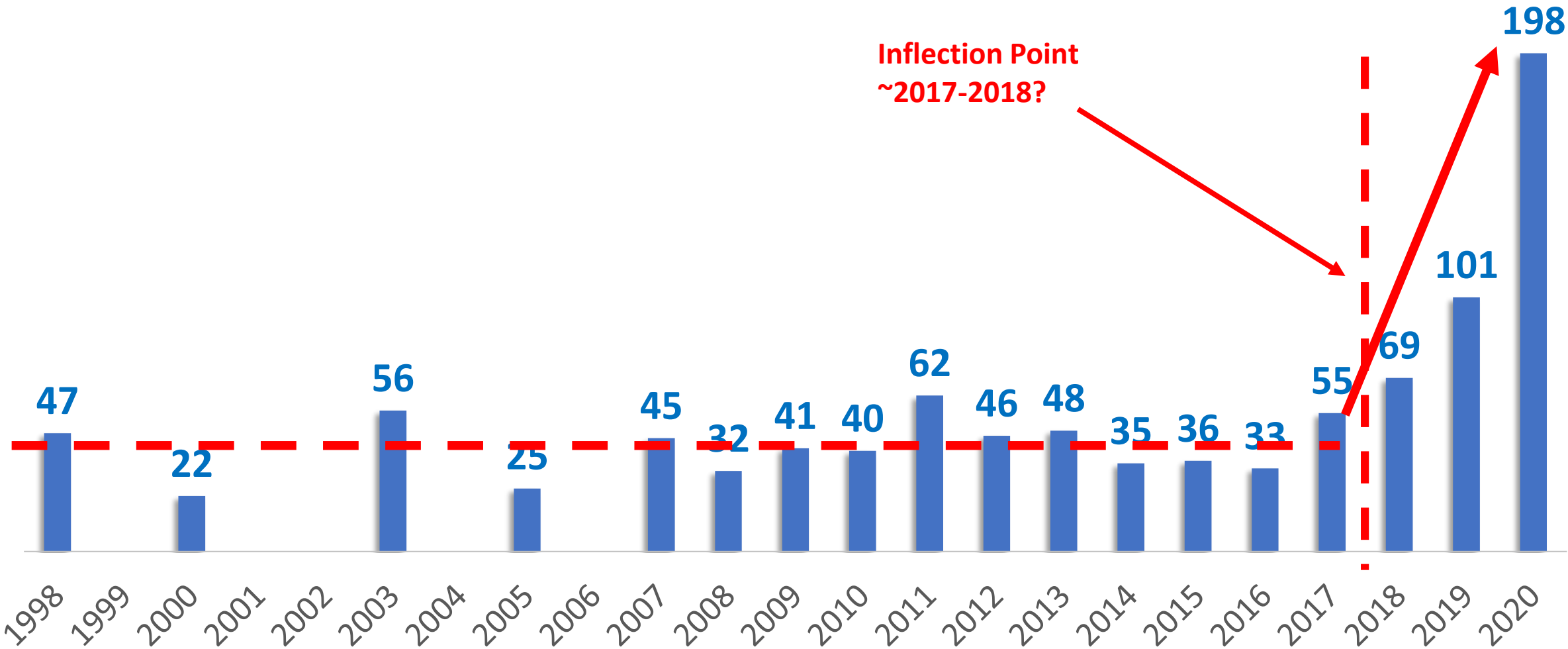
Research topics

2020 Presentations Topics

- Many: Weather Forecasts – Precipitation - Climate - Tropical Cyclones
- Several: - Hail Classification – Energy – Space Weather – Tornadoes – Clouds – S2S – Air Quality – Satellite Imagery – Radar Imagery – Computer Science & Methods
- Cool topics: Detecting Birds in Radar – Economic Value (2) – Water Quality (2)
- ***Other trends:***
 - Interpretable AI
 - Physics guided/aware AI
 - Education & broad initiative talks
 - Data sets building/curation

Growth of AI: Increase in Attendance at AMS AI

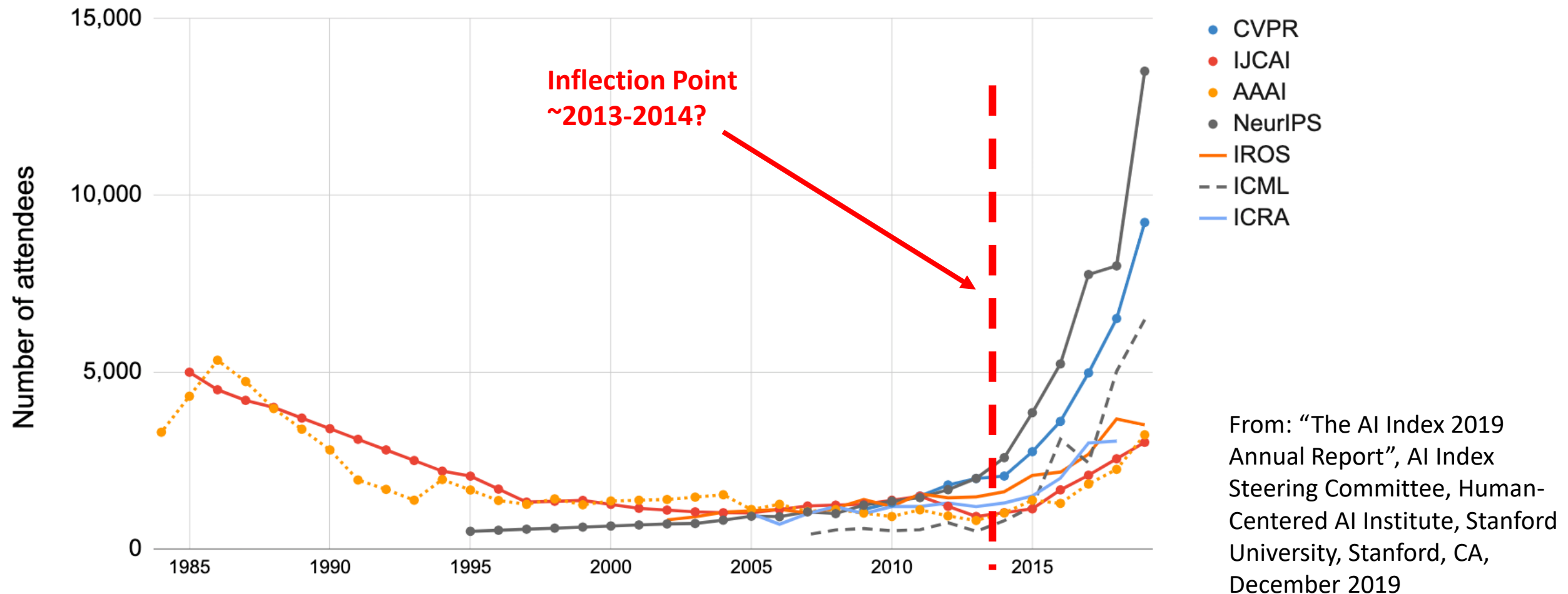
Presentations at AMS AI Conferences



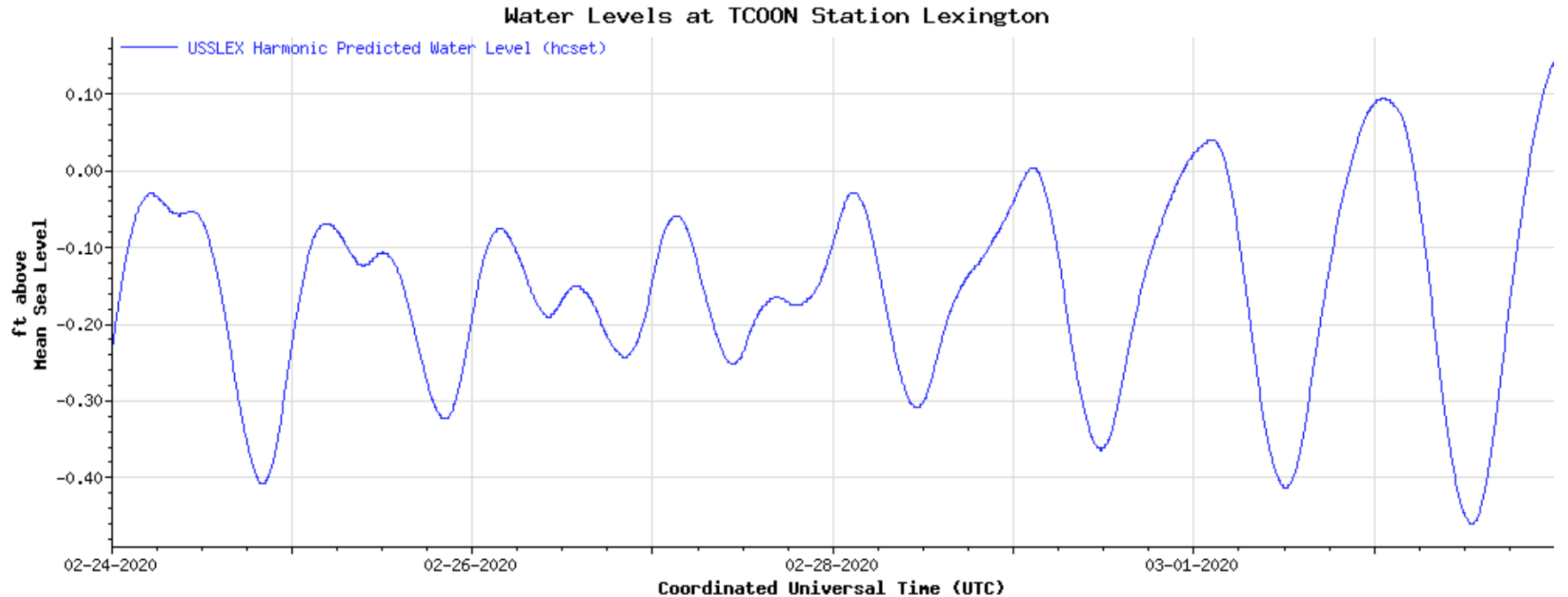
Growth of AI: Increase in Attendance at AI/CS Conferences

Attendance at large conferences (1984-2019)

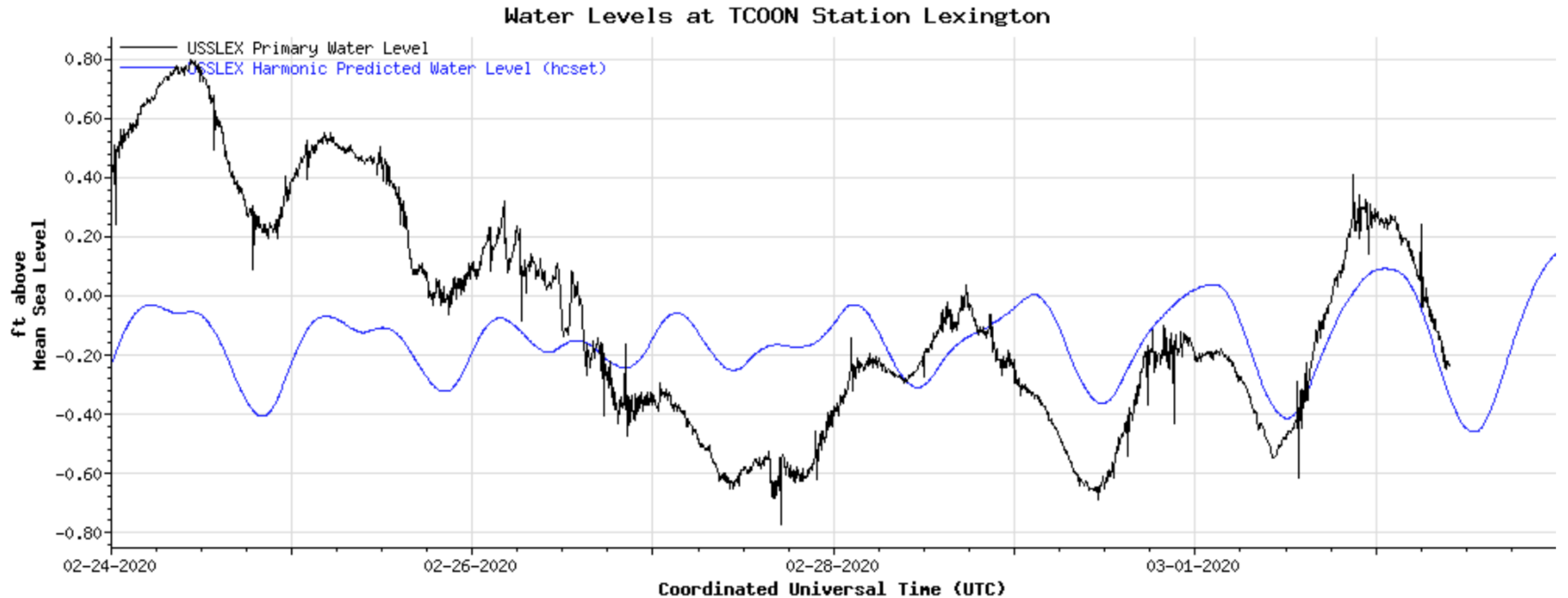
Source: Conference provided data.



