Artificial Intelligence for Tropical Meteorology: Challenges and Opportunities

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AI for Good – March 8th, 2023


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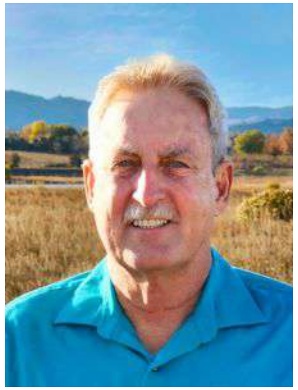
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A **huge** thank you to our many contributors and collaborators!

<u>Tropical Cyclones</u>: Rotating, (warm-core) organized system of clouds that has a closed low-level circulation of air

Video source 1 = https://www.youtube.com/watch?v=Fw8VWSn9Lps&ab_channel=Denver7

<u>Definitions:</u>
AMS Glossary of Meteorology
<u>Video source</u>:
Denver7,
with materials from CIRA & NOAA

Video source 2 =
https://www.youtube.com/watch?v=al8yTiCVfro&ab_channel=MaxOlsonChasing ,
Video source 3 =
https://www.youtube.com/watch?v=3vF4fCoRwH0&ab_channel=KHOU11,
Hurricane Ian flooding: Water rises in Central Florida | Raw video, KHOU 11

Storm surge triggered by hurricane Ian (FL, USA)
Video source: Max Olson Chasing

Video source: NOAA
&

Dynamical forecasting: Integrate equations of motion on a rotating sphere to predict the weather

$$\frac{\partial}{\partial t}\left(\frac{\partial p}{\partial \eta}\right) + \nabla \cdot \left(\mathbf{v}_{\mathrm{H}} \frac{\partial p}{\partial \eta}\right) + \frac{\partial}{\partial \eta}\left(\dot{\eta}\frac{\partial p}{\partial \eta}\right) = 0$$

$$\frac{\partial U}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial U}{\partial \lambda} + V\cos\theta\frac{\partial U}{\partial \theta}\right\} + \dot{\eta}\frac{\partial U}{\partial \eta} - fV + \frac{1}{a}\left\{\frac{\partial \phi}{\partial \lambda} + R_{\mathrm{dry}}T_{\mathrm{v}}\frac{\partial}{\partial \lambda}(\ln p)\right\}$$

$$\frac{\partial V}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial V}{\partial \lambda} + V\cos\theta\frac{\partial V}{\partial \theta} + \sin\theta(U^2+V^2)\right\} + \dot{\eta}\frac{\partial V}{\partial \eta} + fU + \frac{\cos\theta}{a}\left\{\frac{\partial \phi}{\partial \theta} + R_{\mathrm{dry}}T_{\mathrm{v}}\frac{\partial}{\partial \theta}(\ln p)\right\}$$

$$\frac{\partial T}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial T}{\partial \lambda} + V\cos\theta\frac{\partial T}{\partial \theta}\right\} + \dot{\eta}\frac{\partial T}{\partial \eta} - \frac{\kappa T_{\mathrm{v}}\omega}{(1+(\delta-1)q)p}$$

$$\frac{\partial q}{\partial t} + \frac{1}{a\cos^2\theta}\left\{U\frac{\partial q}{\partial \lambda} + V\cos\theta\frac{\partial q}{\partial \theta}\right\} +$$

Source: IFS Documentation cy47r3

Statistical forecasting: Use past observations for prediction

Dynamical forecasting: Integrate equations of motion on a rotating sphere to predict the weather

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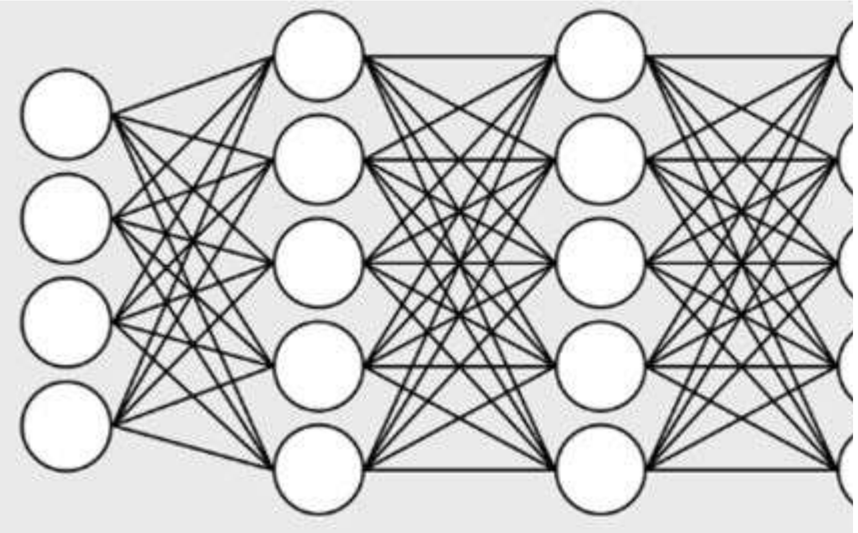
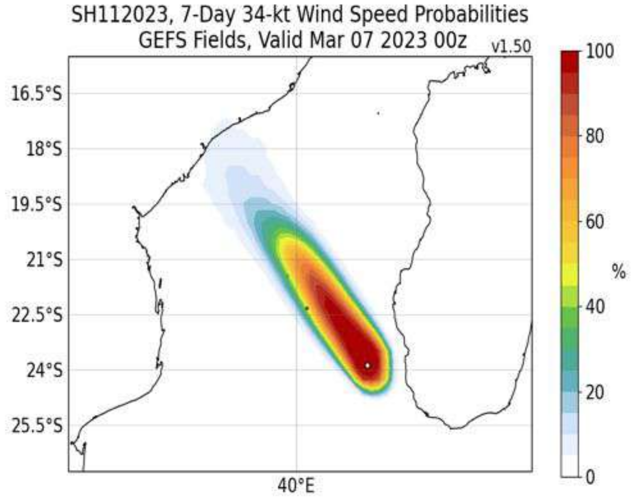
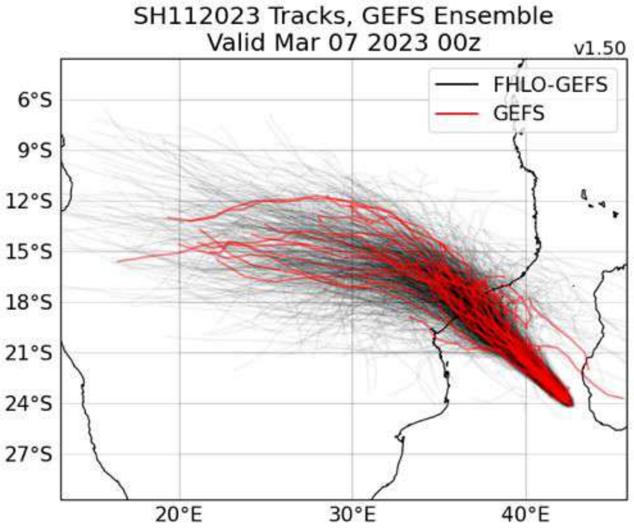
Source: IFS Documentation cy47r3, Windy (Mar 7, 2023)

Statistical forecasting: Use past observations for prediction

Model Output Statistics: Links dynamical forecasts to obs. using statistics







Dynamical forecast

Statistical model

Hybrid forecast

Source: IFS Documentation cy47r3, Windy (Mar 7, 2023),
American Meteorological Society Glossary of Meteorology, FHLO (Emanuel 2017; Lin et al., 2020)

Challenges of Statistical Forecasting Specific to Tropical Meteorology

- Rarity of extreme events ↔ Data quality/scarcity
  - TCs are temporally rare and spatially rare
  - In situ observations (sondes, radar) are hard to get
  - We can (and do) use satellite data but it's hard to get the information we need at the scales we need (a few km spatially, 1 km or less vertically to know what clouds are doing, and new information every few hrs or less when landfall is close)

- Complexity of physics ↔ Anticipate TC response to changes in environment
  - TCs are governed complex fluid thermodynamics and dynamics:
    - Rotating vortex on a rotating sphere, with big impacts from boundary layer between air/ocean
    - Thermodynamics (phase changes, cloud physics, rain, lightning) can impact dynamics

Opportunities brought by Machine Learning

1) Improvement in prediction quality (algorithms, optimization)

2) Improvements in understanding (new spatiotemporal connectivities, nonlinearities, predictors, etc.)

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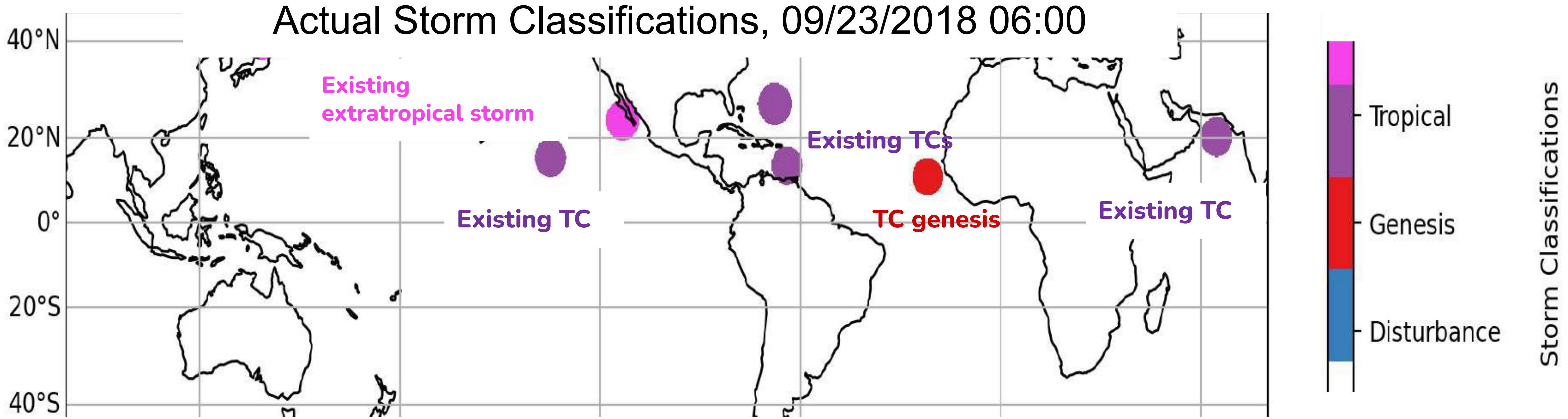
i) Can we use machine learning to predict tropical cyclone formation (**tropical cyclogenesis**)?

- Existing statistical products mostly based on **linear algorithms** [e.g. Schumacher et al. 2009]) (can suffer from **false alarms**)
- Recent success at forecasting tropical cyclogenesis with ML on very short timescales (couple of hours) [e.g., Zhang et al 2019, Kim et al. 2019]

- **Q1:** Can we use machine learning models with existing statistical products to **improve tropical cyclogenesis forecasting**?
- **Q2:** How can we adapt and leverage machine learning models to better deal with **rare events**?

Simple ML-based tropical cyclogenesis models skillfully predict TC genesis at up to 12 hrs, with fewer false alarms.



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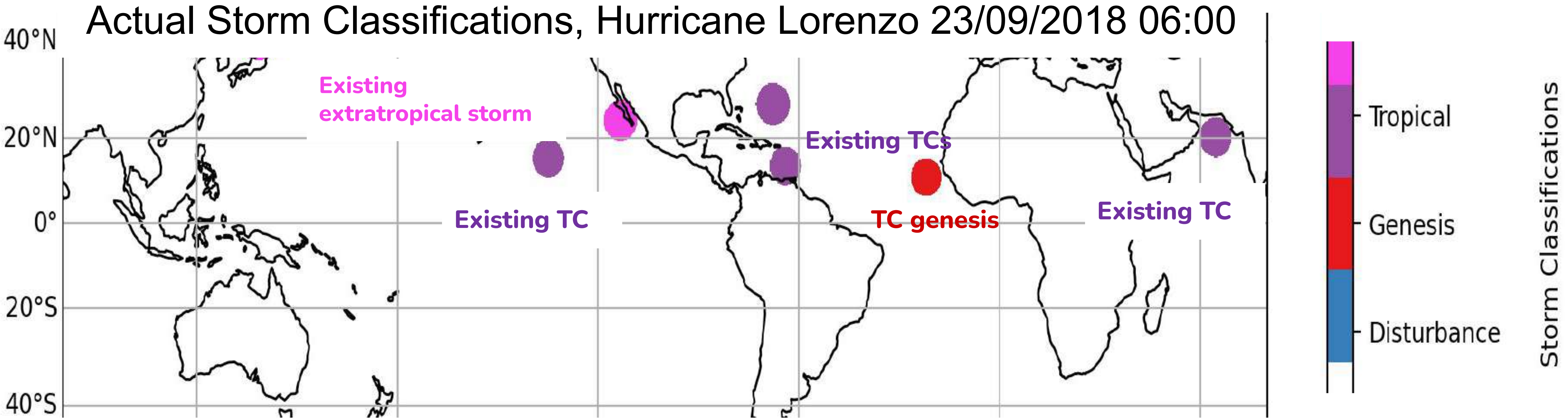

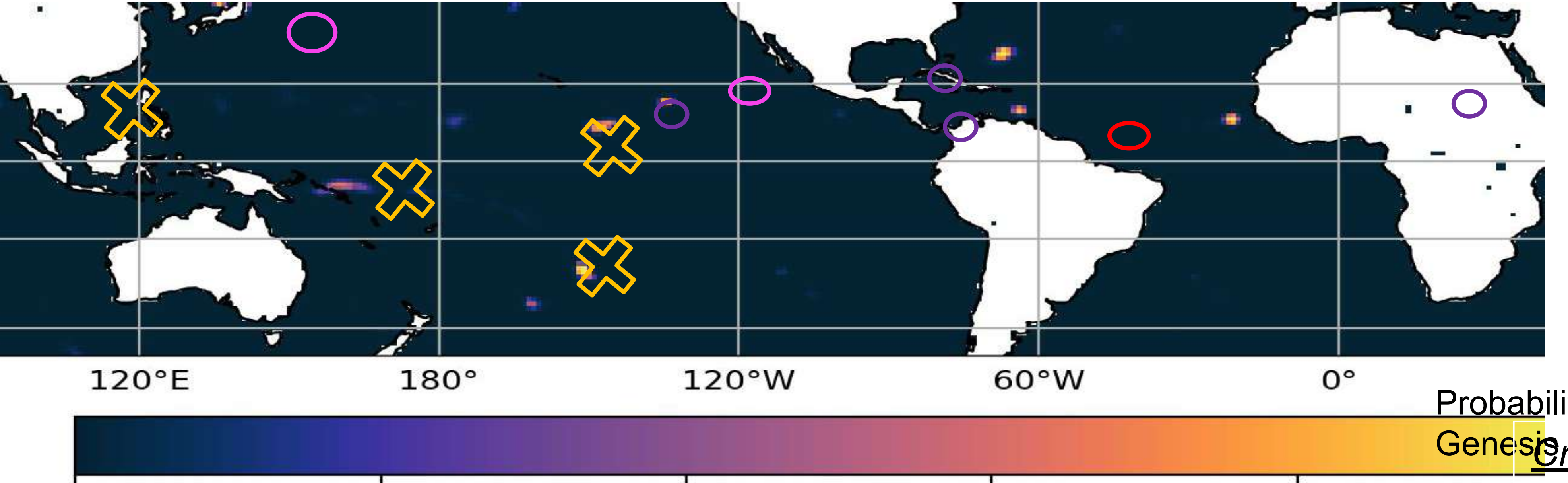

Current model (linear) 6-hr forecast for 23/09/2018 06:00

Credit: Marshall Baldwin, OU

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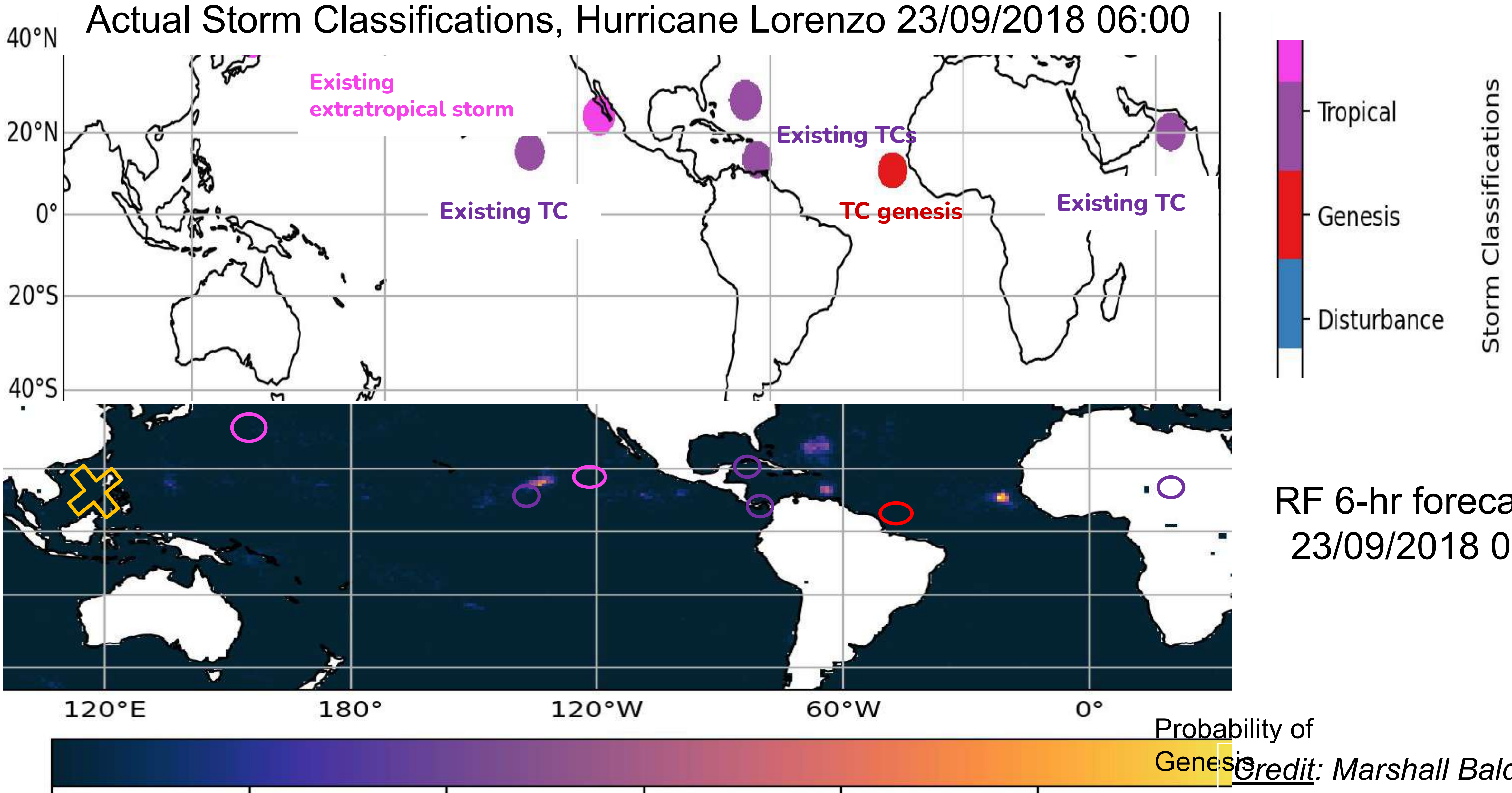

RF 6-hr forecast for 23/09/2018 06:00

Credit: Marshall Baldwin, OU

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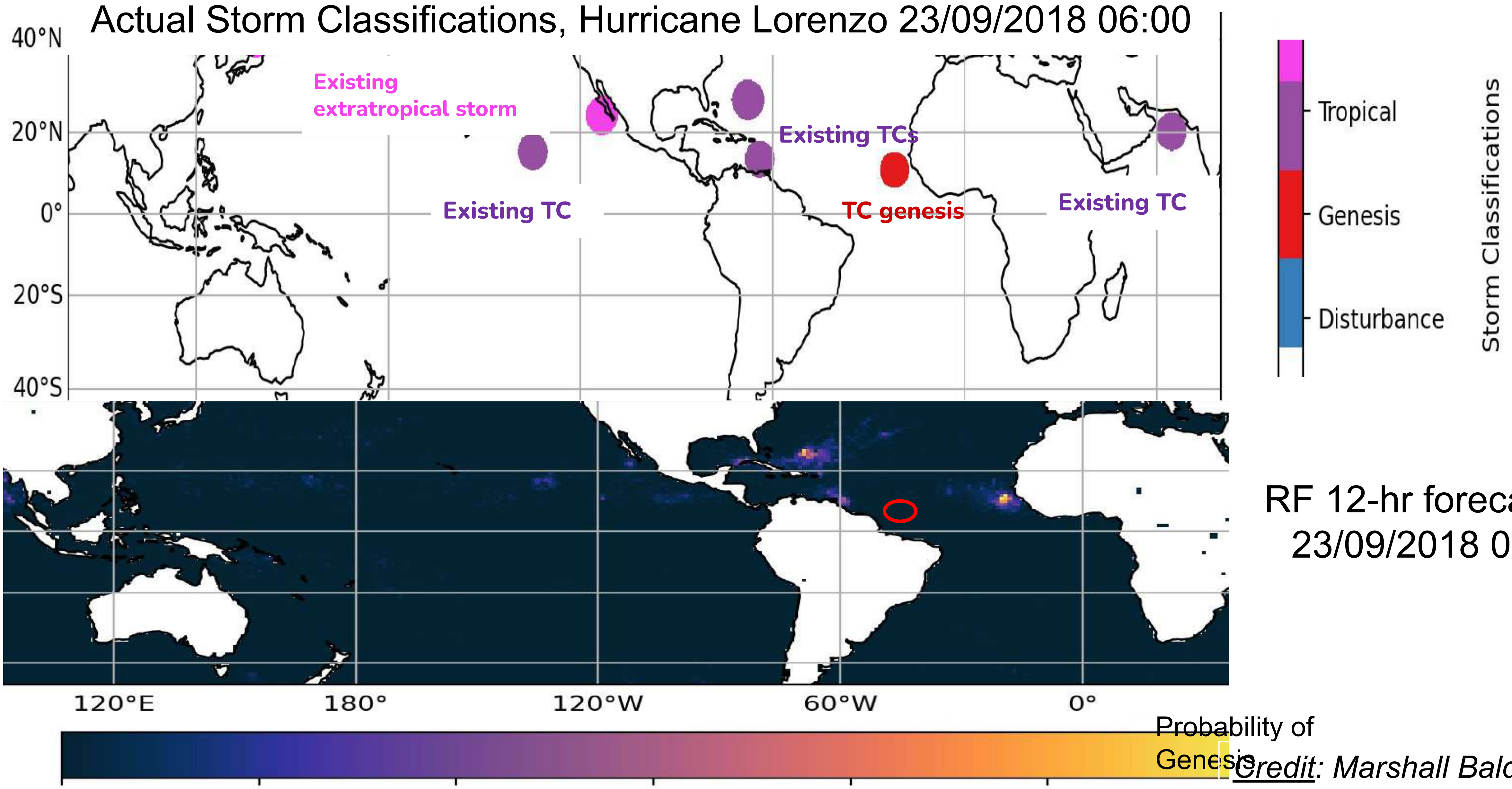

RF 12-hr forecast for 23/09/2018 06:00

Credit: Marshall Baldwin, OU

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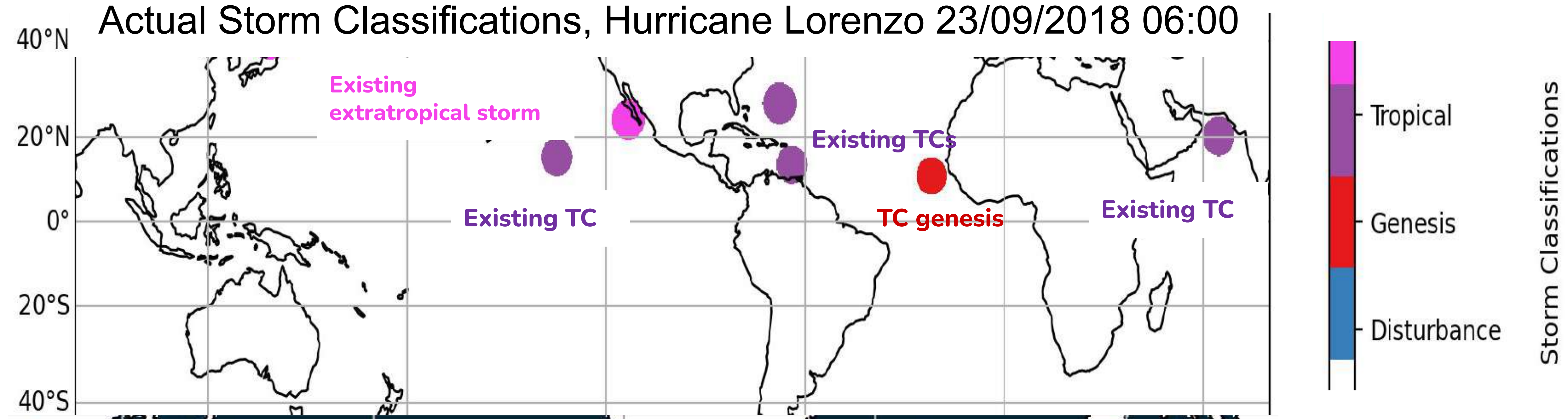

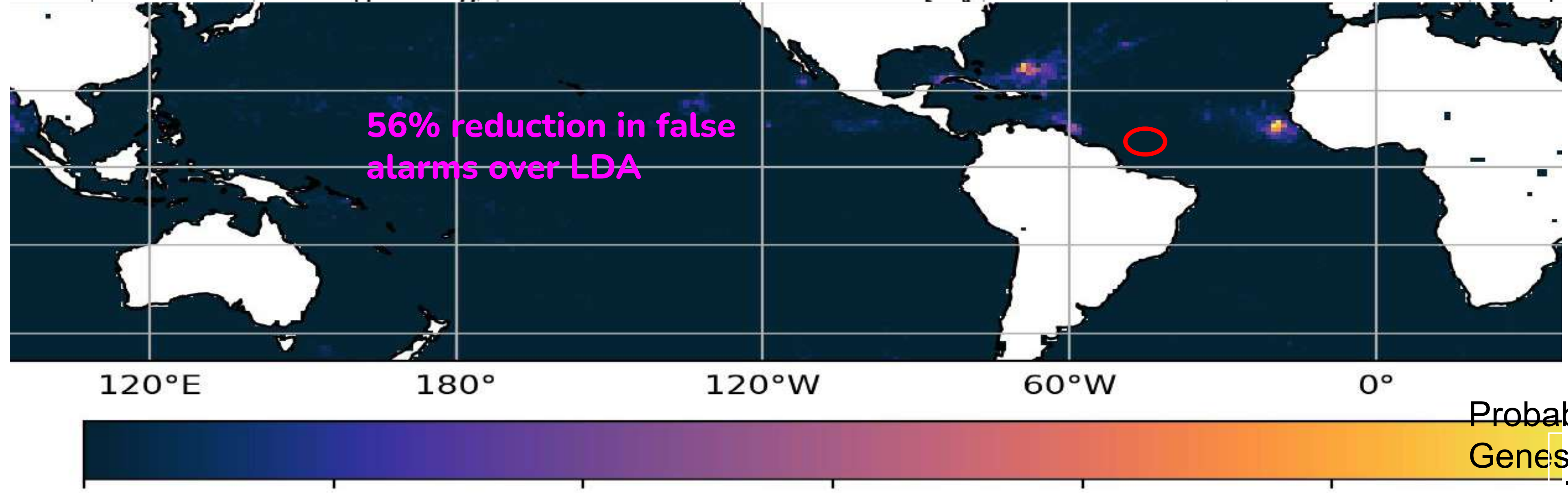

RF 12-hr forecast for
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Problem 2: Tropical cyclogenesis is a **rare event**, and making skillful predictions of rare events is difficult.

- Most of the time (less than **0.1% of the time**), a tropical cyclone is NOT forming→we have an **imbalanced dataset**

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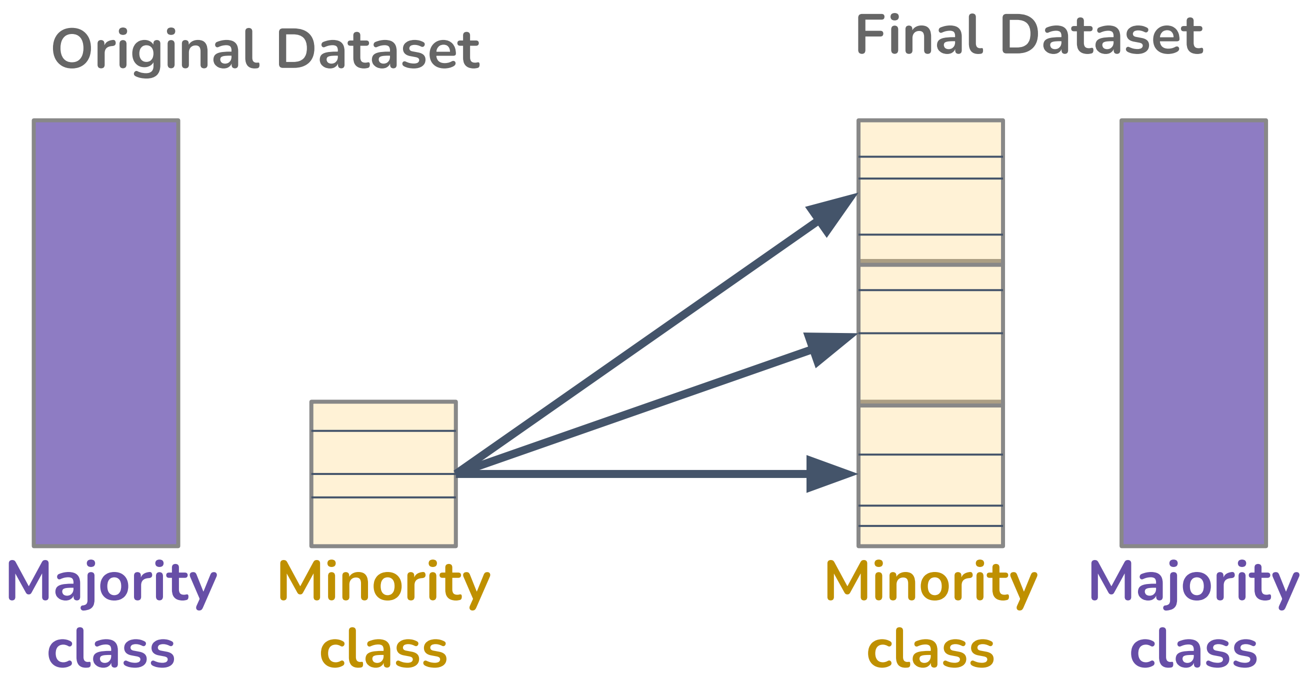
  - **Oversampling**



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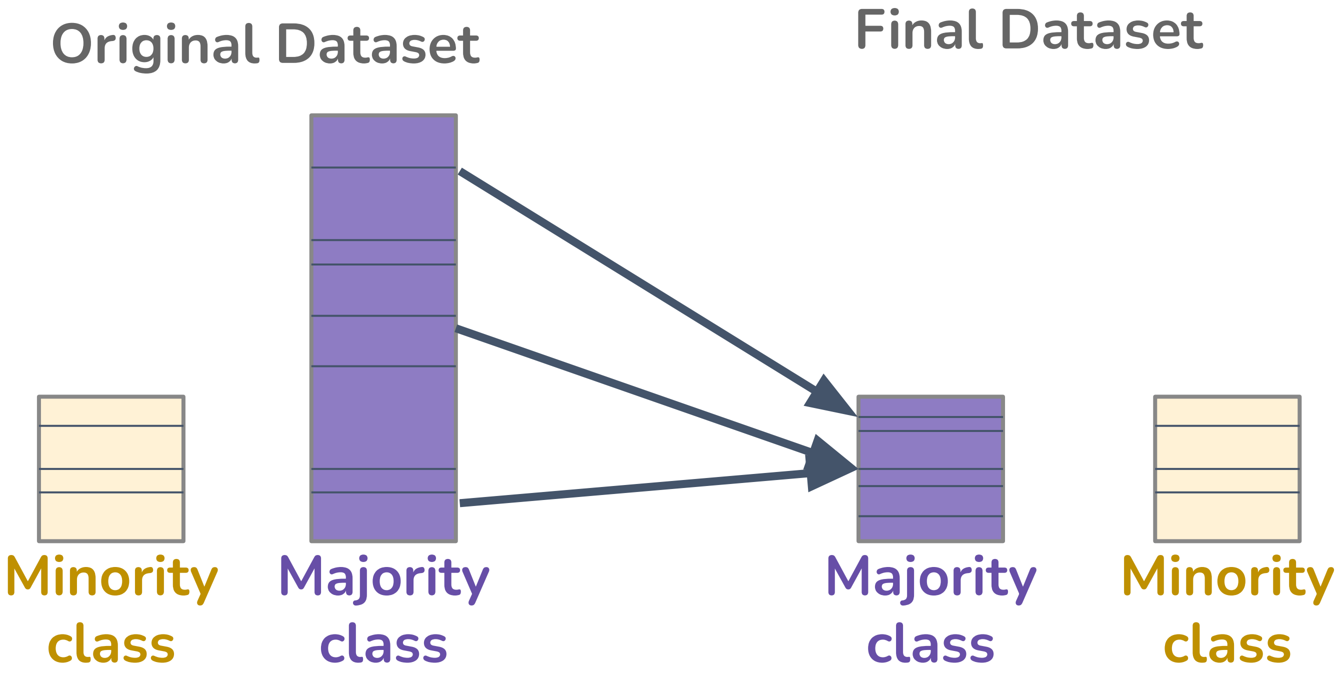