Start of AI at TAMUCC-CBI: Water Level Predictions

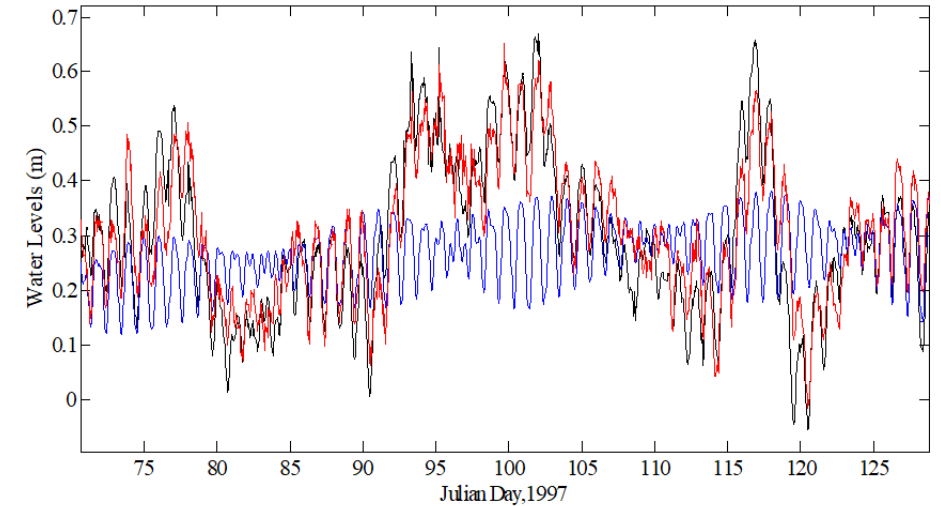
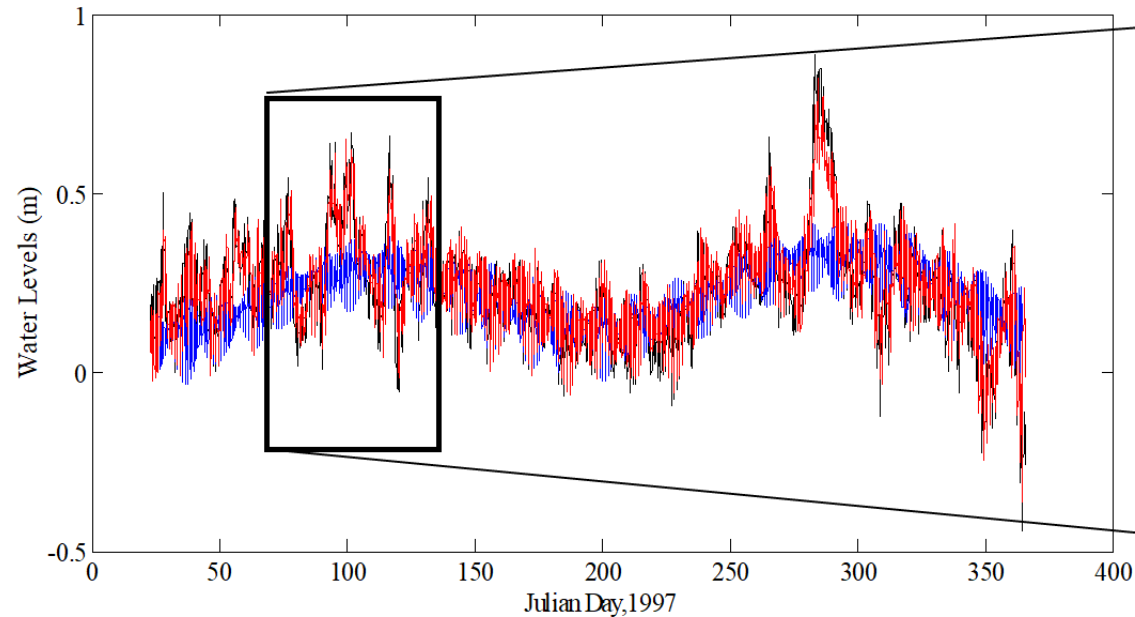


Start of AI at TAMUCC-CBI: Water Level Predictions



Shallow Neural Networks Operational Predictions

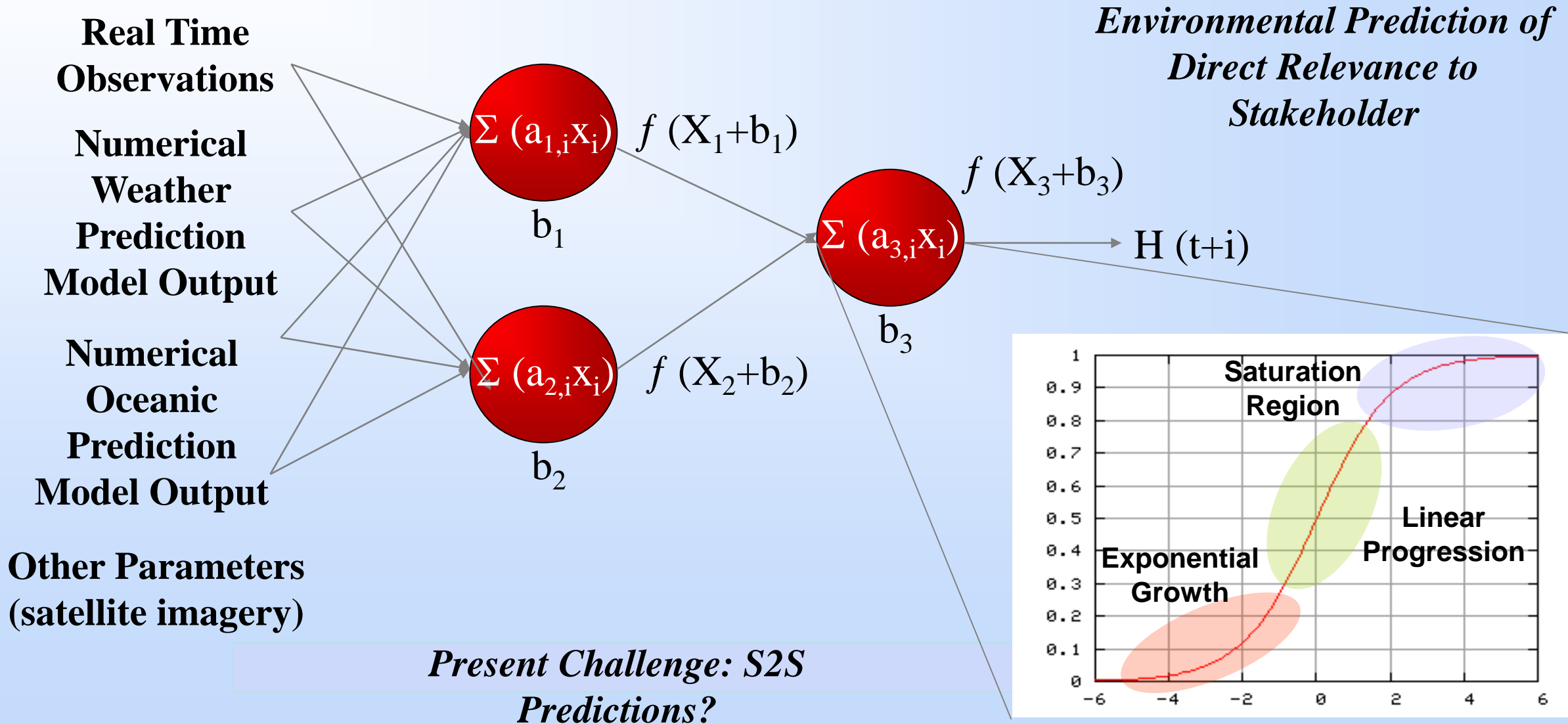
Comparison of 24 h ANN predictions with measurements for Corpus Christi Naval Air Station