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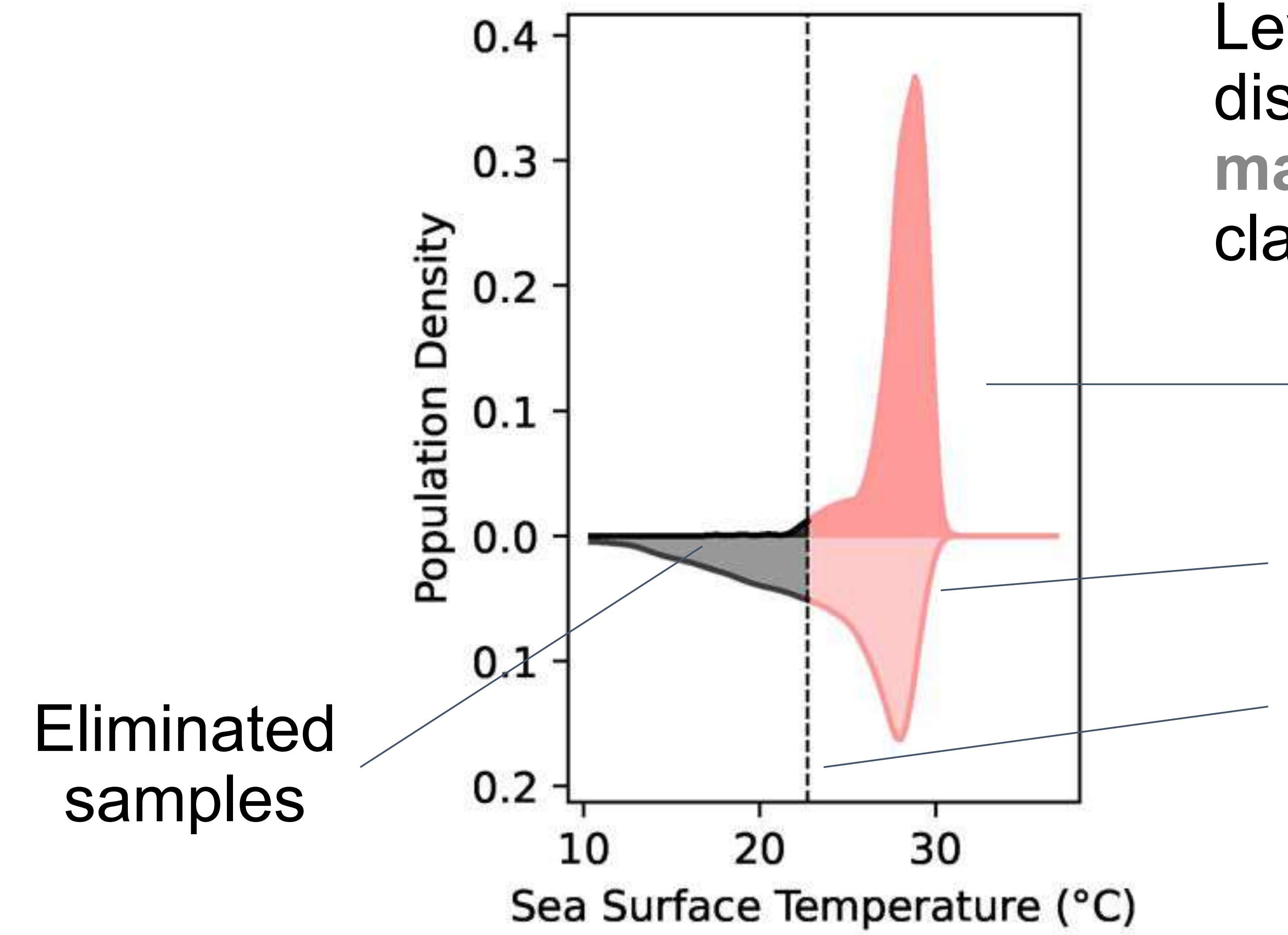
- **Problem:** Can't re-balance the data at test time, meaning we need to re-adjust the probabilities at test time (difficult)
- **One solution**: use data-driven thresholding to reduce class imbalance **BEFORE** we make our predictions.
  - Examine PDF of each feature and look for thresholding criteria to reduce class imbalance;
  - **Advantages:** can be done at test time; thresholds are **interpretable** (and often, can be evaluated in the context of domain knowledge)

Credit: Milton Gomez, UNIL

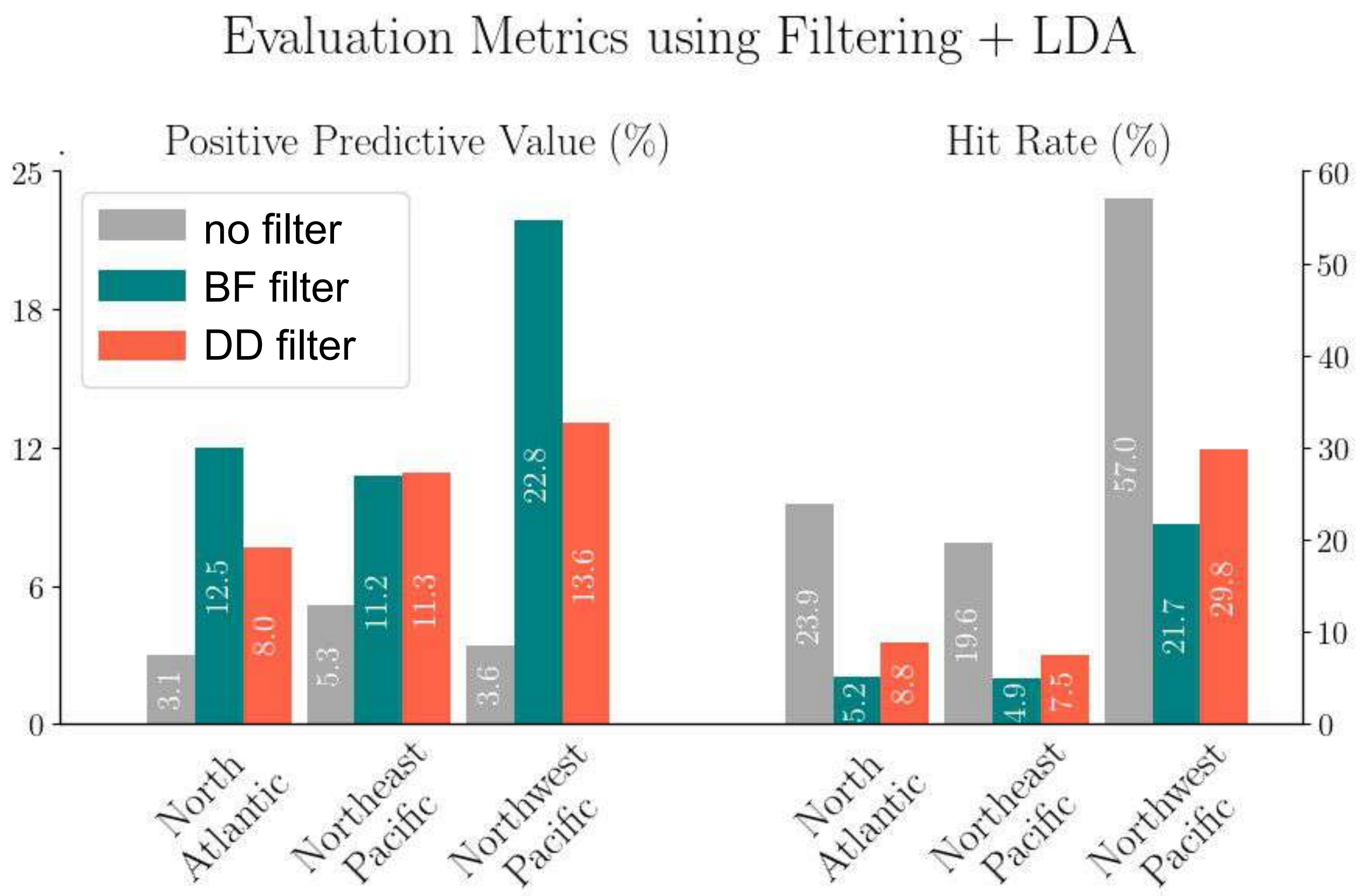
Thresholding criteria based on sea surface temperature–no cyclogenesis in cold SSTs.



Leverage labels to distinguish between the **majority** and **minority** classes

<u>Credit</u>: Milton Gomez, UNIL

Data-driven thresholding improves HR without compromising FAR



No filter: statistical tropical cyclogenesis predictive model with **no** filtering

BF filter: existing statistical tropical cyclogenesis predictive model (uses a **brute force filter**)

DD filter: statistical model with the addition of data-driven filtering

Data-driven filtering has higher positive predictive value than **unfiltered model** and a higher hit rate than **BF filter**

Credit: Milton Gomez, UNIL

Opportunities brought by Machine Learning

1) Improvement in prediction quality (algorithms, optimization)
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ii) Using Machine Learning to Improve Forecasts of TCs

- Current **statistical forecasting models** make **skillful forecasts** of tropical cyclone intensity on par with explicitly physics-simulating models
  - **Statistical TC intensity forecasts:** based on environmental conditions (winds, ocean, etc) and **persistence** (what has the storm been doing in the past 12-24 hours?)
  - **Current algorithms:** based on simple models, like linear discriminant analysis

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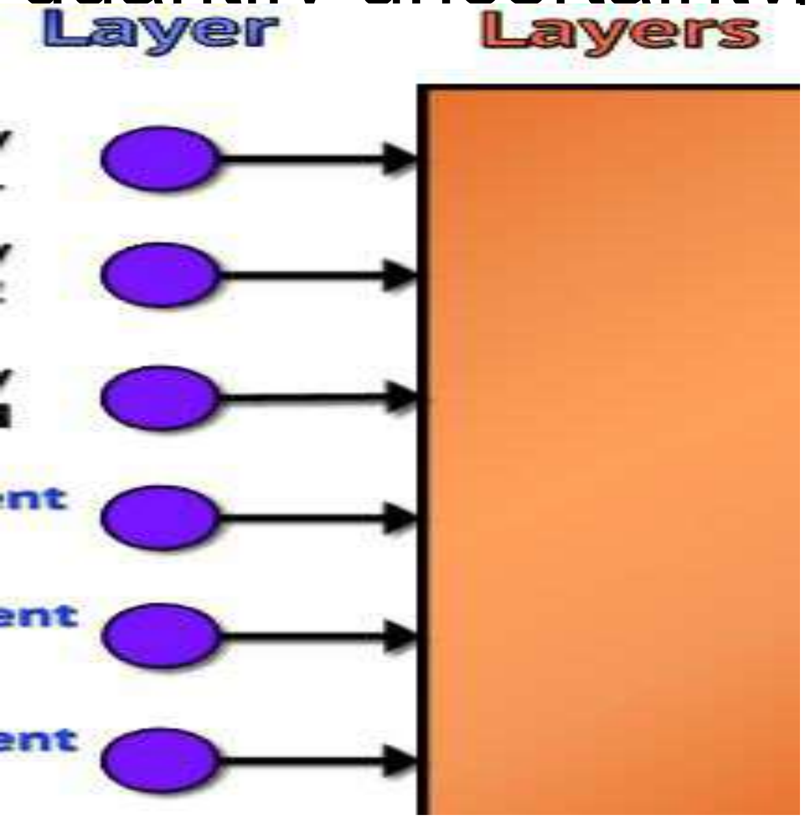
- Recent studies have used neural networks to classify TC intensity based on satellite imagery [e.g., Wimmers et al. 2019, Chen et al. 2019, Zhang et al. 2020, Wang et al. 2021]

ii) Using Machine Learning to Improve Forecasts of TCs…Including Uncertainty

- **Q1:** can we train a skillful AI-based TC prediction model on the datasets used to produce the **existing statistical forecasts**?
  - Computationally efficient
  - Easier transition into **operational forecasting**
  - (in progress) Compatible with eXplainable AI (XAI) tools
- **Q2:** in addition to a **central prediction** of TC intensity, can we predict the **uncertainty** around our central prediction?

Neural networks can be designed to predict TC intensity **distributions** in addition to a central prediction, letting us quantify uncertainty.



μ = mean
σ = scale (variance)
γ = skewness
τ = tail

- **Inputs: existing TC intensity models** as well as **environmental predictors** included in existing models

- NN predicts **mean** (central value), **variance**, and (optional) **skewness** and **tailweight–**we use these values to construct a **probability distribution**

- Model everything using a **sinh-arcsinh distribution** (more general than a normal distribution)

- **NOTE:** can use whatever distribution you want but must define it *a priori*

Barnes et al. (2022)

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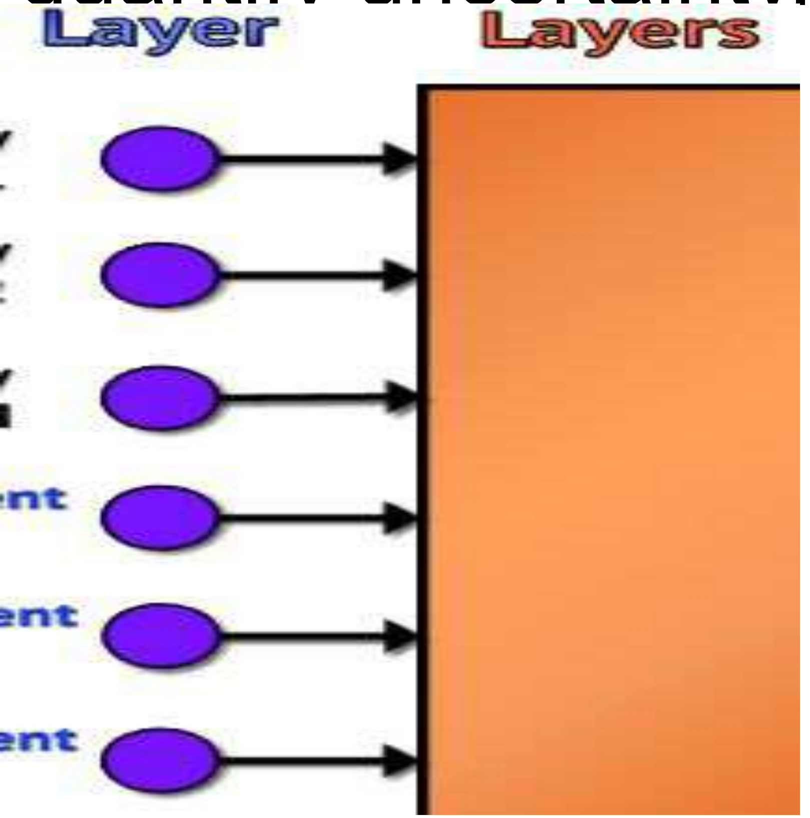

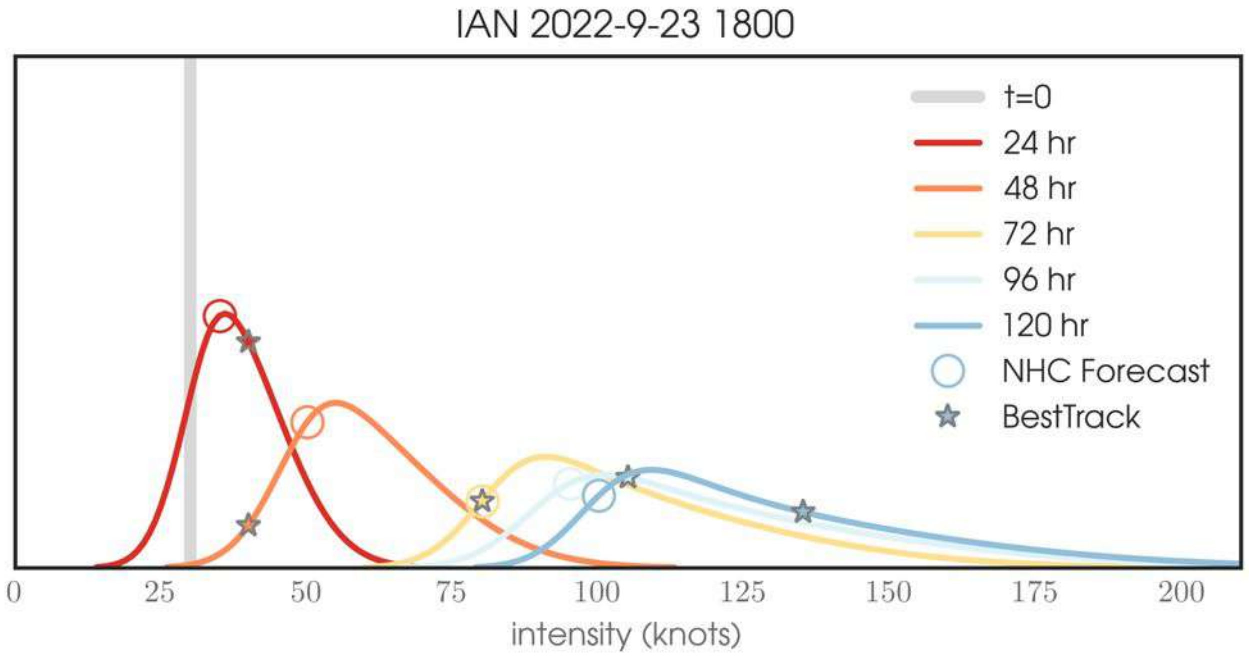

Example of 1 through 5 day intensity forecasts made by the neural network (left) for Hurricane Ian. Stars indicate the best-track intensity forecast, adjusted at the end of the season (our “truth”), while open circles indicate the real-time intensity forecasts made by the NHC.