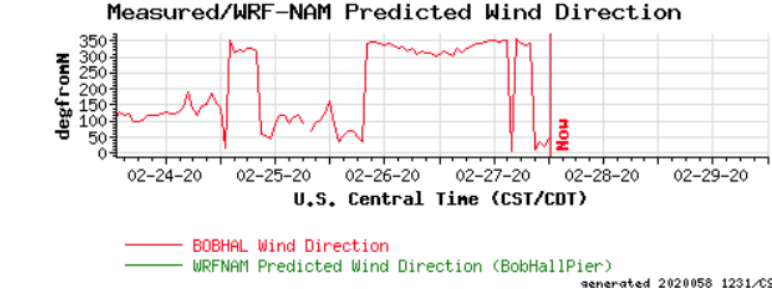
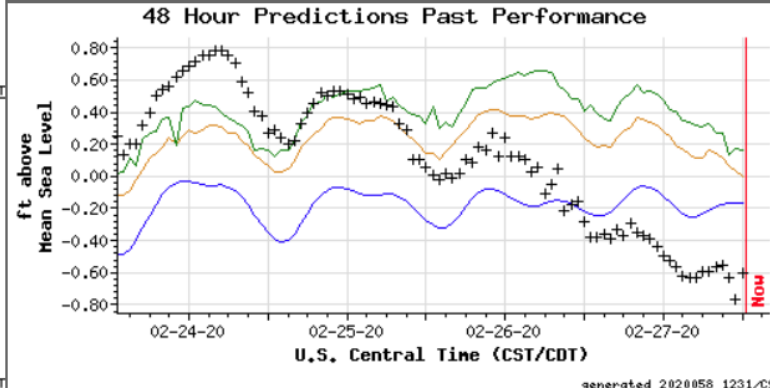
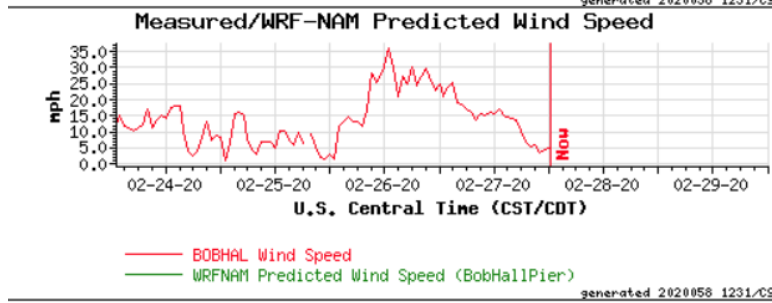
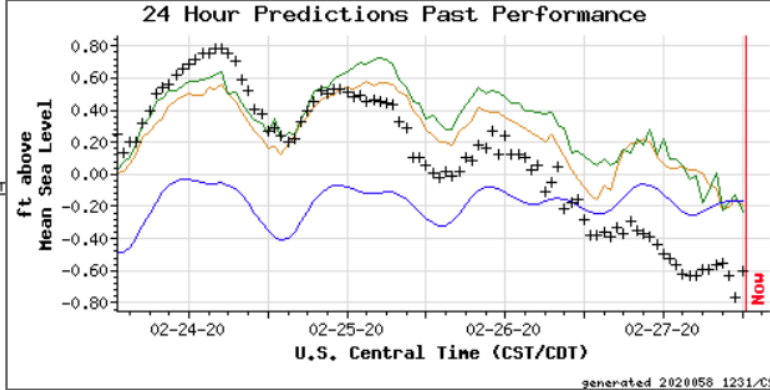
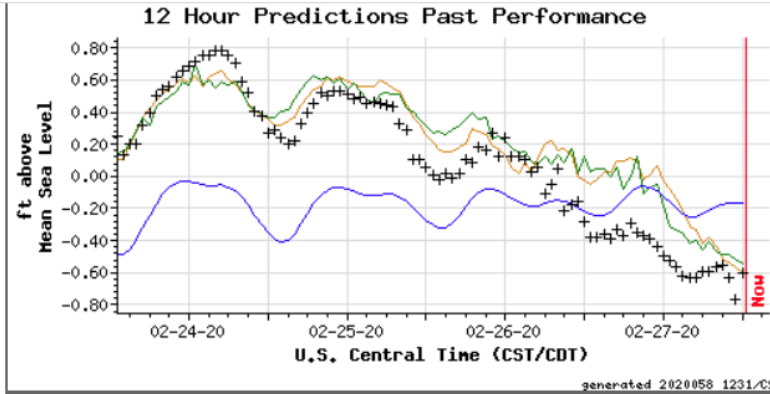
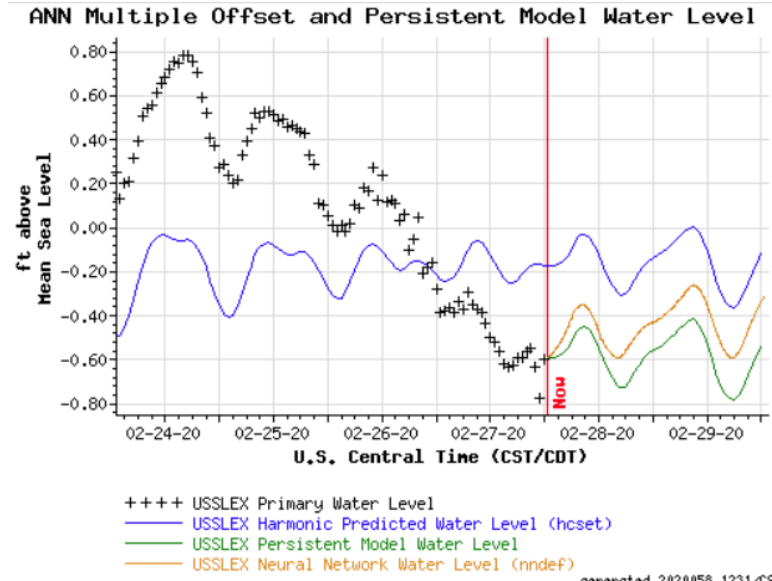
Cox, D. T., Tissot, P.E. and Michaud P. (2002). Water Level Observations and Short-Term Predictions Including Meteorological Events for Entrance of Galveston Bay, Texas. *Journal of Waterway, Port, Coastal and Ocean Engineering*, 128-1, 21-29. doi: 10.1061/(ASCE)0733-950X(2002)128:1(21).

Tissot, P.E., Cox, D.T. & Michaud, P.R. (2003). Optimization and Performance of a Neural Network Model Forecasting Water Levels for the Corpus Christi, Texas, Estuary. *Proceedings of the 3rd Conference on the Applications of Artificial Intelligence to Environmental Science*, part of the 2003 American Meteorological Society Annual Meeting, Long Beach, California.

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



Shallow Neural Networks Operational Predictions

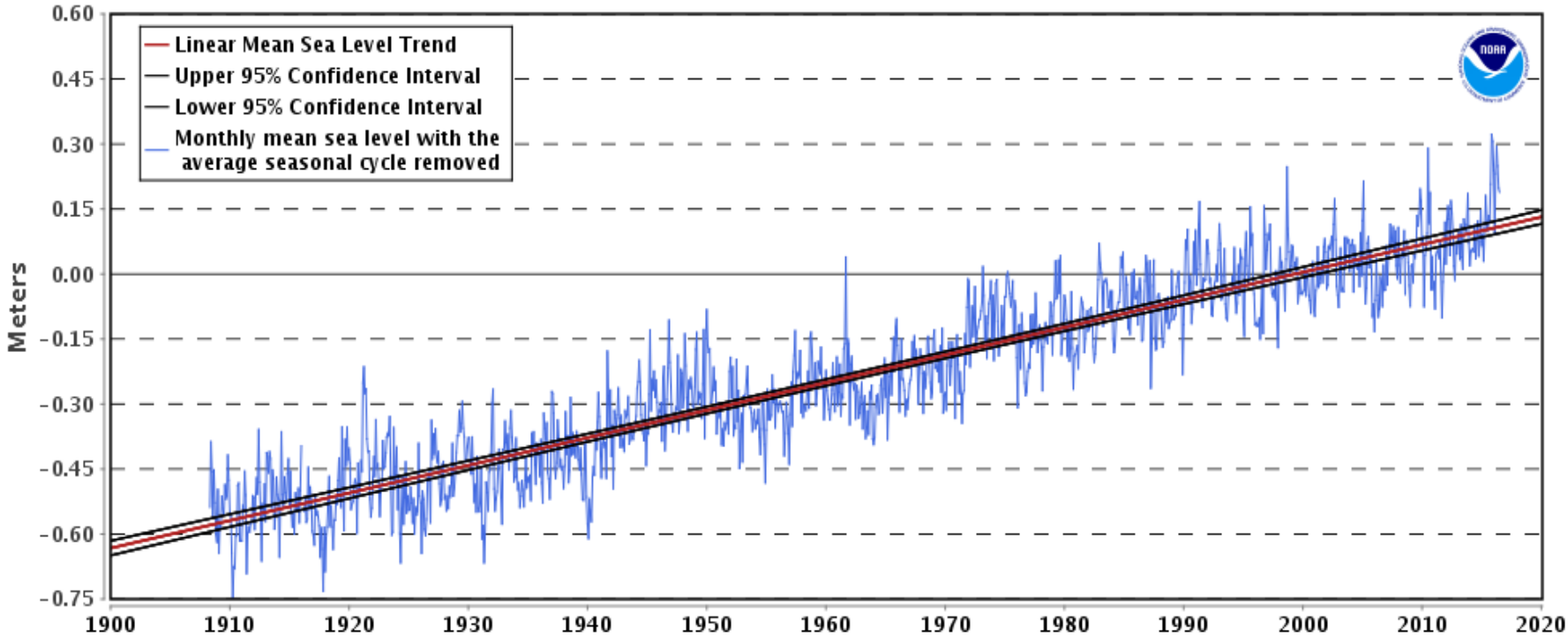


Water level predictions for Corpus Christi Bay Lexington (2/27/2020)