μ = mean
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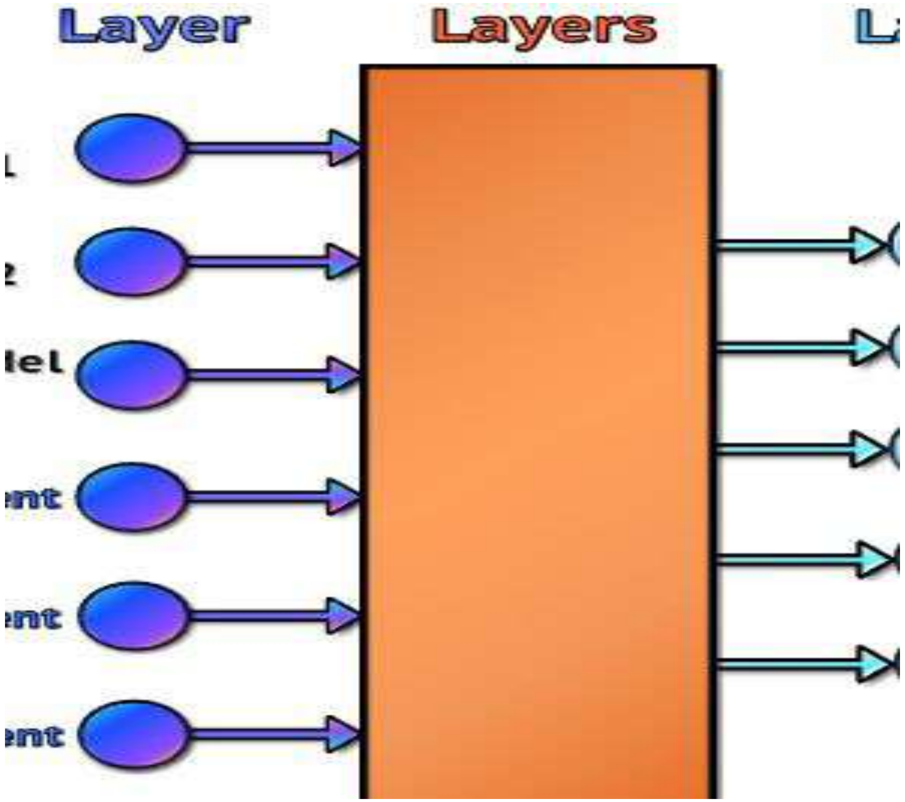
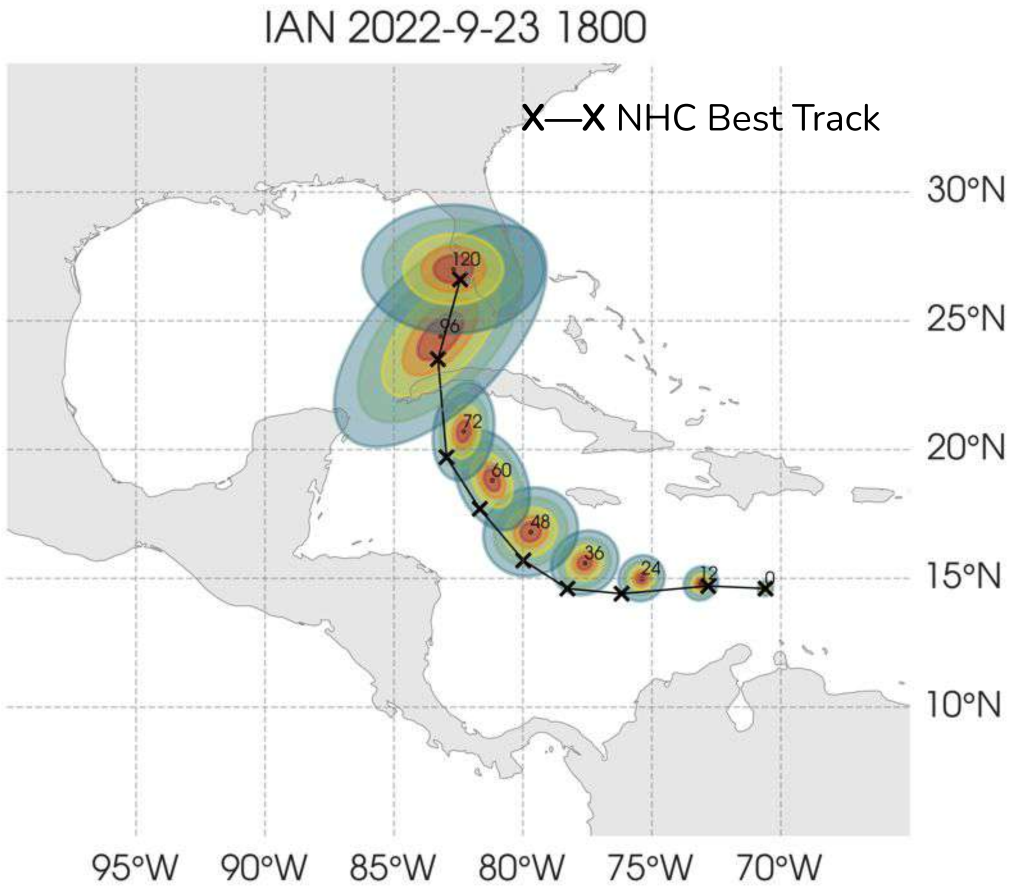
Barnes et al. (2022)

A similar NN architecture can be used to make forecasts of TC track, and the uncertainty around the track in both directions.



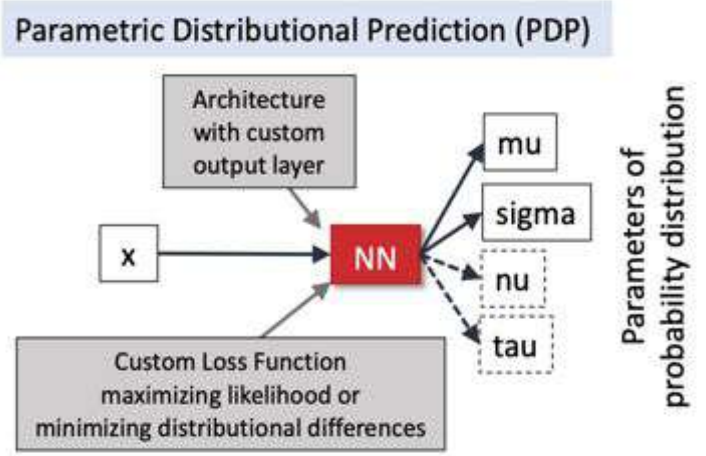


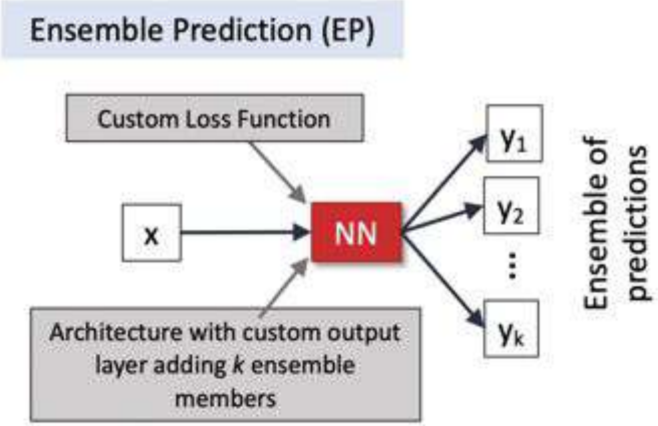
μ_x , μ_y = forecast biases in the x,y directions
σ_x ,σ_y = standard deviations of x and y errors
$\rho(x,y)$ = correlation of x and y errors

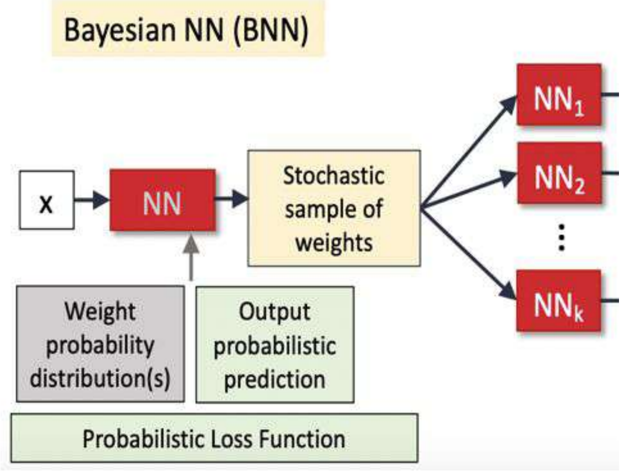
Example of 1 through 5 day track forecasts made by the neural network (left) for Hurricane Ian. Xs indicate best-track; shading indicates uncertainty around track forecast.

Barnes et al. (2022); DeMaria et al (2023)

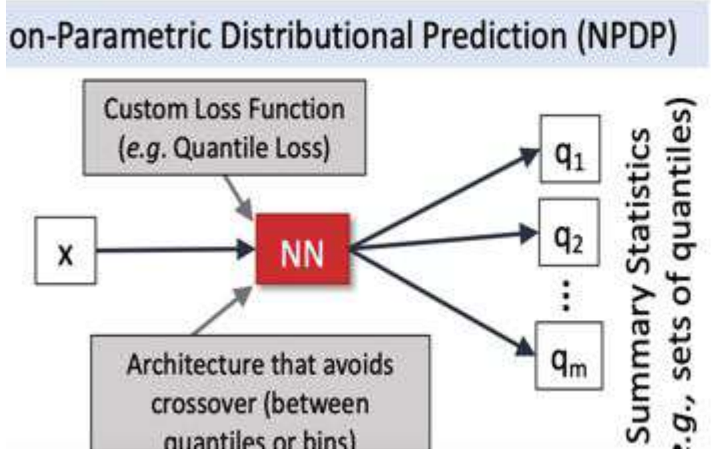
Quantifying uncertainty is critical for weather and climate prediction–no one size fits all method

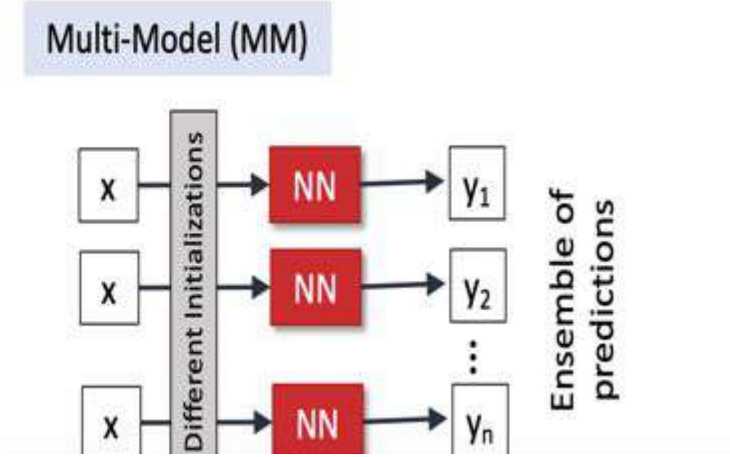


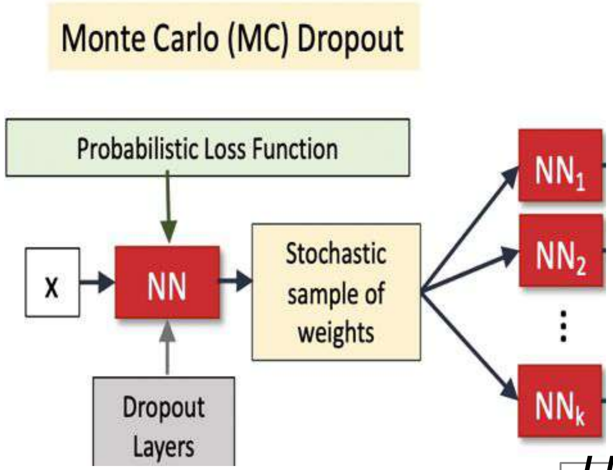




Ensemble of deterministic predictors (probabilistic predictions)







Ensemble of deterministic predictors (probabilistic predictions)

Haynes et al. (2023)

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Parametric Distributional Prediction (PDP)

Examples: NNs for ensemble post-processing of weather forecasts (e.g., Rasp and Lerch 2018), estimating TC intensity (Barnes et al. 2022), atmospheric river prediction (Chapman et al. 2022)

probability distribution

Ensemble Prediction (EP)

Examples: Custom loss functions based on continuous rank probability score (CRPS) (e.g., Scheuerer et al. 2020, Chapman et al. 2022)

predictions

members

Bayesian NN (BNN)

Examples: Bayesian NNs and precipitation detection (Orescanin et al. 2021), Bayesian NNs for satellite datasets (Ortiz et al. 2022)

Probabilistic Loss Function

Ensemble of deterministic predictors (probabilistic prediction)

Non-Parametric Distributional Prediction (NPDP)

Examples: Quantized softmax (e.g. Wimmers et al. 2019); quantile regression and convection (Bremnes 2020, Haynes et al. 2023)

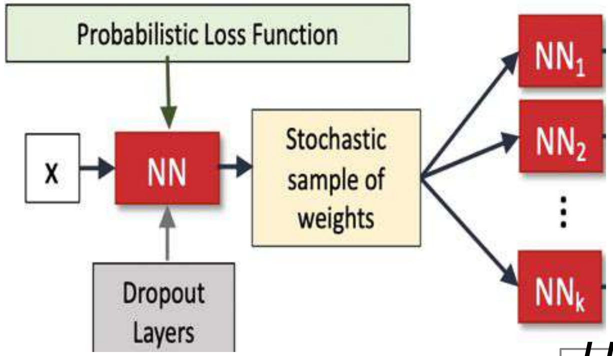
(e.g., sets of quantiles)

crossover (between quantiles or bins)

Multi-Model (MM)

Examples: MM ensemble of convection simulations over Europe (Beck et al. 2016); Model weighting for MM forecasts (DelSole et al. 2013)

Monte Carlo (MC) Dropout



Ensemble of deterministic predictors (probabilistic prediction)

Haynes et al. (2023)

Opportunities brought by Machine Learning

1) Improvement in prediction quality (algorithms, optimization)
   i. Prediction of tropical cyclone formation
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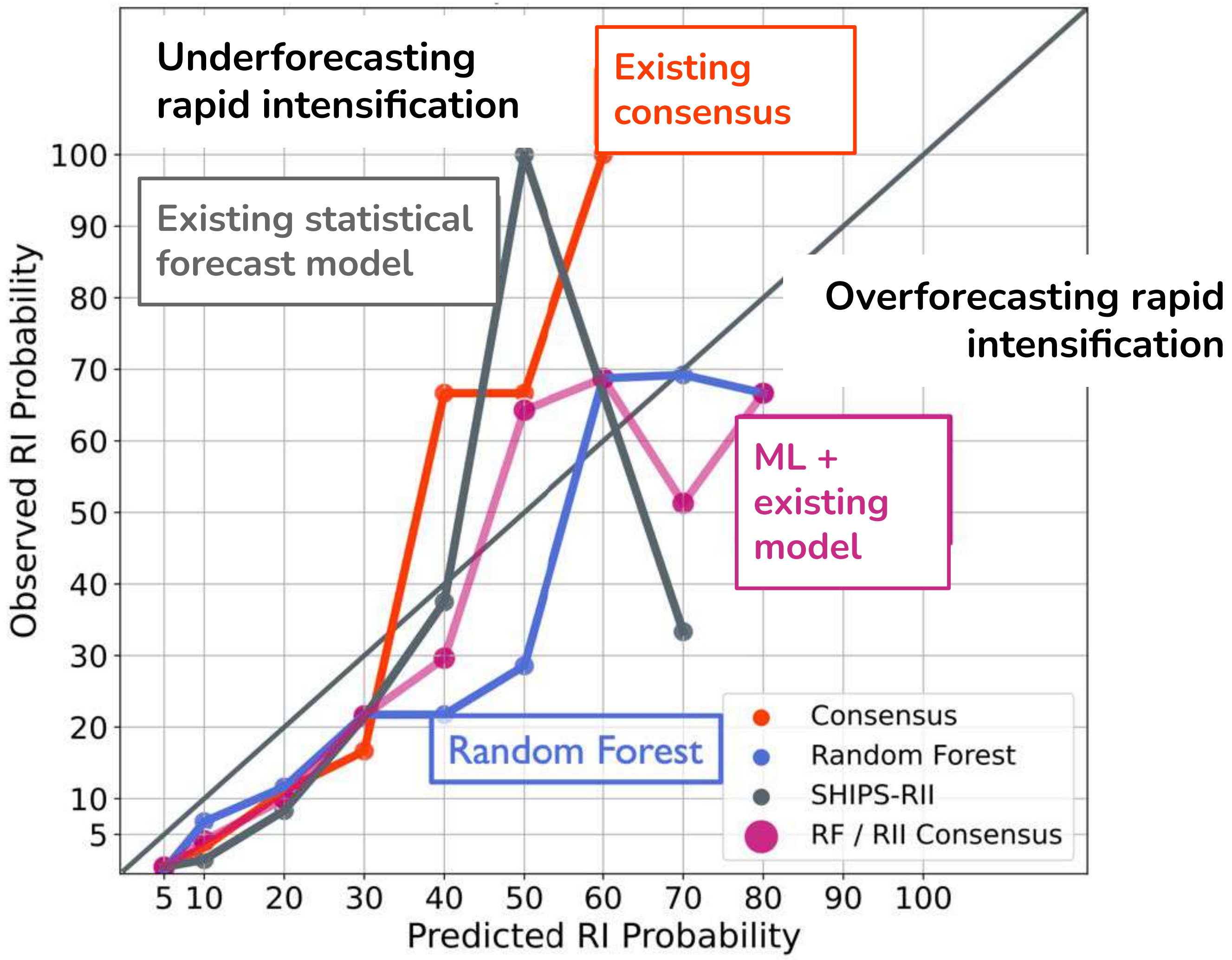
   iii. Prediction of rare events of a rare event

iii) ML models can also make skillful forecasts of **extreme events** such as **rapid intensification**

SHIPS-RII: used to forecast **rapid intensification** (big changes in intensity over short periods of time)

A random forest model trained on the same data as the existing **SHIPS-RII model** improves RI forecasting, especially when added to consensus

TC Rapid Intensification Forecasts, Atlantic, 2019-2021



McGraw et al. (in prep.)

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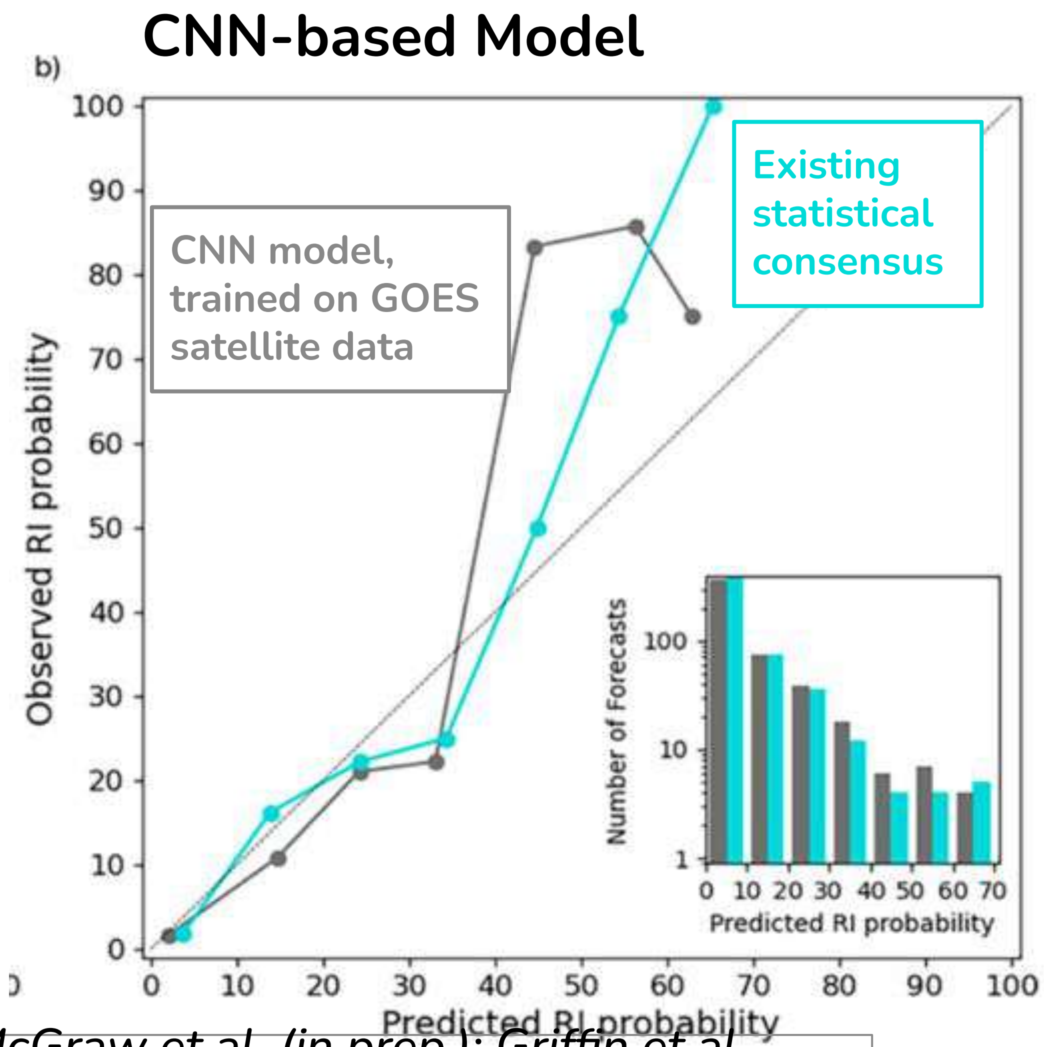

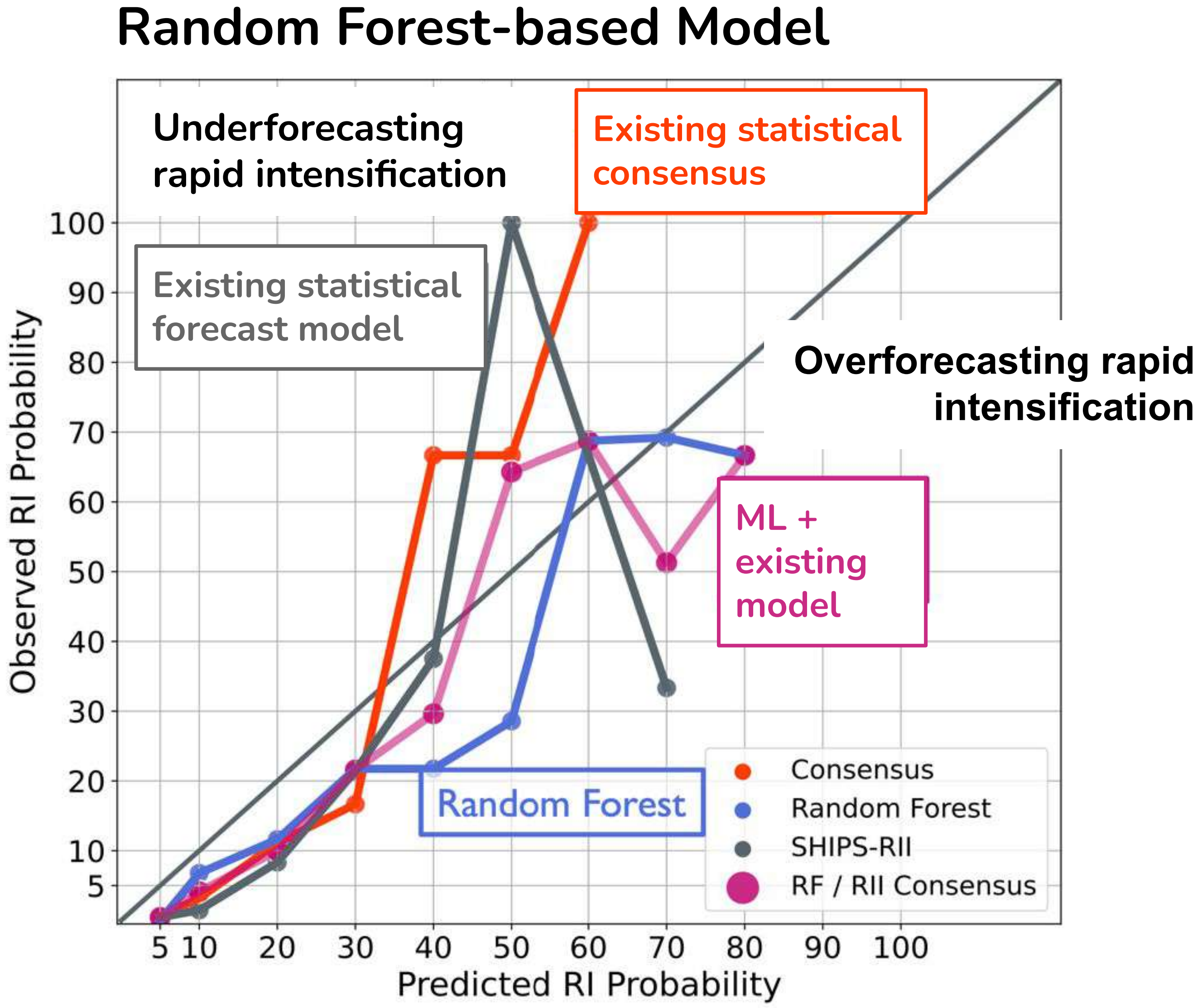

McGraw et al. (in prep.); Griffin et al. (2022)

Machine learning models can make skillful TC forecasts with uncertainty

- AI-based models can be used to **successfully predict** tropical cyclone intensity and track
- We can design AI models that also include **uncertainty** in their predictions
- AI-based models can skillfully predict **extreme events**, such as TC rapid intensification
- AI-based models are currently being introduced into the **research-to-operations** process at operational forecast centers like the National Hurricane Center

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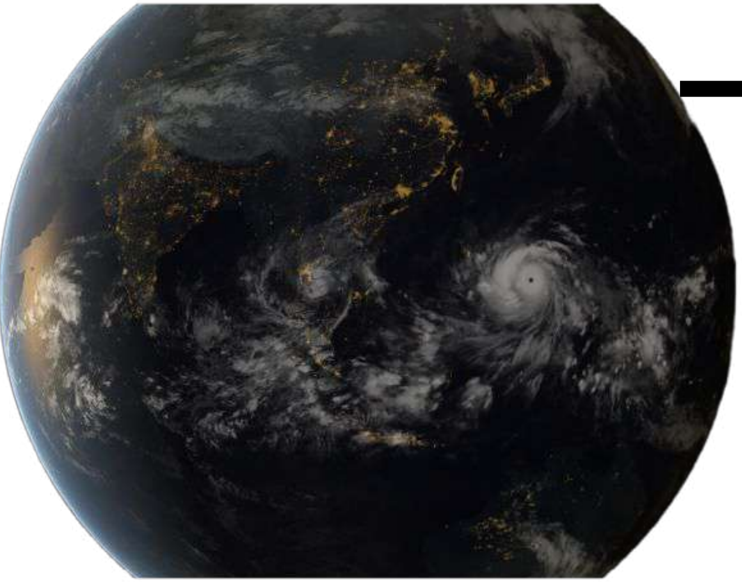
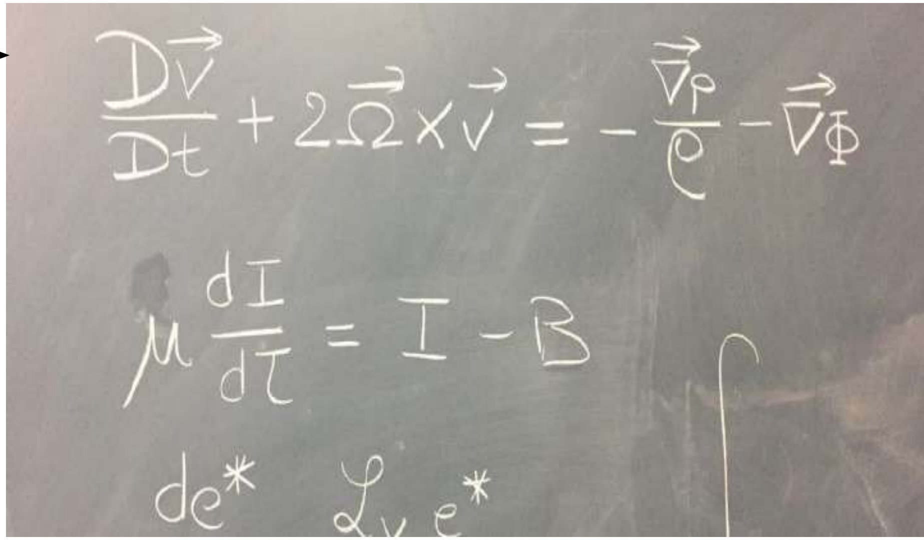
Machine learning facilitates the interaction between data and knowledge

Use ML to extract knowledge from data

Data-Driven Discovery

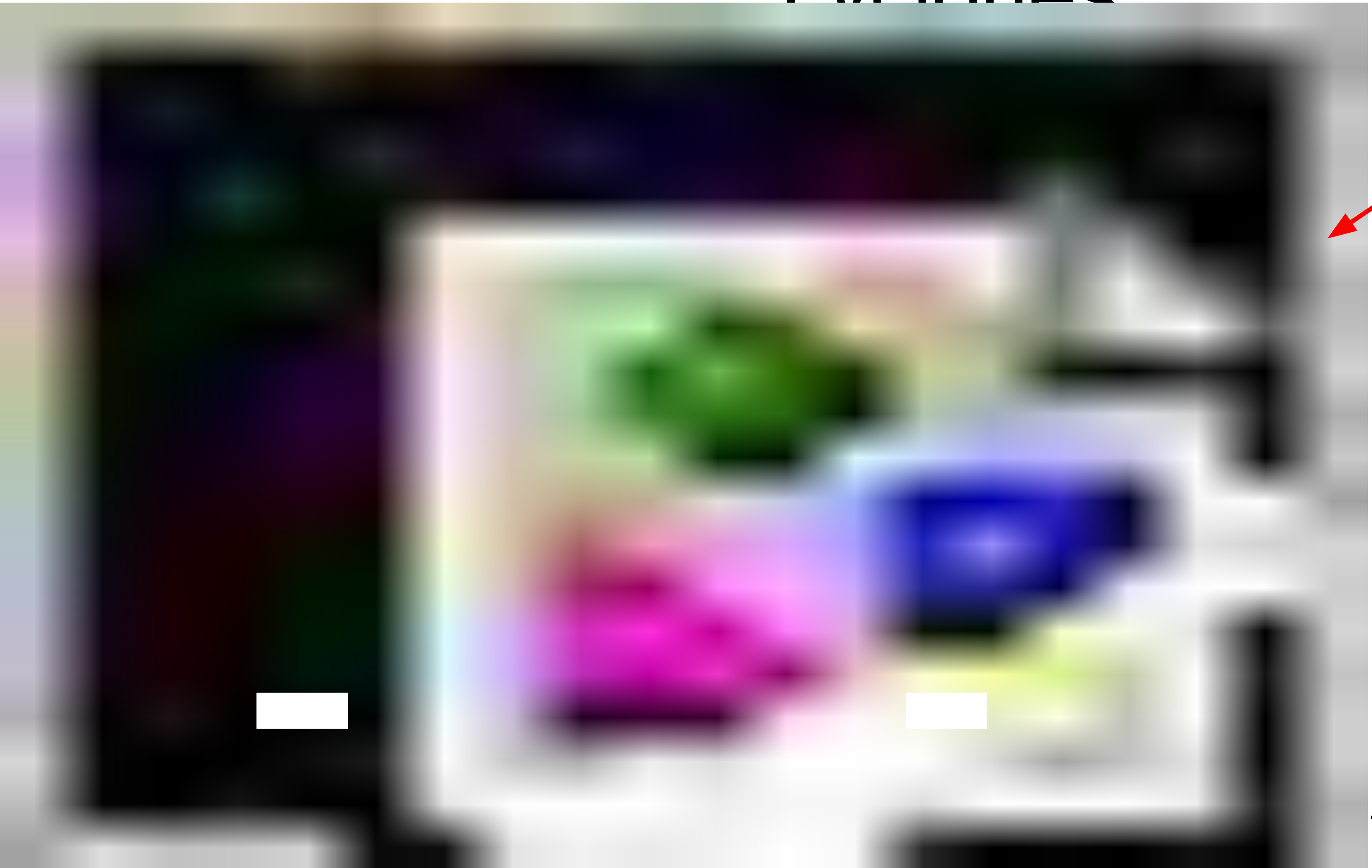


Observational & high-fidelity model data



Physical knowledge

Hypothesis: Cloud-radiative feedback can be critical to the early intensification of tropical cyclones