Relative Sea Level Rise: Galveston Pier 21

8771450 Galveston Pier 21, Texas

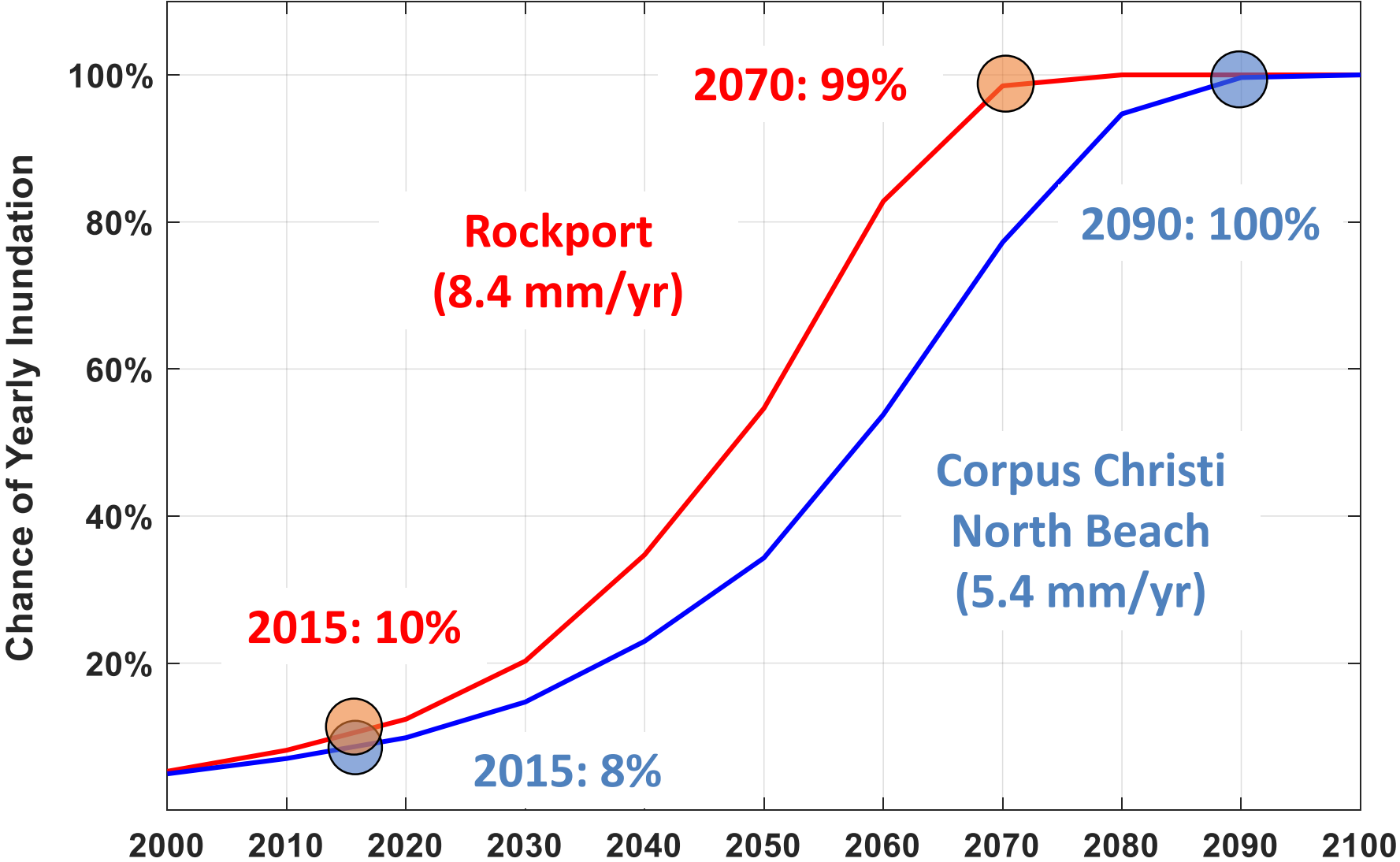
6.37 +/- 0.24 mm/yr



Galveston Pier 21: 0.25" / year - 100 years = 2.1 ft

Inundation Frequency

Probability of at Least one Innundation

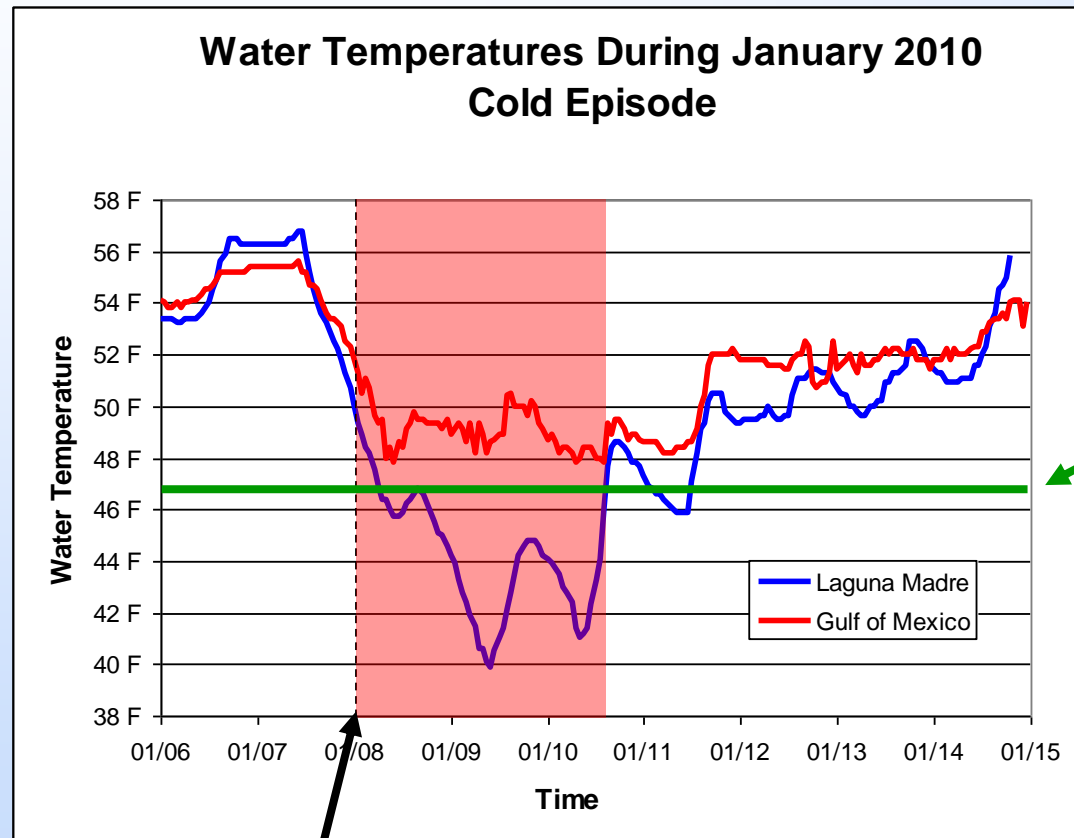


While sea level rise is presently close to linear, inundation frequency for a set elevation is initially exponential

Cold Stunning Event Predictions



January 2010 Cold Spell



Goal: avoid barge traffic when water temperature is below 8°C (46.4F)

Performance: maximum prediction error was 2°C for Bird Island (up to 48hrs predictions).

Closing advice issued Thursday evening Jan. 7 for Friday evening January 8, 10:00PM through Sunday January 10 12:00PM

Shaver DJ, Tissot PE, Streich MM, Walker JS, Rubio C, et al. (2017) Hypothermic stunning of green sea turtles in a western Gulf of Mexico foraging habitat. PLOS ONE 12(3): e0173920. <https://doi.org/10.1371/journal.pone.0173920>
<http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0173920>

January 2010 Cold Spell

- Model used during January 8-10, 2010 to voluntarily cease barge traffic in the Laguna Madre
- Economic value of \$21,000 - American Commercial Line, Blessey Marine Service and Florida Marine Transporters

From the Wheelhouse

Voluntary Tow Stoppage in Laguna Madre

The Laguna Madre reach of the Gulf Intracoastal Waterway is a very unique and fragile coastal ecosystem spanning the southern Texas coast from Corpus Christi to Brownsville. Its average depth is two to three feet, except for the nine to ten feet of deep water in the Intracoastal Waterway.

Prior to the arrival of the Intracoastal Waterway, the Laguna Madre was a hyper-saline "deserted" body of water. Today, the water in the Laguna is home to the clearest water and one of the most productive game fish ecosystems anywhere. The Lower Laguna Madre is home to the Texas State Record Speckled Trout, a 37-incher and almost 16 pounds, caught by Carl Rowland in May 2002. It is arguably the "Mecca" for all inland saltwater fishing enthusiasts who seek the largest trout of their lives in its waters.

When the strong northers of the south Texas winters arrive, on rare occasions the water temperature in the Laguna Madre reaches the danger zone for these prized game fish, endangering them and the future fish crops they bear. This temperature seems to be around 42 degrees Fahrenheit. It usually takes days of extremely low temperatures to drive the water temperature to these levels, but it does happen. During the winter of 1989, an extremely hard freeze hit the area with several days of sub-freezing temperatures. Results were a devastating fish kill that virtually wiped out the game fish population in the Laguna Madre. It took several years before stocks returned to normal levels.

Biologists have learned that when water temperatures in the normally shallow expanse of the Laguna fall to these low levels, fish head for the safety of warmer waters, deep in the Intracoastal Waterway. They also become very lethargic during these times and cannot escape predators or the wheels of our towboats as easily.

As a result of our work several years ago to address certain threats to the GIWW in the Laguna Madre, GICA fostered a relationship with the Coastal Conservation Association, the Gulf Coast's main sport fishing representative body. That "partnership" began as an adversarial relationship over dredging practices used to maintain the waterway. After many discussions

and meetings, we found common ground where both associations could help one another to keep the waterway functioning for both recreation and commerce.

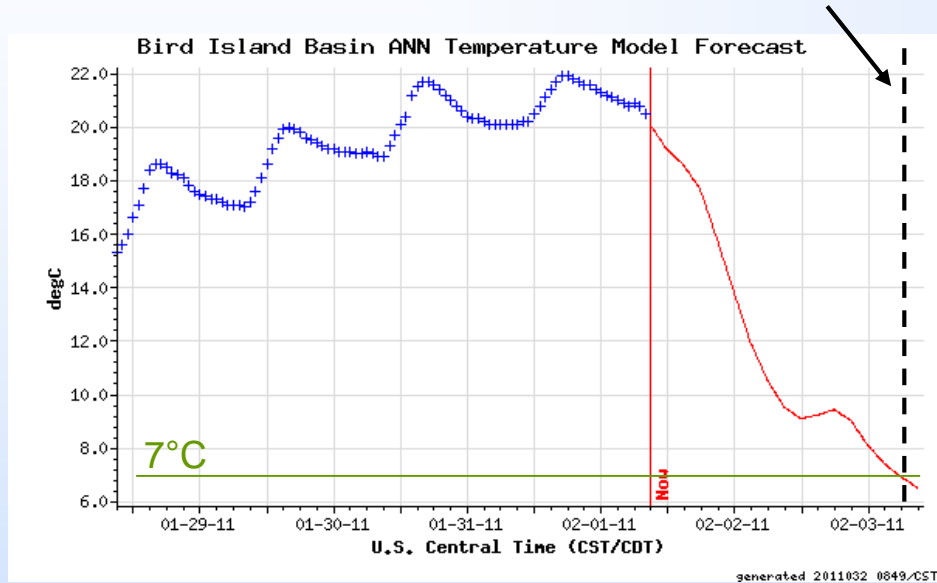
We found common ground to help keep the waterway functioning for both recreation and commerce

We found that during these rare times of extreme cold, the barge industry might assist in reducing game fish mortality by voluntarily stopping transits of the Laguna Madre. GICA brokered this idea among our members and most all seemed to favor a brief stoppage of commerce in order to help. We had the opportunity to try this concept out for the first time during the weekend of January 9-10, an extremely cold period in south Texas. Support for the idea was strong among our members. American Commercial Lines, Blessey Marine Service, and Florida Marine Transporters actually stopped or held tows for the requested period from January 9 through Monday morning, January 11. Additionally, AEP, Cenac/TEPPCO, Brownwater Marine, and Kirby Corporation all responded favorably, indicating they would support a voluntary stoppage of traffic if they had equipment in the area. We don't foresee this event happening more than once or twice in a year, or it lasting over 72 hours at most.

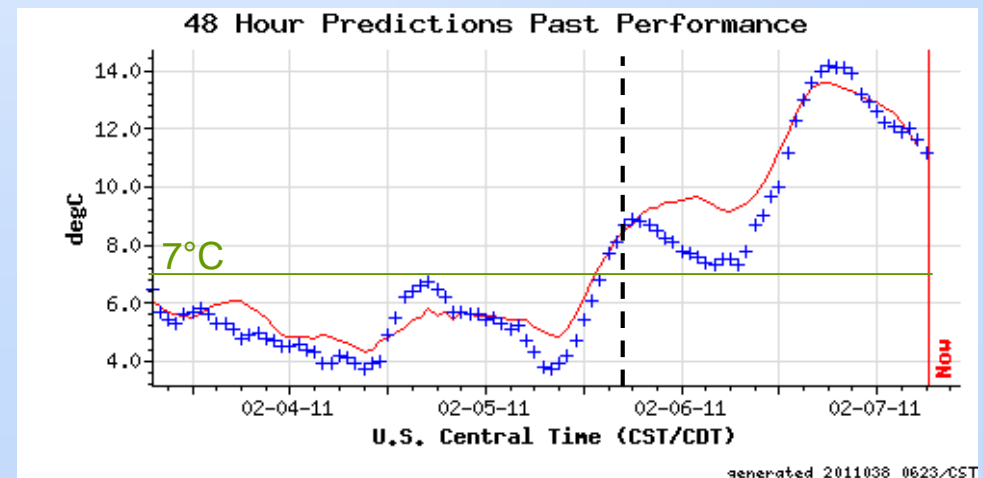
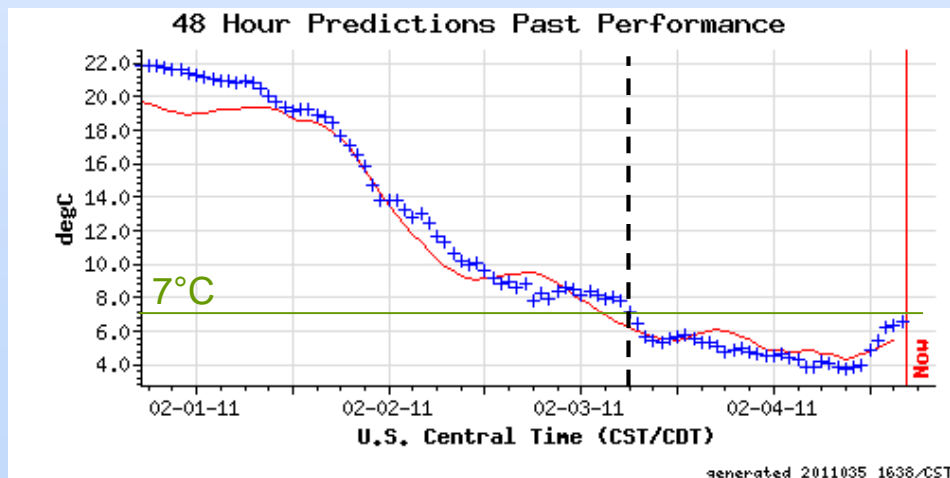
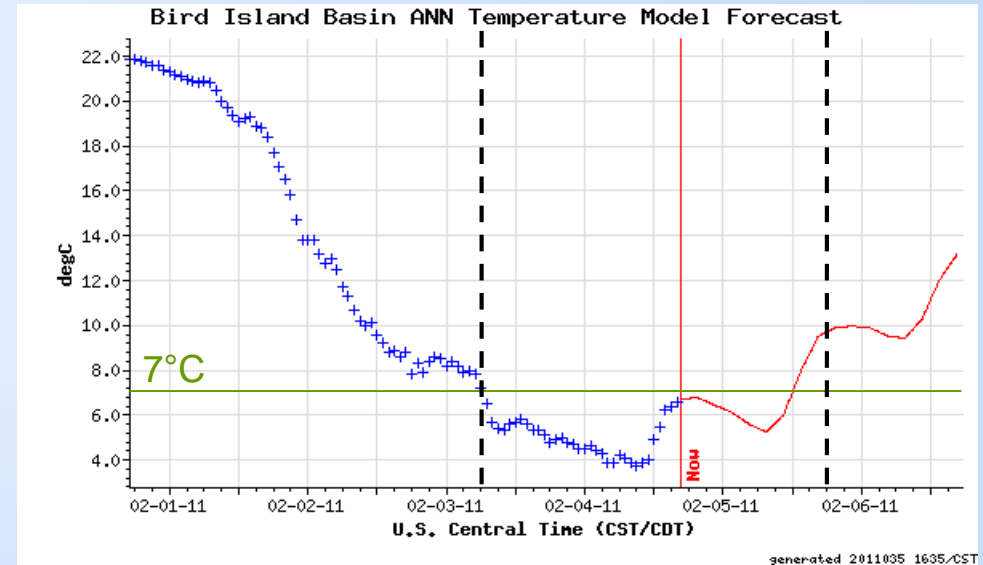
We thank everyone who made economic sacrifices and those who agreed to help in the future. We hope this innovative partnering effort serves to build a stronger bond between our industry and the sport fishing community, with the common goal of keeping the GIWW maintained and productive for us all.