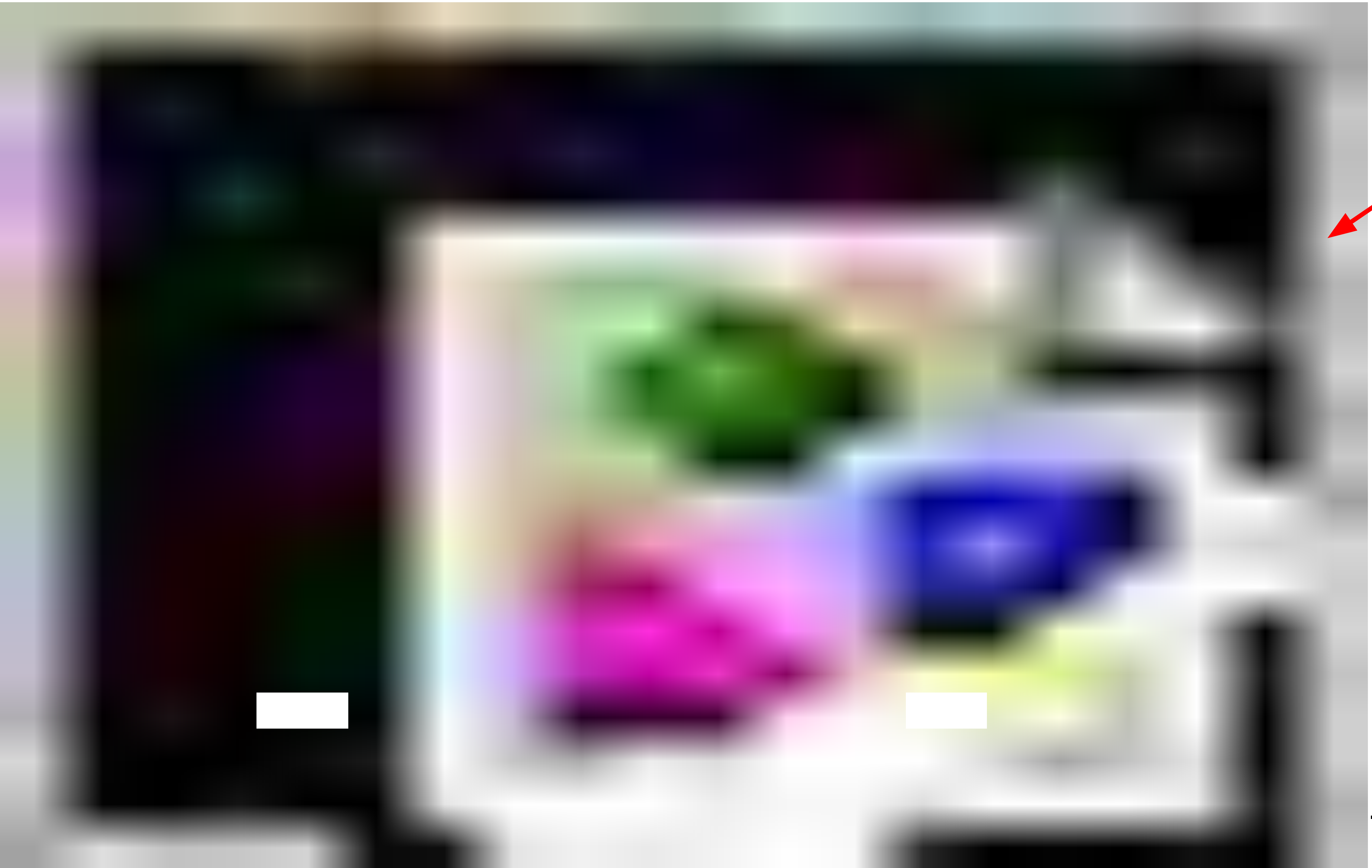


Artificial world where cloud radiative feedback is suppressed

Video source 1 = https://www.youtube.com/watch?v=Fw8VWSn9Lps&ab_channel=Denver7

See: Bu et al. (2014); Ruppert et al. (2020); Wu et al. (2021)

What spatial patterns of radiative heating promote/prevent tropical cyclone intensification?



Artificial world where cloud radiative feedback is suppressed

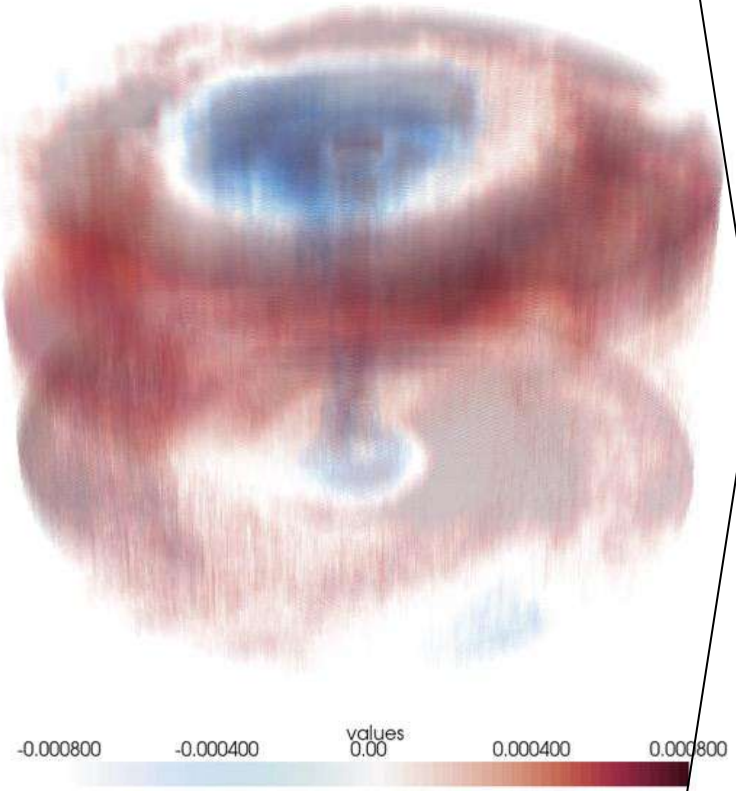
Video source 1 = https://www.youtube.com/watch?v=Fw8VWSn9Lps&ab_channel=Denver7

See: Bu et al. (2014); Ruppert et al. (2020); Wu et al. (2021)

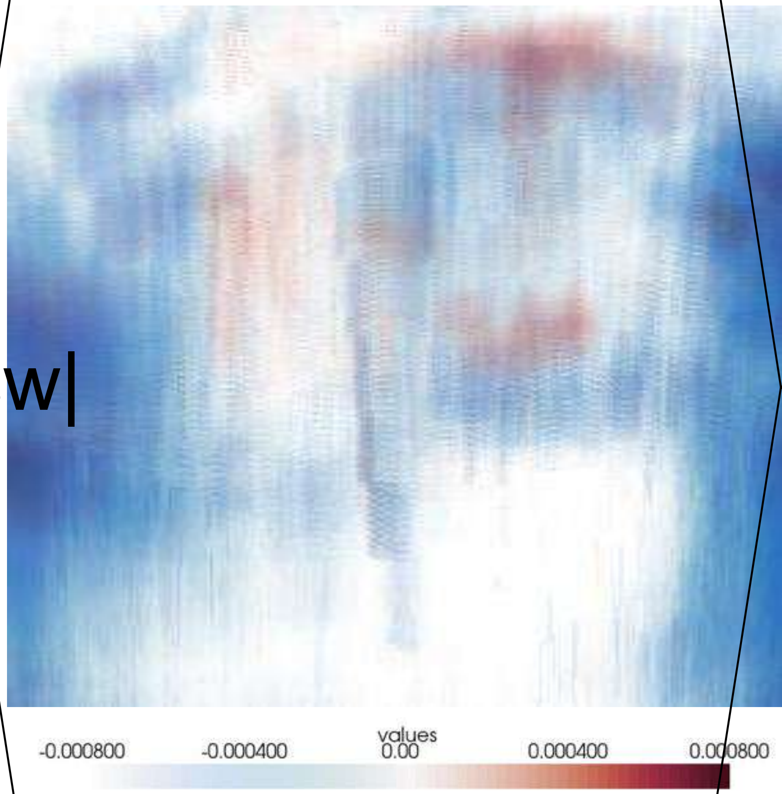
Method: “Transparent” Principal Component Regression

Result: Spatial structure most relevant to intensification for each TC

$$\frac{d(\text{TC intensity})}{dt} = b + a_{\mathrm{lw}} \left\langle \mathrm{lw} \middle| \right.$$



$$\left. \right\rangle + a_{\mathrm{sw}} \left\langle \mathrm{sw} \middle| \right.$$



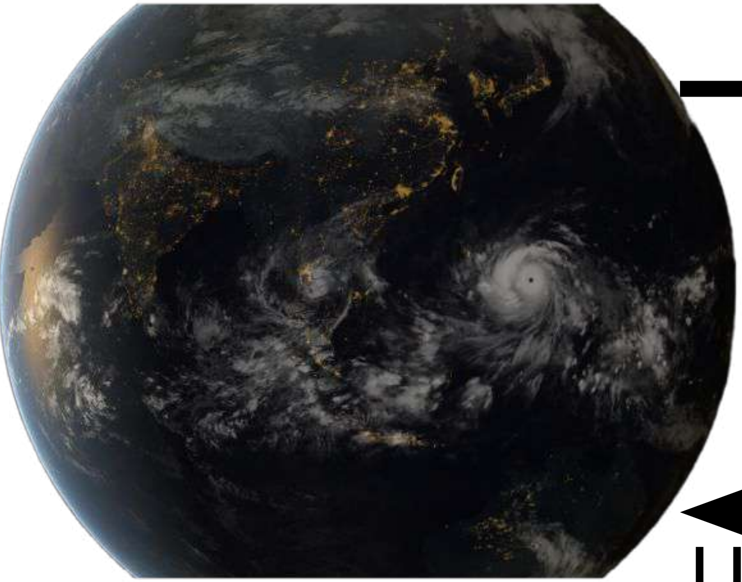
$$\left. \right\rangle$$

Longwave structure

Shortwave structure

Credits: Frederick Iat-Hin Tam (UNIL)

Machine learning facilitates the interaction between data and knowledge

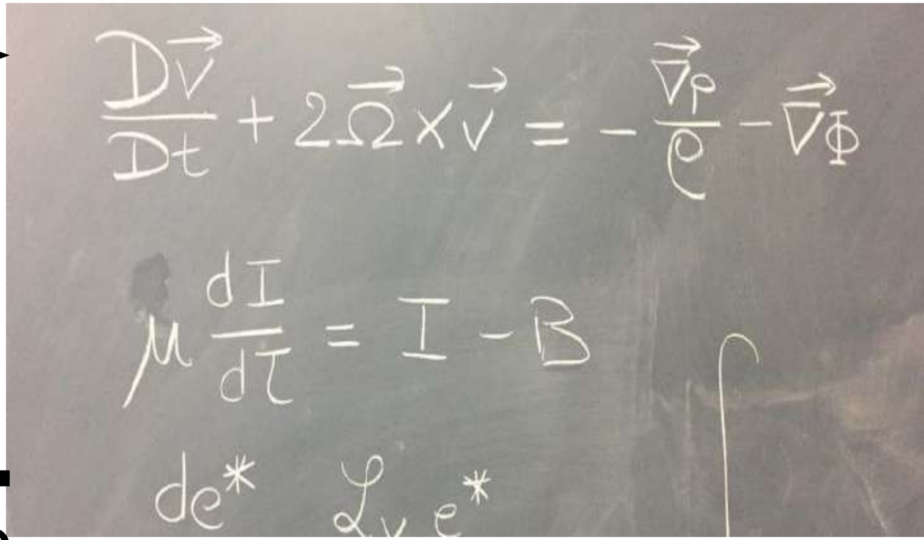


Use ML to extract knowledge from data

Data-Driven Discovery

Physics-Guided ML

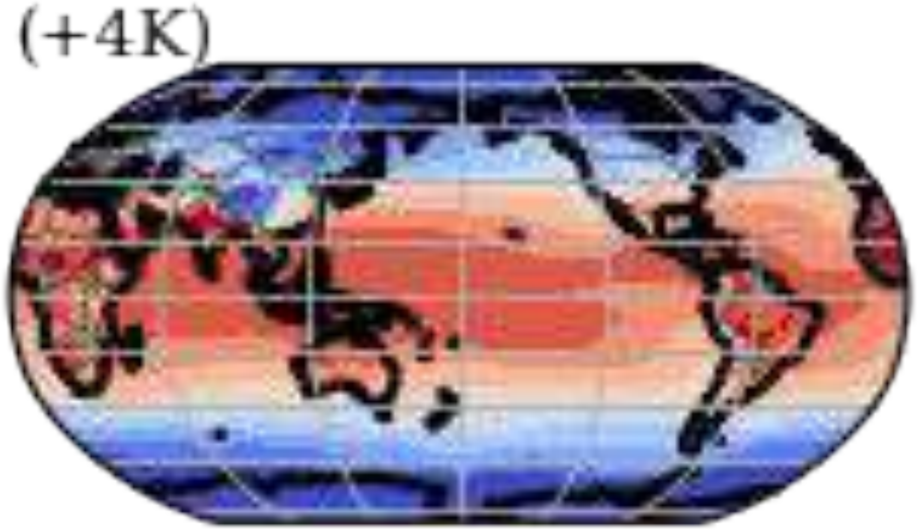
Use physics to improve the robustness of ML predictions



Motivation: For climate modeling, physically rescaling inputs allows neural nets to generalize from cold to warm climate