Automated System: February 3-5, 2011 Cold Front

Advice for start of traffic Interruption: 2-3 06:00



Advice for end of traffic Interruption: 2-5 18:00



Random Forests: Variable Importance

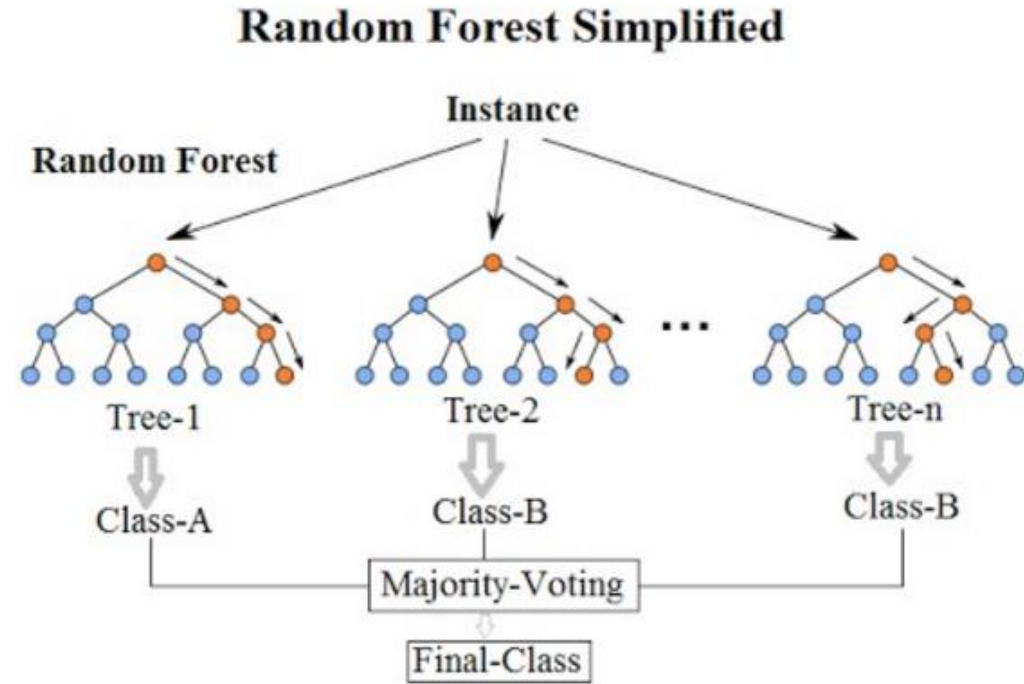
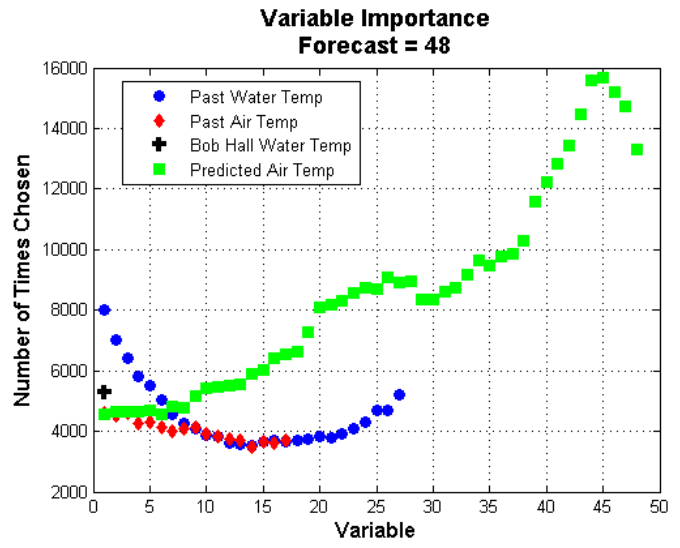
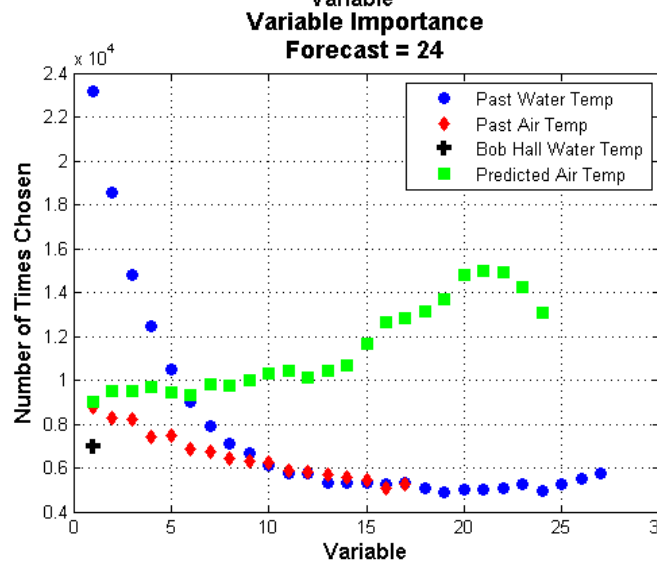
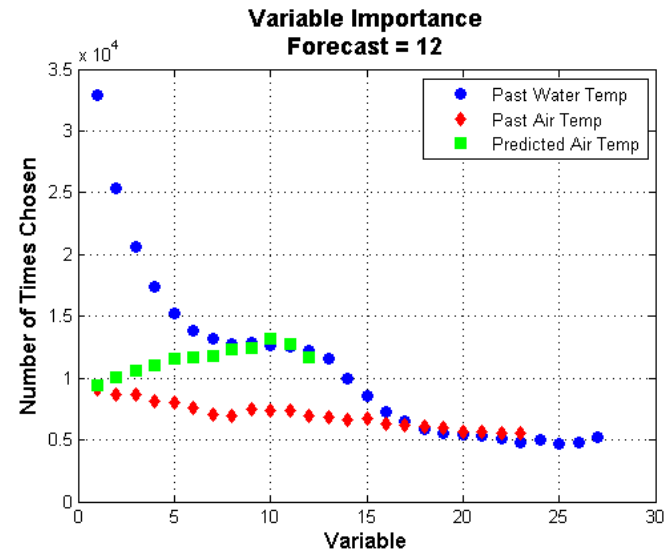
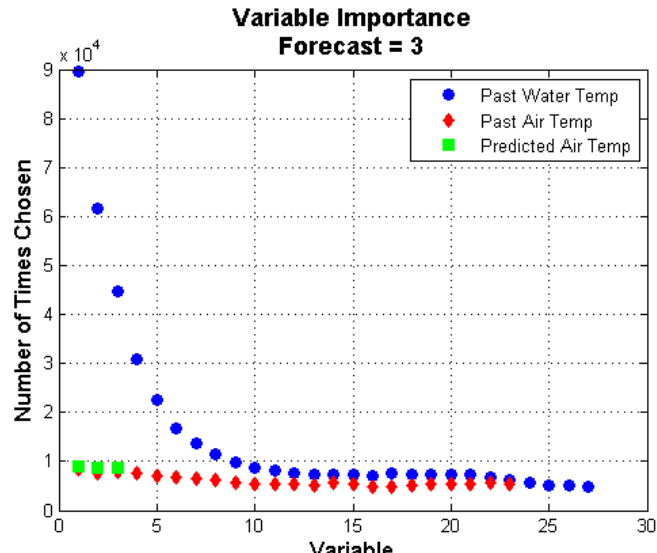


Figure above from Machine Hack: Random Forest Regression
<https://www.machinehack.com/course/machinehack-practise-5-random-forest-regression/>

IT'S NOT ABOUT THE ALGORITHM

The data that transformed AI research—and possibly the world

July 26, 2017

By Dave Gershgorn
Contributor

Stanford professor and Google Cloud chief scientist Fei-Fei Li changed everything.

AP PHOTO/STEF DRIU

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FROM OUR OBSESSION

Machines with Brains

AI is upending companies, industries, and humanity.

>

Reference: Quartz, July 26, 2017, Dave Gershgorn: <https://qz.com/1034972/the-data-that-changed-the-direction-of-ai-research-and-possibly-the-world/>

Imagenet/Deep Learning

2006 Fei-Fei Li: “We’re going to map out the entire world of objects.”

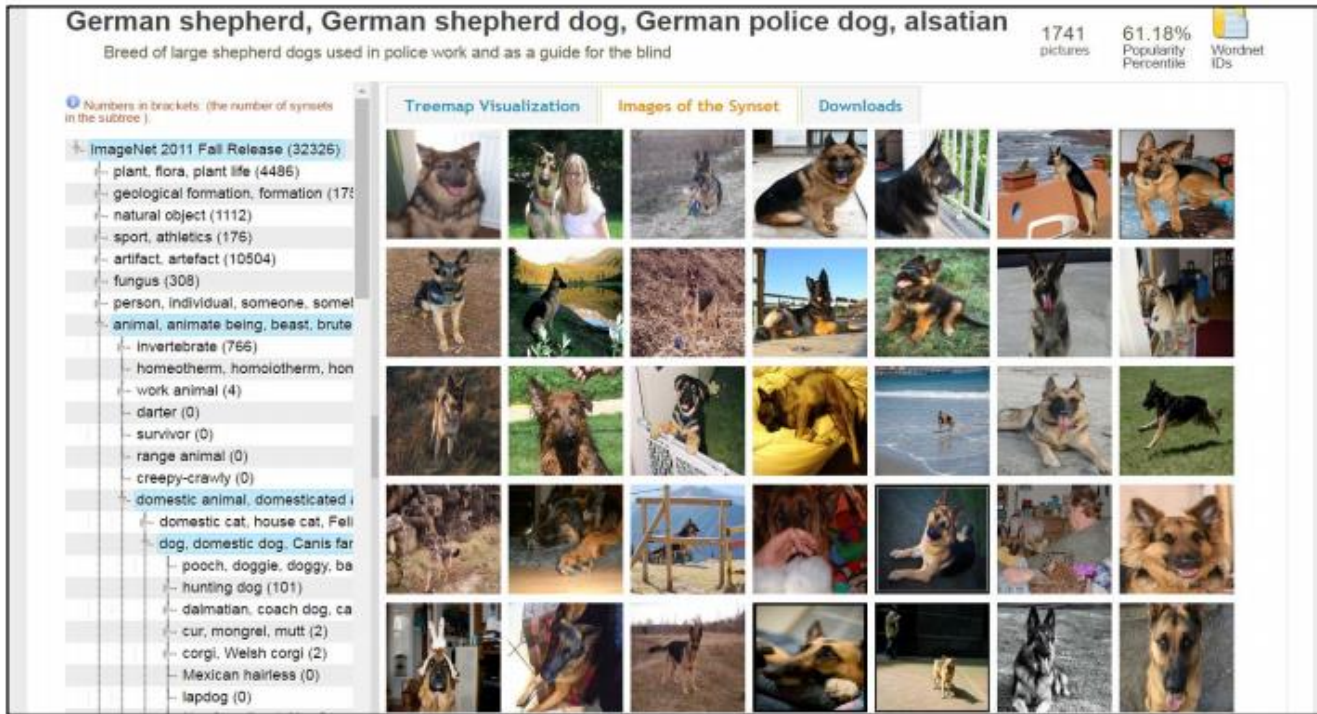
2006 Geoffrey Hinton paper on deep belief nets (and others)

2009 Imagenet dataset and competition: which algorithm can identify objects in the dataset’s images with the lowest error rate.

2010-2017: Accuracy in classifying objects in the dataset rose from 71.8% to 97.3%.

2012: Hinton’s team wins the competition with AlexNet, 10.8 percentage point margin!

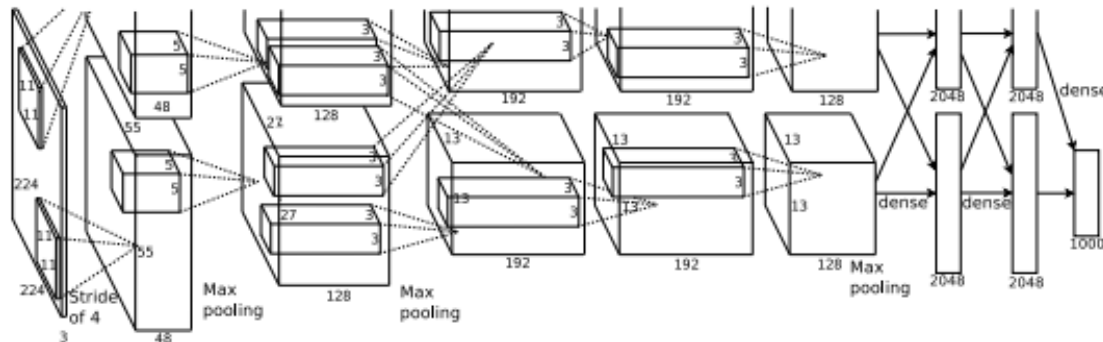
Fei-Fei Li: “*Data will redefine how we think about models.*”



Imagenet/Deep Learning

- Needs millions of images
- The data is key
- Needs large computational power
- Could not have happened 15-20 years ago
- From cats and dogs to cancer detection!

“If the artificial intelligence boom we see today could be attributed to a single event, it would be the announcement of the 2012 ImageNet challenge results”

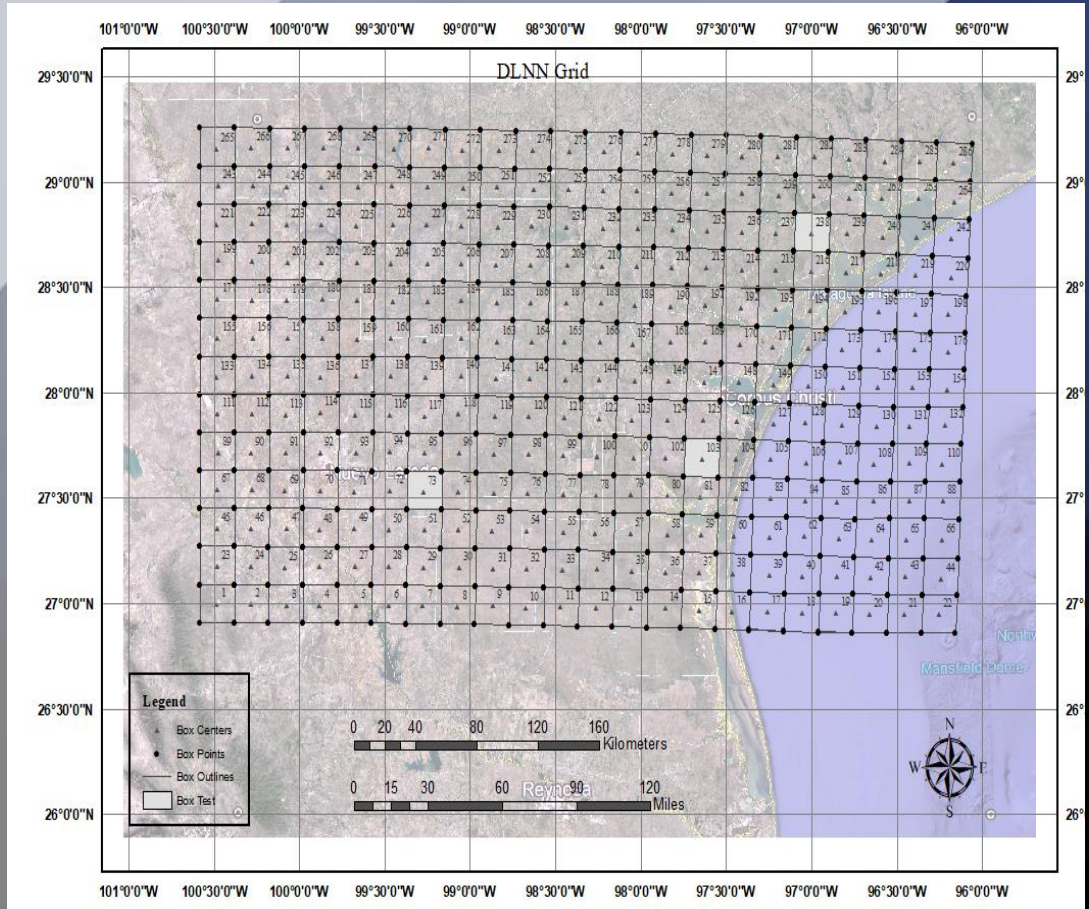


References:

Deng, Jia, et al. "Imagenet: A large-scale hierarchical image database." *2009 IEEE conference on computer vision and pattern recognition*. Ieee, 2009.

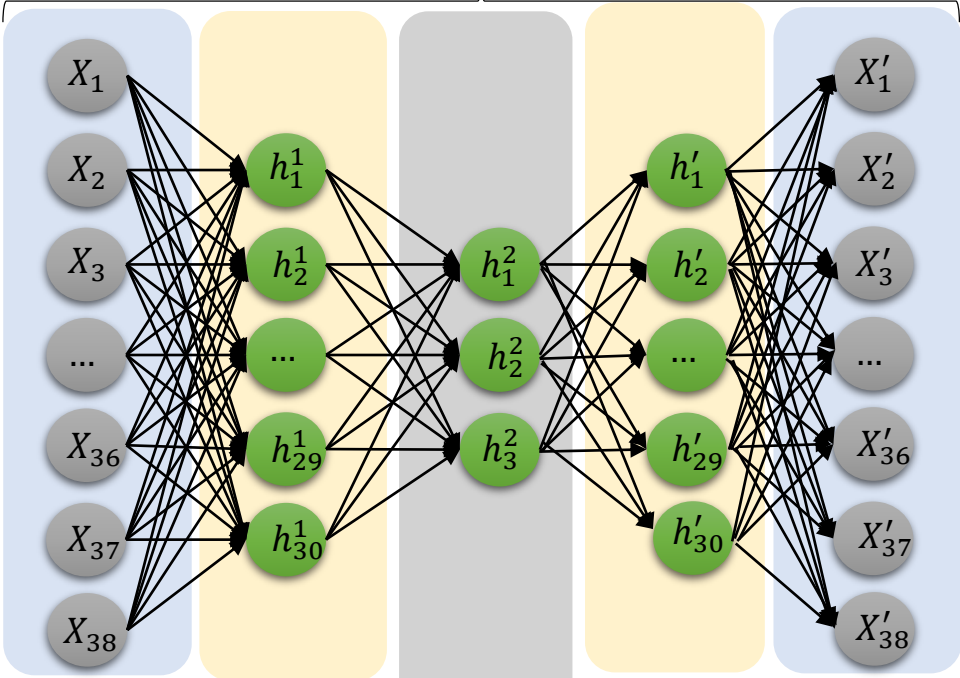
Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

A Deep Learning Model to Predict Thunderstorms within 400 Km² South Texas domains

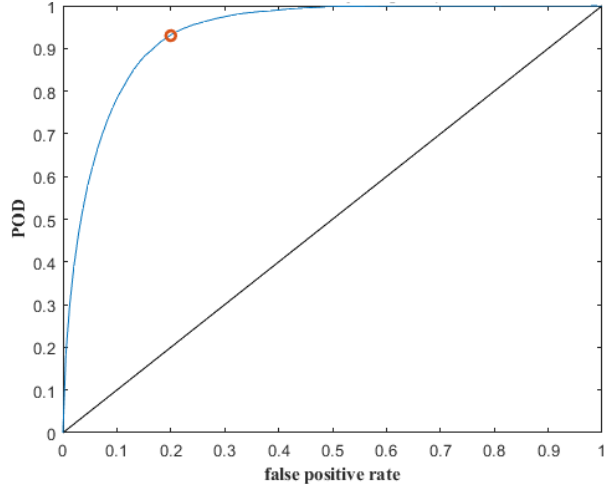
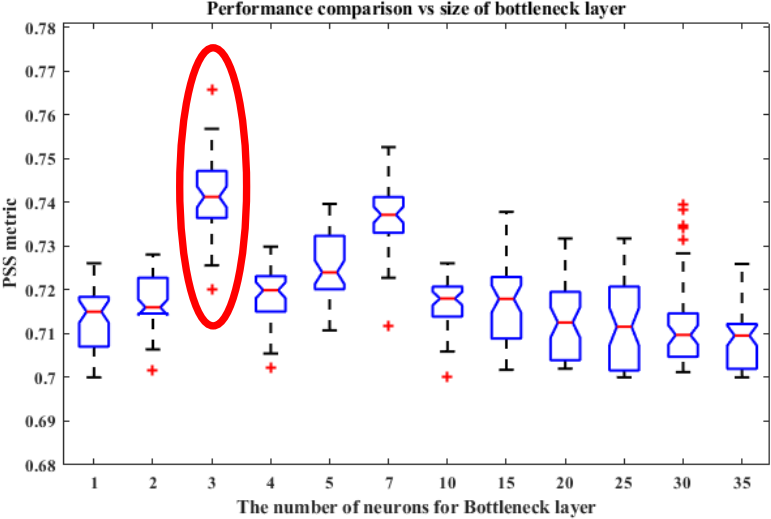


Deep Learning: Lightning Predictions

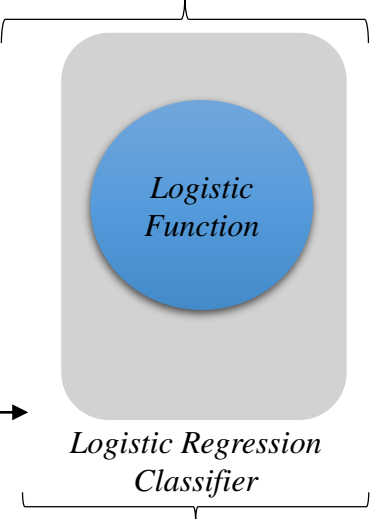
Unsupervised feature learning



Input Predictors First hidden Layer with 30 neurons Bottleneck Layer with 3 neurons Decoded of 30 neurons Decoded 38 Features



Supervised fine-tuning

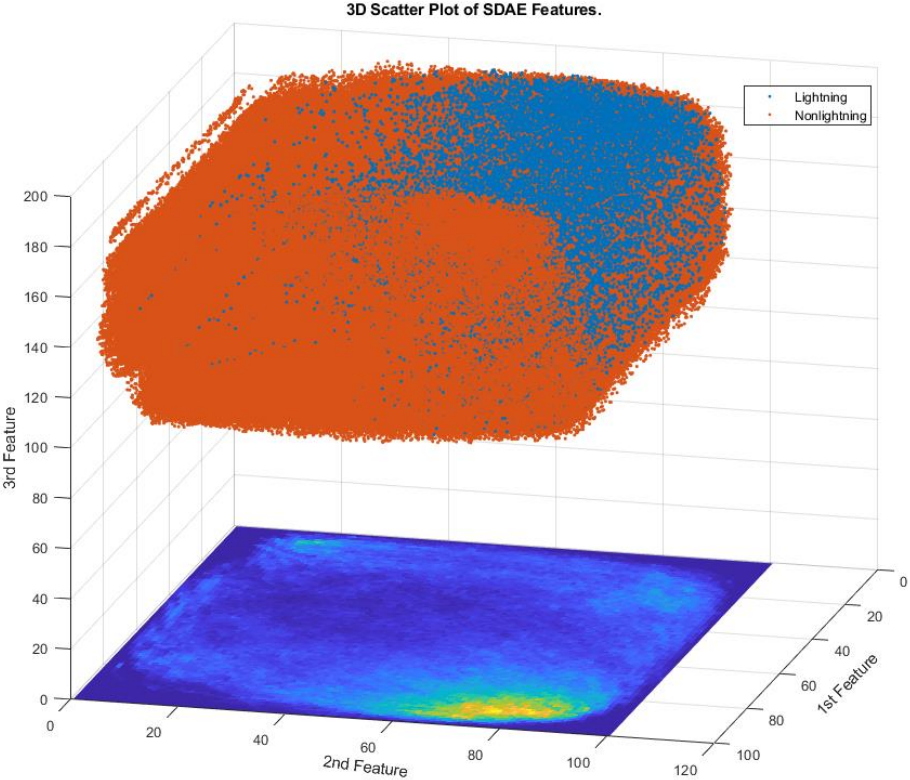


Kamangir, H., Collins, W., Tissot, P. & King, S. (2019). A Deep Learning Model to Predict Thunderstorms within 400 km² South Texas Domains". Meteorological Applications, accepted.