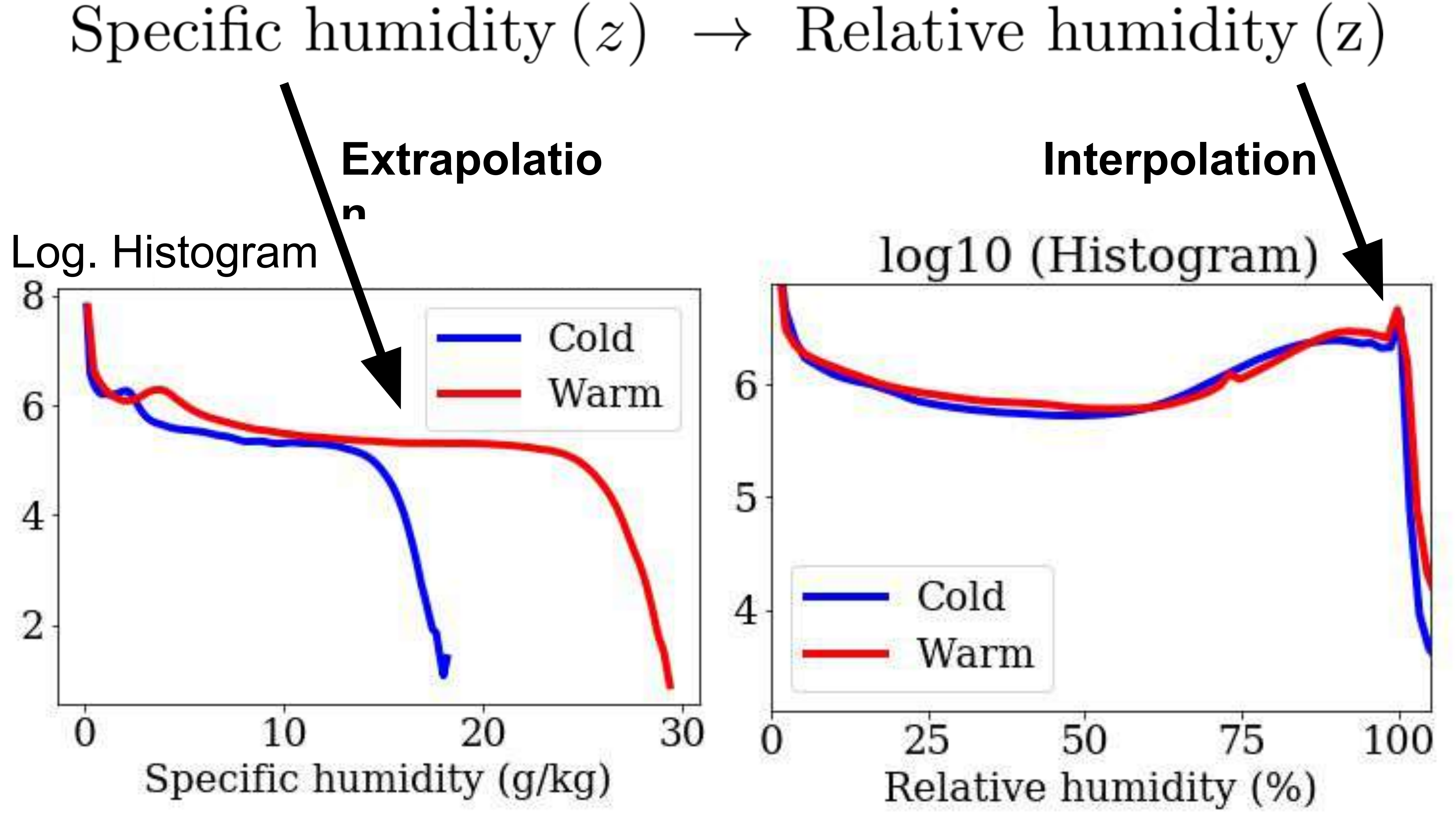
Training/Validation on
cold aquaplanet
simulation

Test on
warm aquaplanet simulation

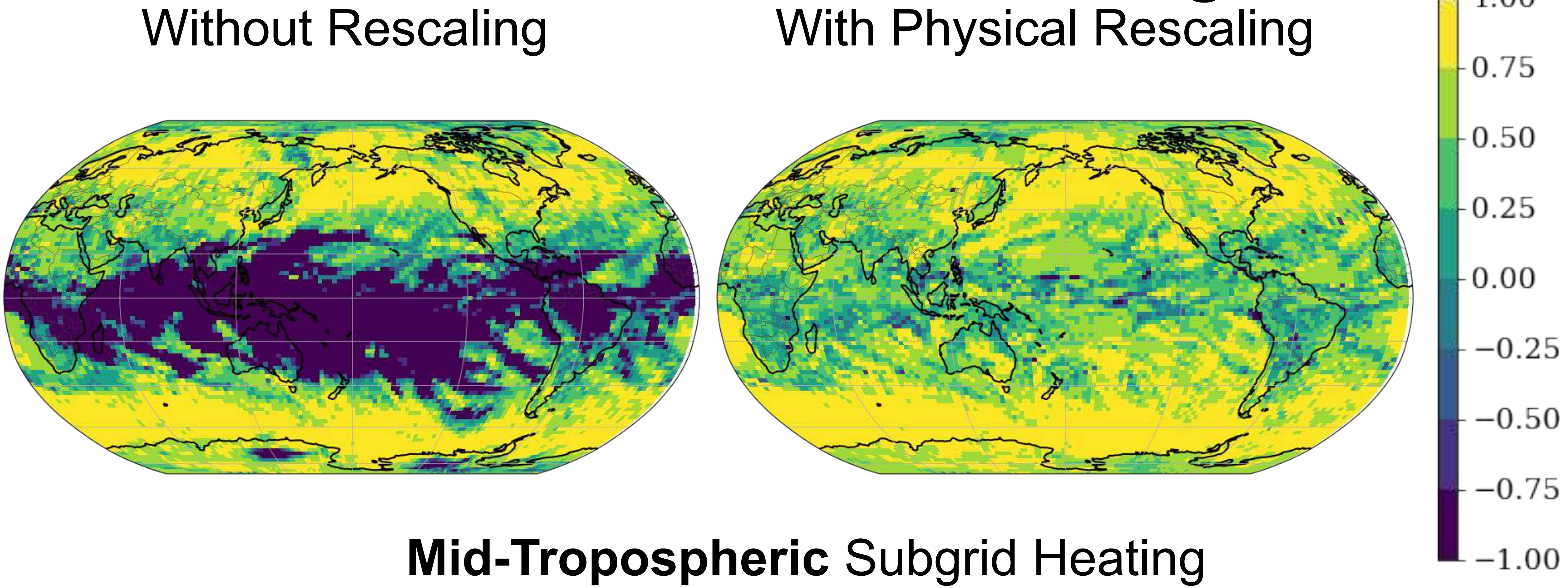


Climate-Invariant nets: Rescale inputs/outputs so that (extrapolation)→ (interpolation)

See: Beucler et al. (2021, arXiv 2112.08440), Mooers et al. (2021), Rasp et al. (2018)


Specific humidity (z) → Relative humidity (z)
Extrapolatio
n
Interpolation
Log. Histogram
8
6
4
2
Cold
Warm
0
10
20
30
Specific humidity (g/kg)
log10 (Histogram)
6
5
4
Cold
Warm
0
25
50
75
100
Relative humidity (%)

Physically-Rescaled Neural Networks Generalize Better Across Climates **in Earth-like configurations**



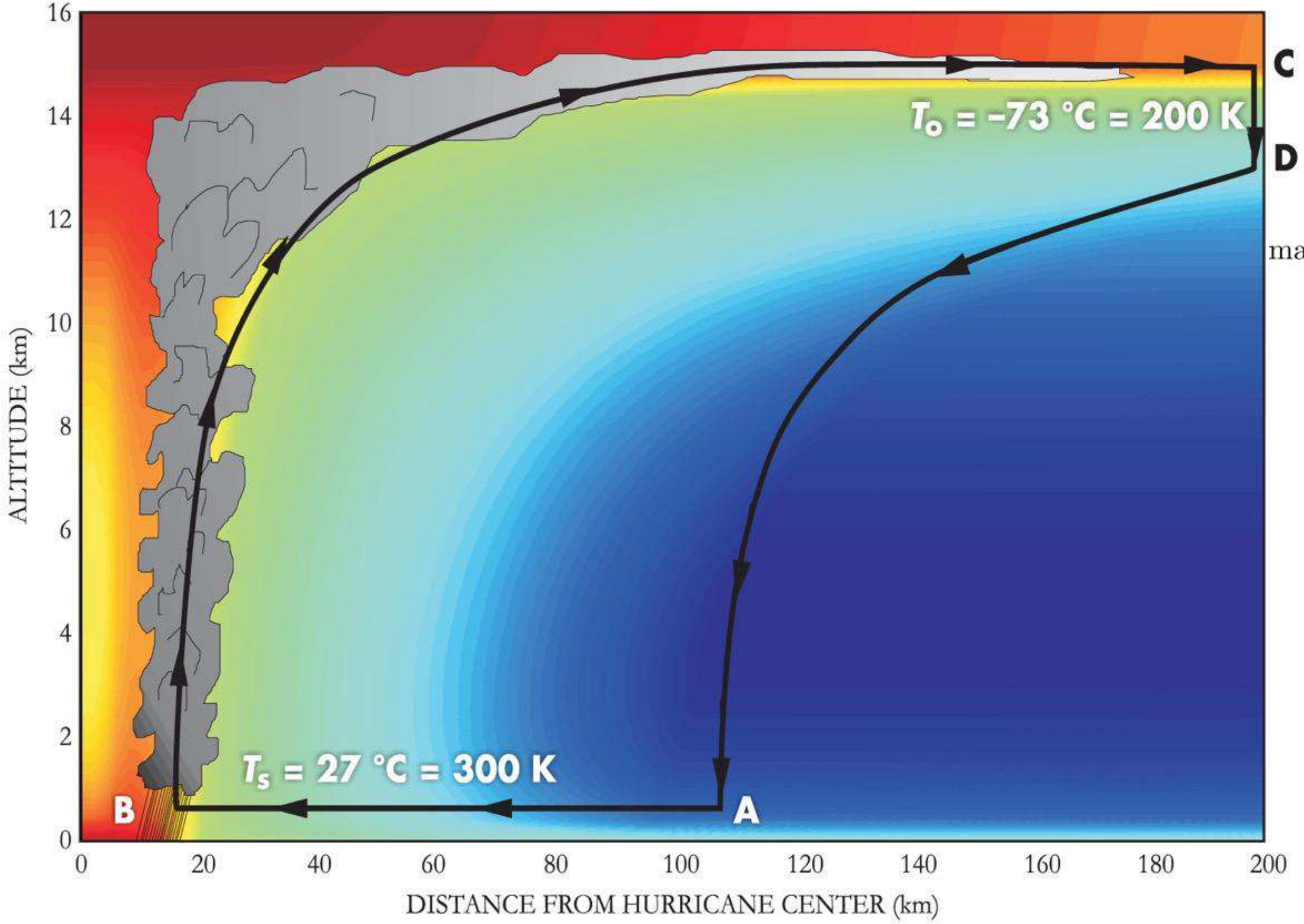
Mid-Tropospheric Subgrid Heating

<u>See:</u> *Beucler et al. (2021, arXiv 2112.08440)*

Motivation: Physical knowledge improves ML *robustness*
= No ↓prediction quality for reasonable data variations

For Tropical Cyclones: Can Potential Intensity theory help machine learning generalize across env. conditions?

For Tropical Cyclones: Can Potential Intensity theory help machine learning generalize across environments?

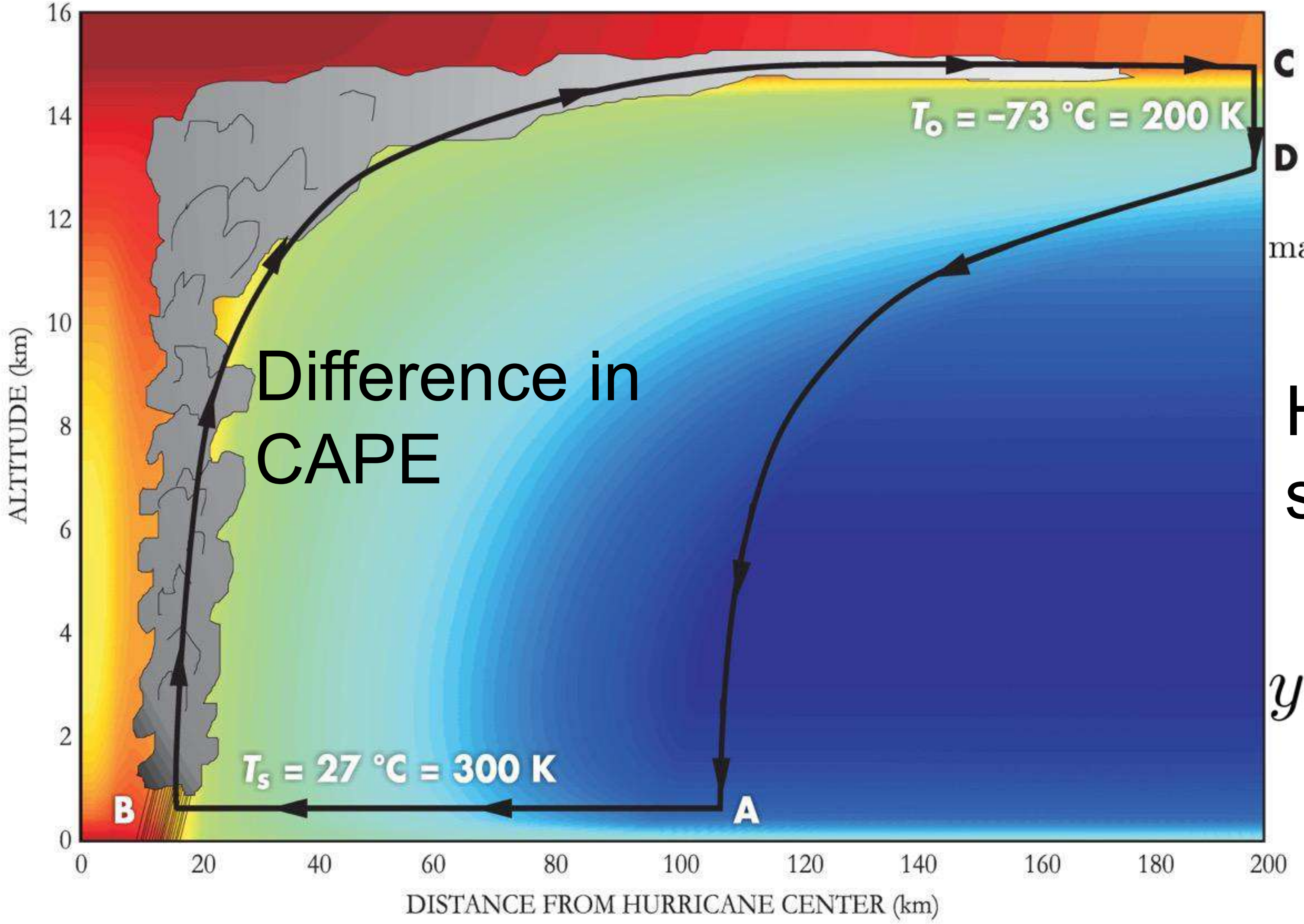


Analytic bound on max winds:

$$\max \mathrm{PI} \approx \sqrt{\frac{T_{\text{surface}} - T_{\text{outflow}}}{T_{\text{surface}}} \times \frac{C_{\text{enthalpy}}}{C_{\text{momentum}}} \times (\text{Near} - \text{surf. enthalpy diseq.})}$$

See: Emanuel (1986), Emanuel (2003), Rousseau-Rizzi et al. (2022), Sroka & Emanuel (2021); Figure source:

For Tropical Cyclones: Can Potential Intensity theory help machine learning generalize across environments?