Collins, W., & Tissot, P. (2015). An artificial neural network model to predict thunderstorms within 400 km² South Texas domains. Meteorological Applications, 22(3), 650-665.

Dimension Reduction: PCA vs Deep Learning (SDAE)

SDAE



PCA

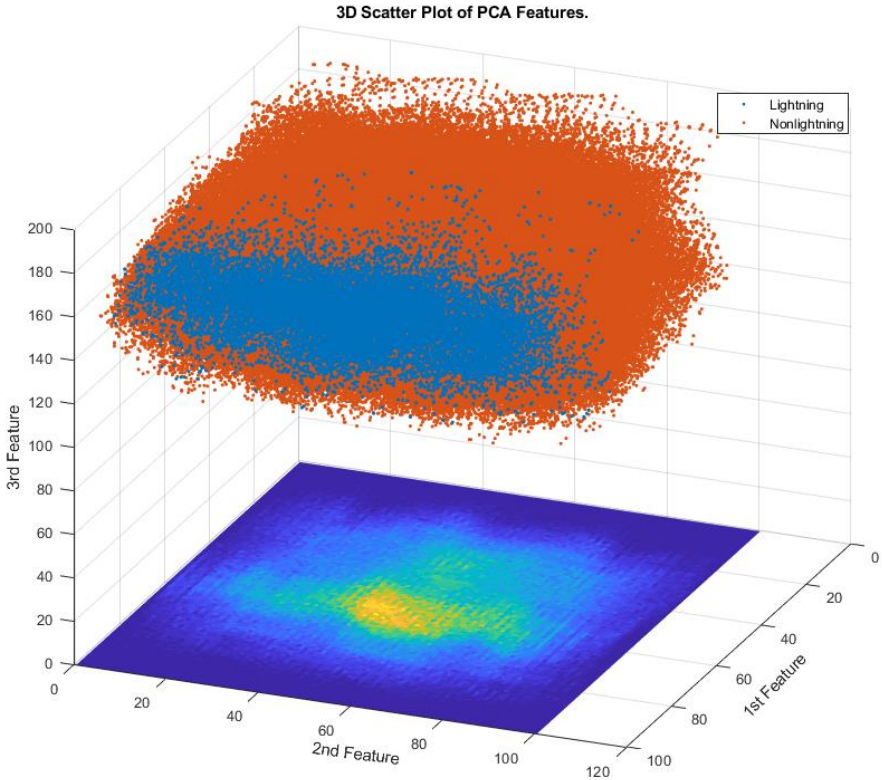


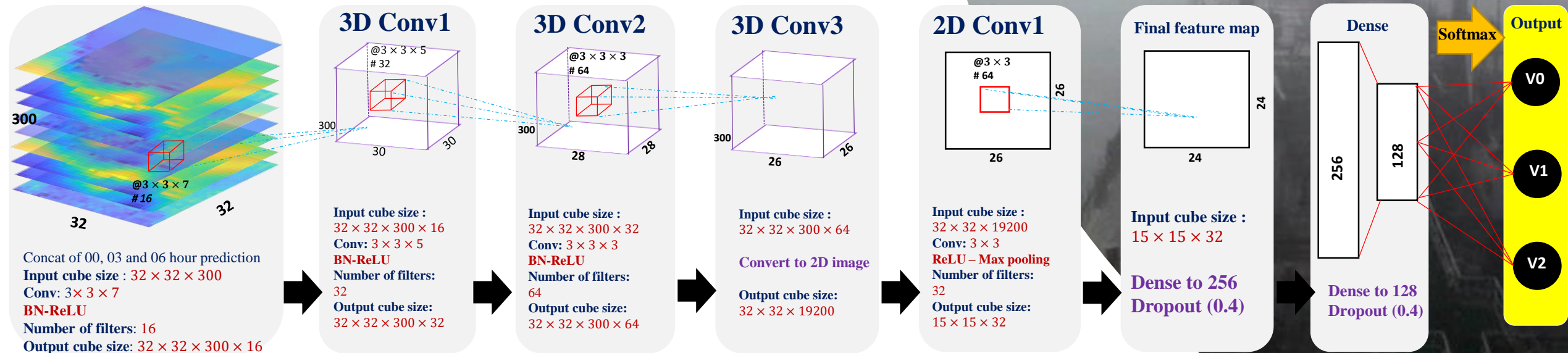
Table 8. Performance results of the deep learning neural network (SDAE) and principal component analysis (PCA) based classifiers developed in this study, the shallow neural network of Collins and Tissot, 2016 (CT2016), and the corresponding performance of the operational forecasters (NDFD) for 12hr prediction.

	POD	F	FAR	CSI	PSS	HSS	ORSS	CSS
Box 73								
SDAE	0.82	0.07	0.36	0.55	0.74	0.66	0.96	0.60
CT2016	0.86	0.29	0.90	0.10	0.57	0.12	0.88	0.09
NDFD	0.91	0.23	0.86	0.14	0.68	0.19	0.94	0.14
PCA	0.89	0.42	0.94	0.05	0.48	0.05	0.84	0.05

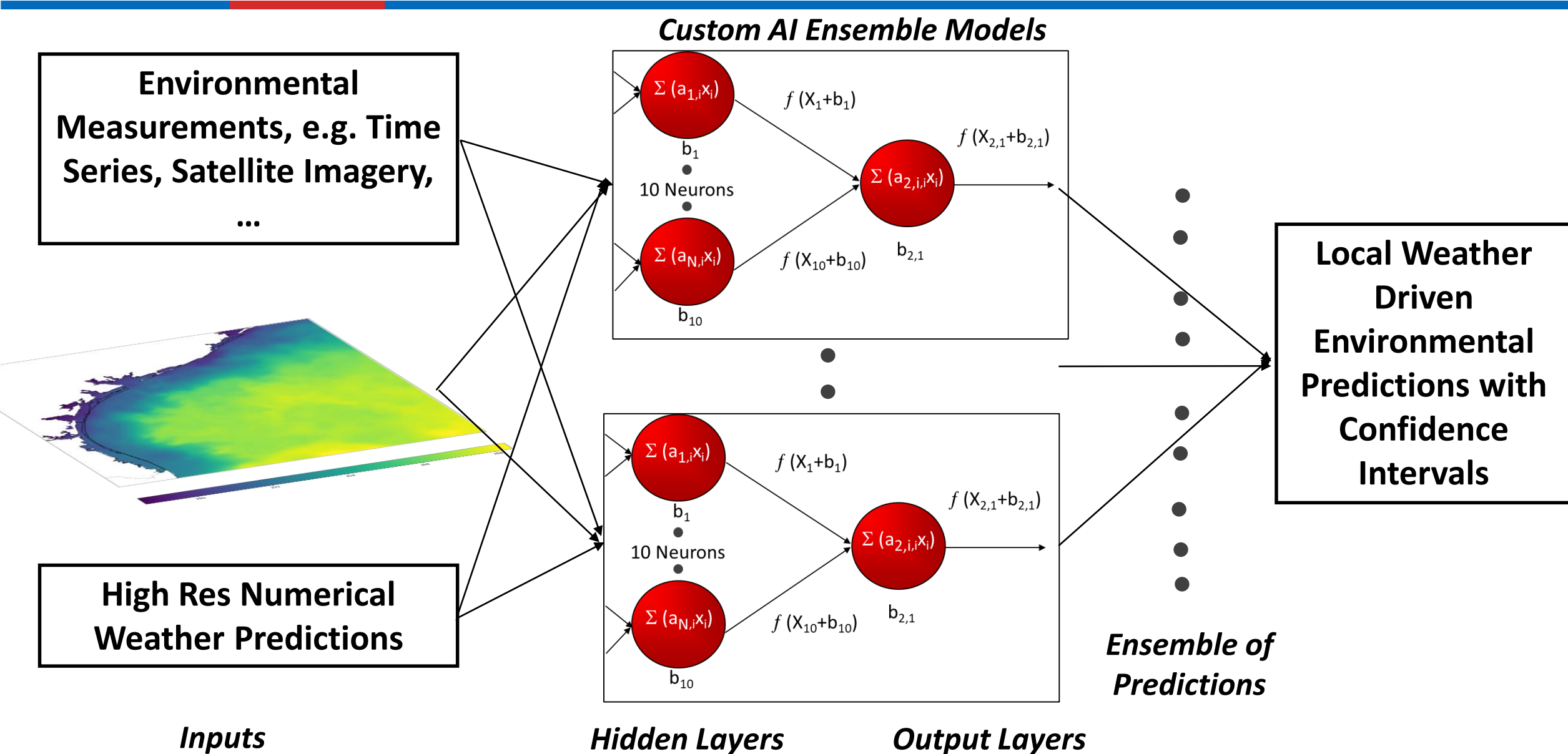
Ongoing Research : 3D CNN

Deep Learning for Marine/Port Fog Predictions:

- Develop method to combine
 - Daily SST maps
 - High frequency coastal measurements
 - Numerical weather predictions
- To predict marine advection fog
- Ongoing contracts to install visibility sensors and other instrumentation



Combining High Res NWP, Satellite Imagery & Local Measurements for Ensemble ML Predictions



Where is the Physics?

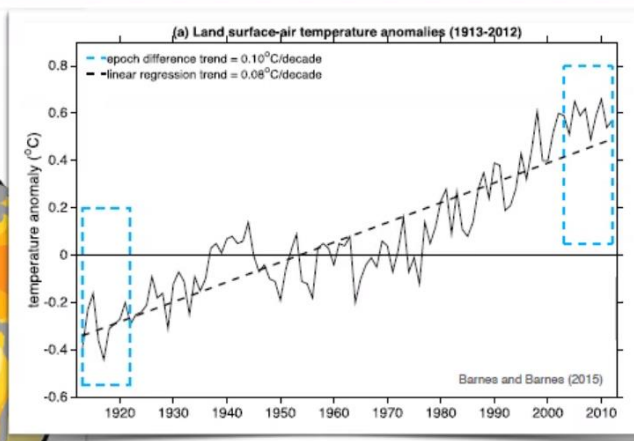
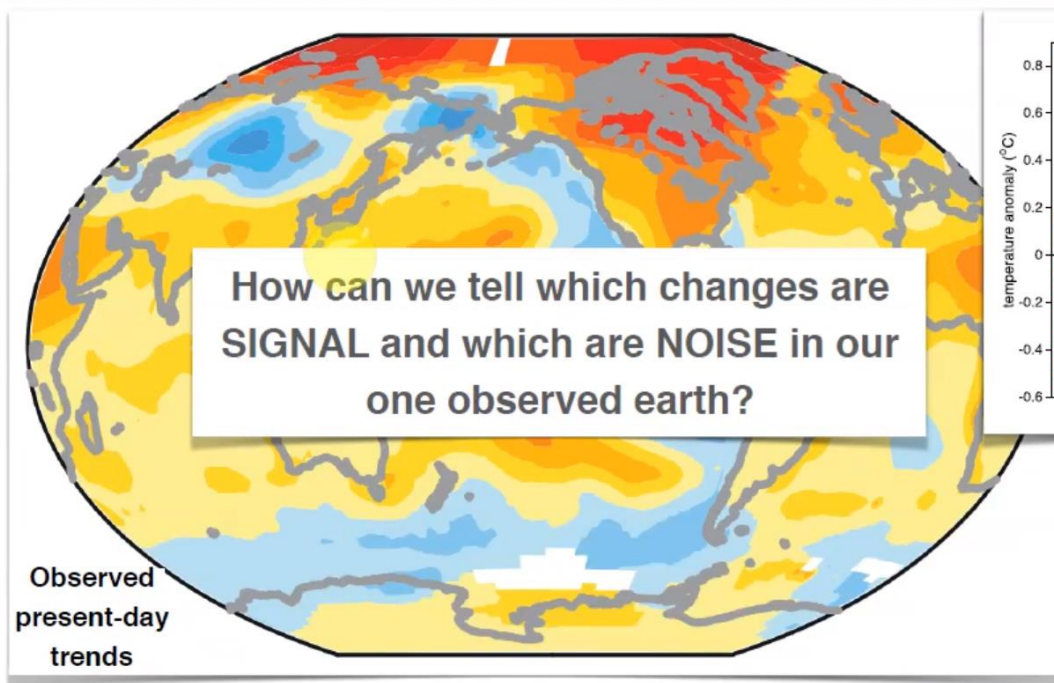
- Performance vs. interpretability
- Nonlinear systems
- incorporating domain-knowledge in model design:
 - Feature selection
 - Data set management (training – validation – independent testing)
- Physics-constrained AI
 - Include Physics in loss function: $\text{Loss Function} = \text{Training Loss} + \text{Physics Loss}$
 - Other methods being investigated

Karpatne, A., Watkins, W., Read, J., & Kumar, V. (2017). Physics-guided neural networks (pgnn): An application in lake temperature modeling. arXiv preprint arXiv:1710.11431.

Wu, J. L., Kashinath, K., Albert, A., Chirila, D., & Xiao, H. (2019). Enforcing statistical constraints in generative adversarial networks for modeling chaotic dynamical systems. arXiv preprint arXiv:1905.06841.

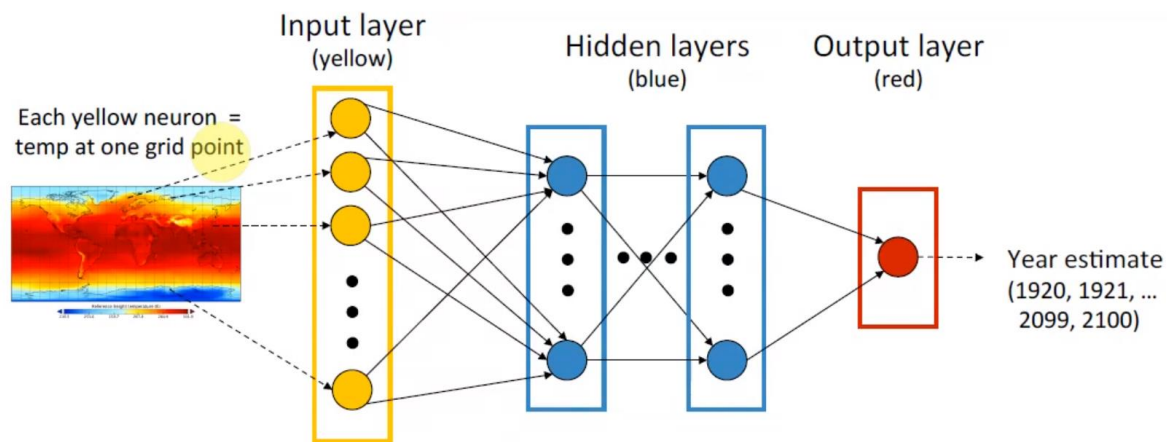
Roscher, R., Bohn, B., Duarte, M. F., & Garcke, J. (2019). Explainable Machine Learning for Scientific Insights and Discoveries. arXiv preprint arXiv:1905.08883.

Climate change in the 21st Century: a signal-to-noise problem



Example:
Elizabeth Barnes,
Ben Toms &
Imme Ebert-
Uphoff (CSU)

Train ANN to predict the year of a map



We use 2 hidden layers with 10 units each.

Barnes et al. (2019; GRL)

Kay et al. (2015)

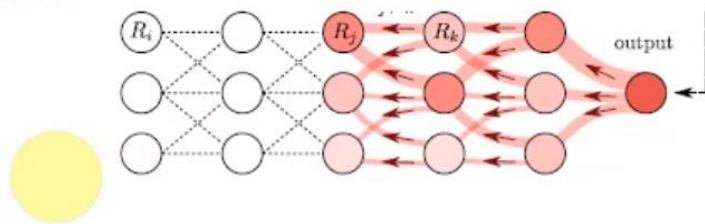
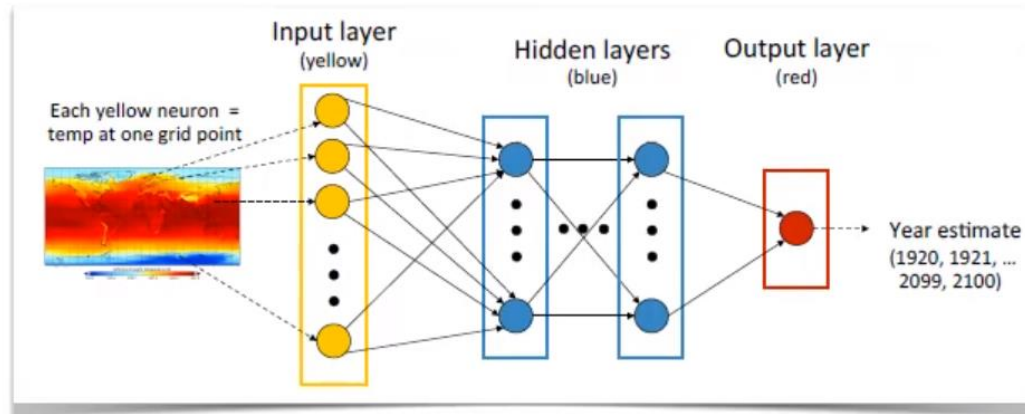
Core Science Keynote presented at
AMS AI 2020, Boston

[Viewing Climate Signals through an AI Lens,](#)
[Elizabeth Barnes et al.](#)

From Elizabeth Barnes, Ben Toms & Imme Ebert-Uphoff

AMS AI 2020, Boston

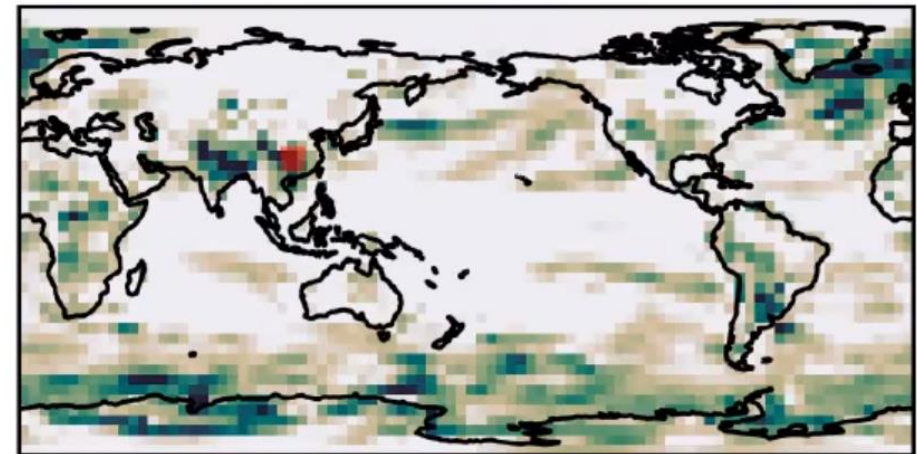
A Visualization Tool: Layer-wise Relevance Propagation



Which regions are **relevant** for correctly predicting a specific year?

Year = 2025

Relevant Regions for Predicting Year from Temperature Map



red box denotes SE Asia region of interest



Relevance

LRP for geoscience described in
Toms, Barnes & Ebert-Uphoff (2019)

Elizabeth A. Barnes

Constants – Changes ...

- **What has changed:**

- Computational Capabilities
- AI Methods
- Number of AI Practitioners

- **What has not changed much:**

- Topics Studied
- Fundamentals: Bias – Overfitting – Data Preparation – Data Management (training – validation – testing)

- **Keep in mind:**

- Fair Comparisons (e.g. new model on latest data vs existing operational model...)
- We are studying nonlinear systems: substantial part of the grey in the “boxes”

Questions/Discussion



Abstract

The field of Artificial Intelligence (AI), including applications in the environmental sciences, is evolving at an accelerating pace. Its progress has been made possible by developments in the computer sciences, the availability of larger and more comprehensive environmental data sets, and the ever-increasing availability of affordable computing power. The presentation will start with the early days of the field, including how the term was coined by John McCarthy. We will then cover the progression of the field, including its ups and downs, through a series of examples.

The American Meteorological Society AI workshops and conferences allow to track this progression. Expert systems were the method of choice in the eighties while Neural Networks took over in the nineties followed by a broadening of the methods including fuzzy logic, tree-based methods, genetic algorithms, support vector machines... At the 2019 and 2020 AMS AI conferences deep learning became by far the method of choice with 36% and over 50% of the presentations based on this new method. We will trace back this explosive growth to its roots including Imagenet, AlexNet and the importance of the datasets in a sense driving the development of these methods.

While the AI methods have changed considerably over the years, the topics not so much. The first AMS AI conference in 1998 included talks on precipitation predictions, satellite retrieval and pattern recognition, climate classification and prediction, image processing, decision aids and natural language systems. We will introduce selected environmental applications and methods developed at the Conrad Blucher Institute (CBI) to provide local operational predictions including for water levels, coastal flooding and a model designed and implemented to predict the cold stunning of sea turtles. These methods combine real-time environmental measurements and numerical weather predictions, typically from NOAA, as the predictors to different types of AI models.

We are expecting the fast growth of AI/ML to continue and as the method is becoming one of the main approaches to better predict and gather a deeper understanding of a wide variety of complex and nonlinear processes in the earth sciences. The presentation will conclude with the introduction of some of the present AI related research questions such as the quantification of uncertainties, interpretability, incorporating domain-knowledge in model design and the further potential for AI applications in the environmental sciences

Philippe Tissot

Philippe Tissot is the Interim Director of the Conrad Blucher Institute and an Associate Research Professor at Texas A&M University-Corpus Christi. For the past 20 years, his research has focused on the development of artificial intelligence methods and other models for the analysis and predictions of environmental systems and coastal physical processes. Projects have included the development and implementation of predictive models supporting navigation and coastal management. Other studies have included the modeling and impact of relative sea level rise and storm surge, the spatial variability of subsidence at the regional scale, tidal studies and local hydrodynamic models. His team's models have been used for over a decade for the prediction of cold stunning of sea turtles allowing to interrupt navigation ahead of these events and other preparation by local stakeholders. Other work has included ML predictions of thunderstorms and the development of ML algorithms to take advantage of 3D point clouds of marsh environments and urban runoff water quality modeling. Dr. Tissot has authored or co-authored over 40 peer reviewed articles, 200 proceedings, abstracts and technical presentations, a Physical Science textbook for future K-12 teachers, and 2 US Patents. Professor Tissot is a member and former chair of the American Meteorological Society Committee on Artificial Intelligence Applications to Environmental Science.