Analytic bound on max winds:

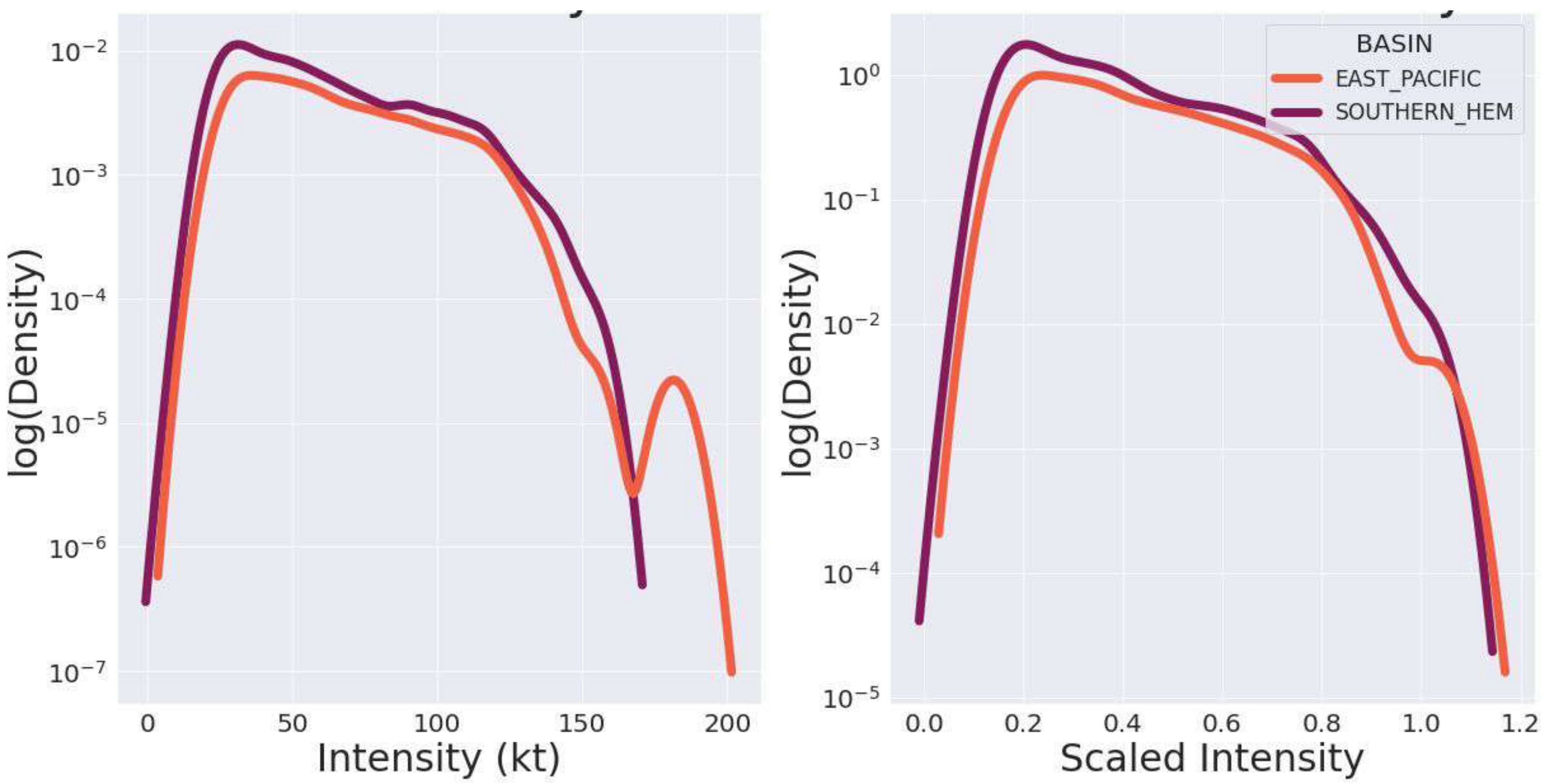
$$\max \mathrm{PI} = \sqrt{\frac{T_{\mathrm{surface}}}{T_{\mathrm{outflow}}} \frac{C_{\mathrm{enthalpy}}}{C_{\mathrm{momentum}}} \left(\mathrm{CAPE}_{\mathrm{eyewall}} - \mathrm{CAPE}_{\mathrm{max\ winds}}\right)}$$

Helps generalize across seasons, basins, climates…

$$y = \mathrm{Intensity} \mapsto \tilde{y} \stackrel{\mathrm{def}}{=} \frac{\mathrm{Intensity}}{\max \mathrm{PI}}$$

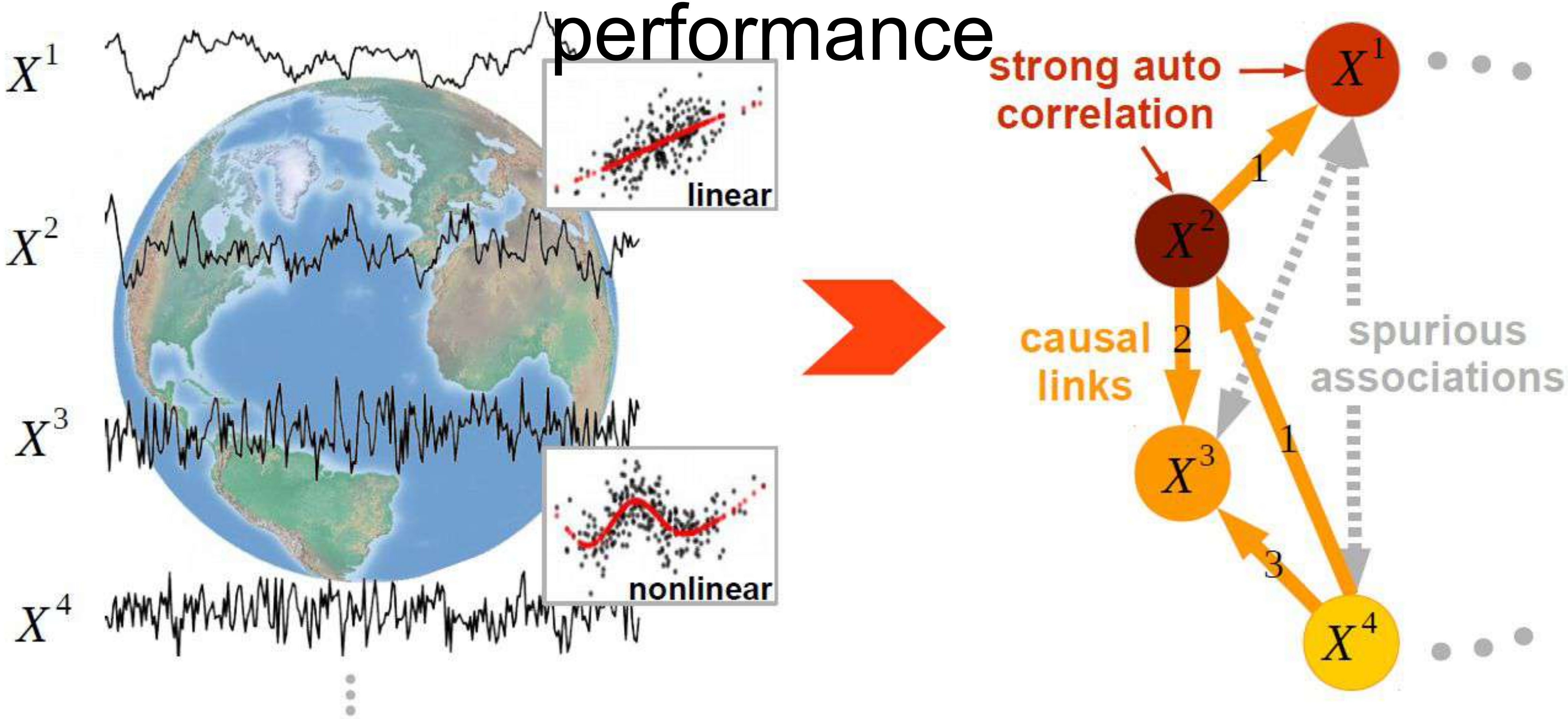
See: Emanuel (1986), Emanuel (2003), Rousseau-Rizzi et al. (2022), Sroka & Emanuel (2021); Figure source:

<u>Preliminary results</u>: Rescaling tropical cyclone intensity transforms extrapolation into interpolation



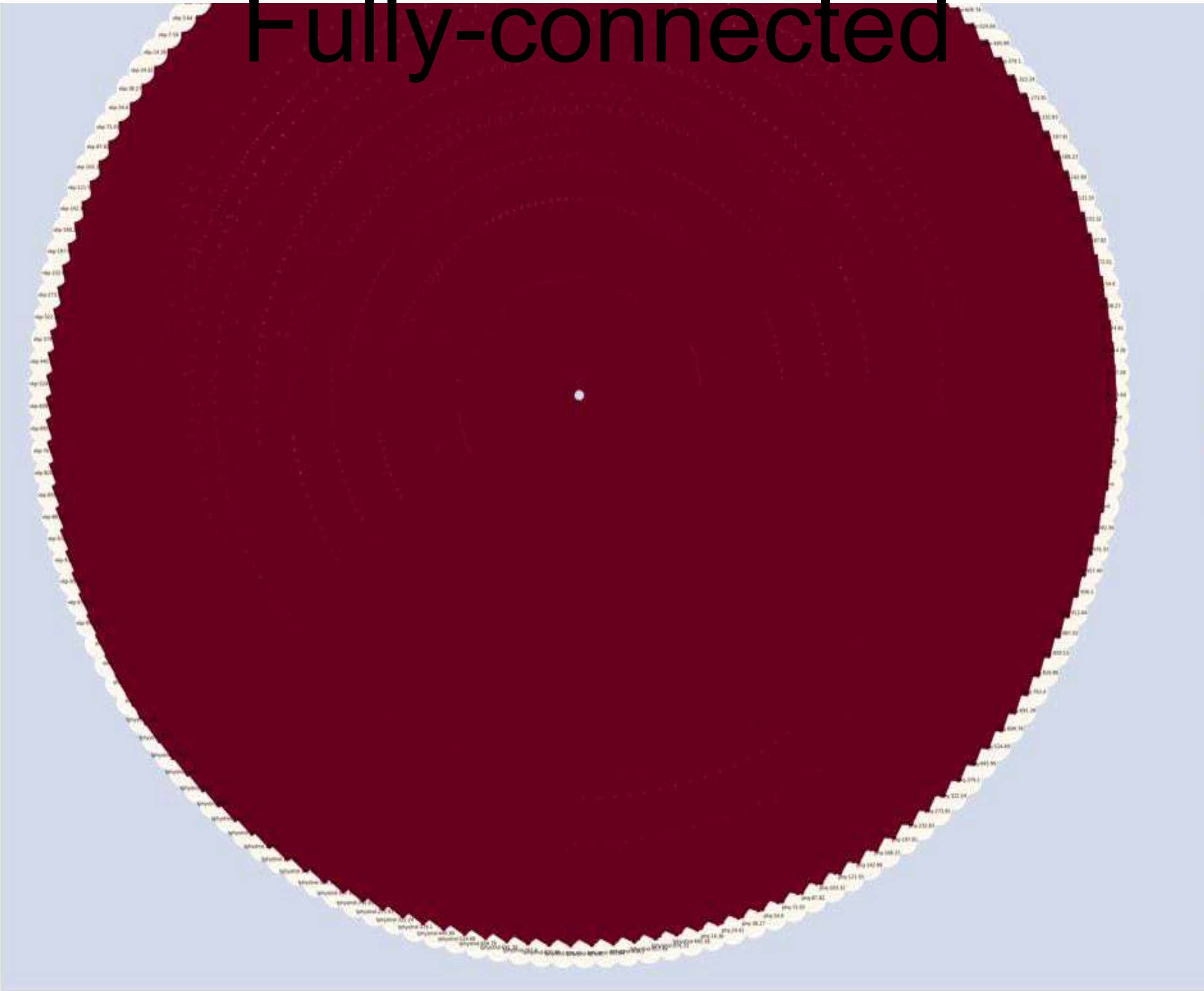
<u>Credits</u>: Marie McGraw (CIRA)

Motivation: Causal machine learning can remove spurious links without degrading performance



Source: Runge et al. (2019), See: Kretschmer et al. (2016), Runge et al. (2019), Spirtes & Glymour (1991)

Before PC1: Fully-connected

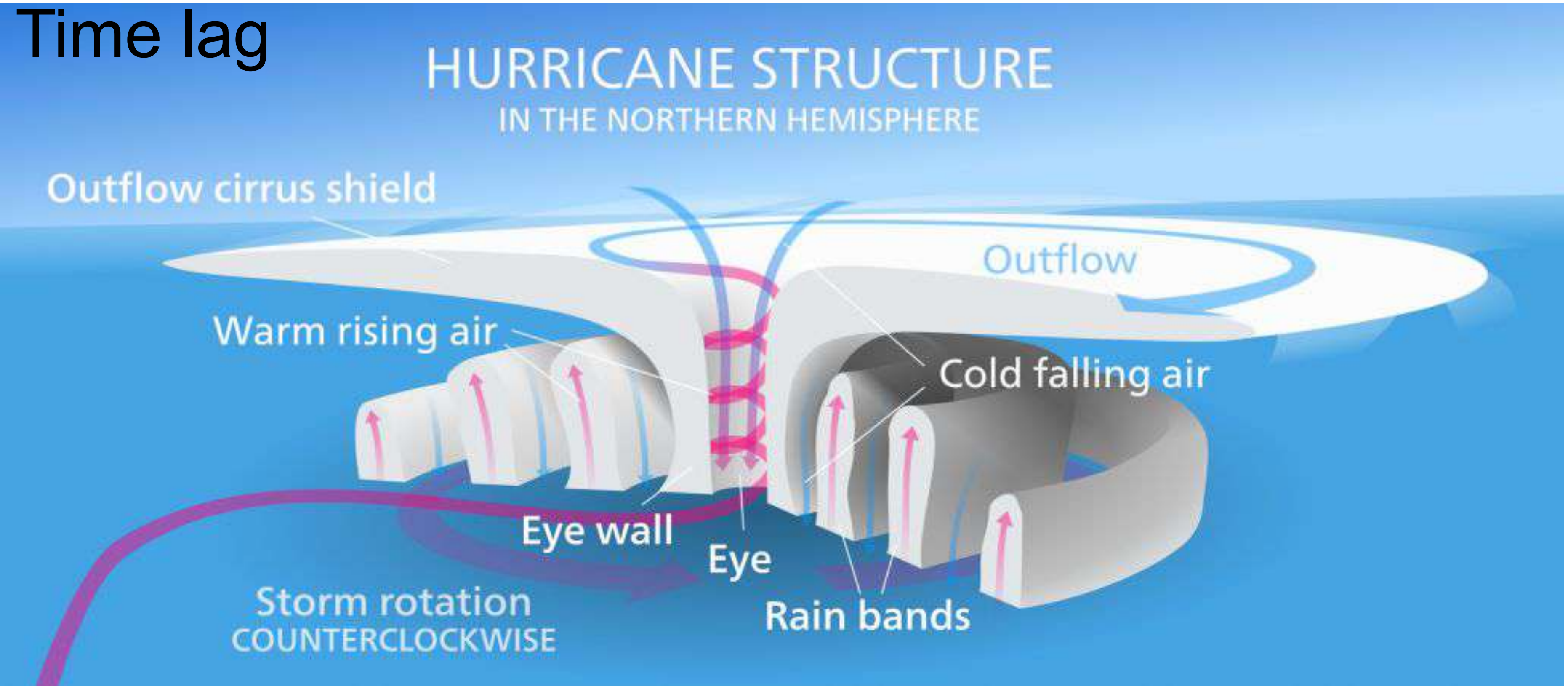


Fully-connected Inputs-to-Outputs

urce: Iglesias-Suarez (DLR), See: Spirtes and Glymour (1991); Addition in this work: Multidata PC1 (Gerhadus & Runge,

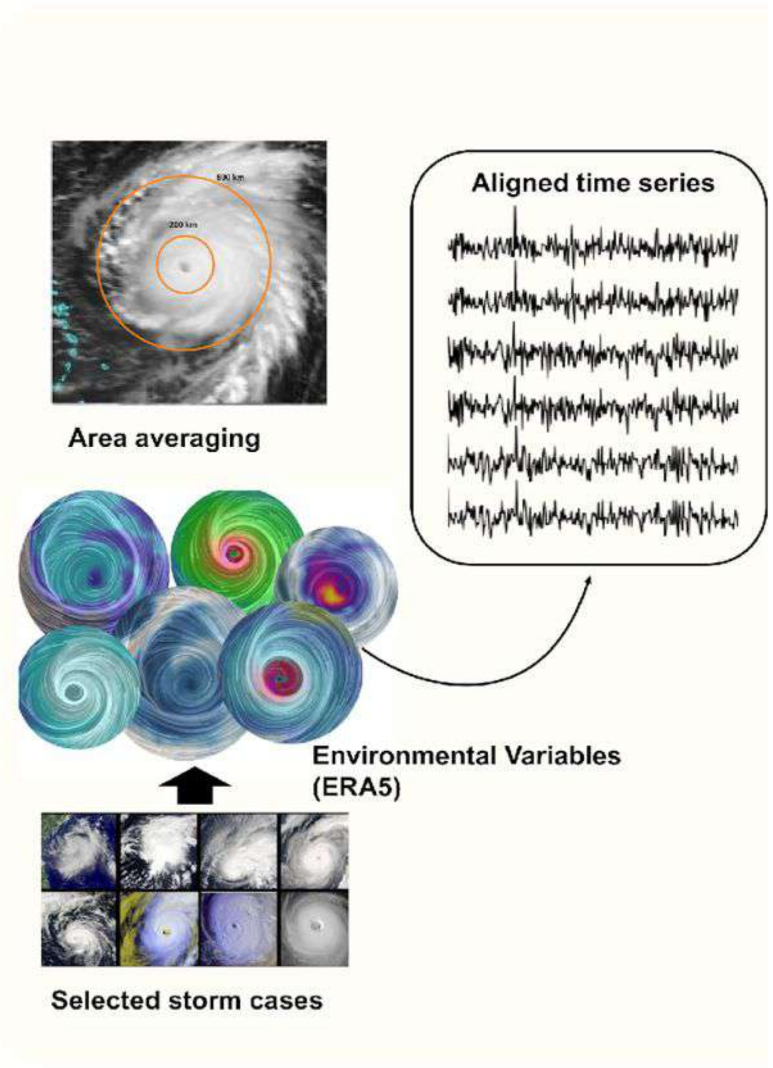
Tropical cyclone prediction: Select optimal set of predictors to improve the robustness of prediction

Feature = Meteorological variable + vertical lev. + horizontal sector + Time lag



- Hor. Divergence
- Vertical velocity
- Relative vorticity
- Relative humidity
- Geopotential z
- Eq. pot. Temp.
- Wind shear
- Column integrals

Image Source: internetgeography.net



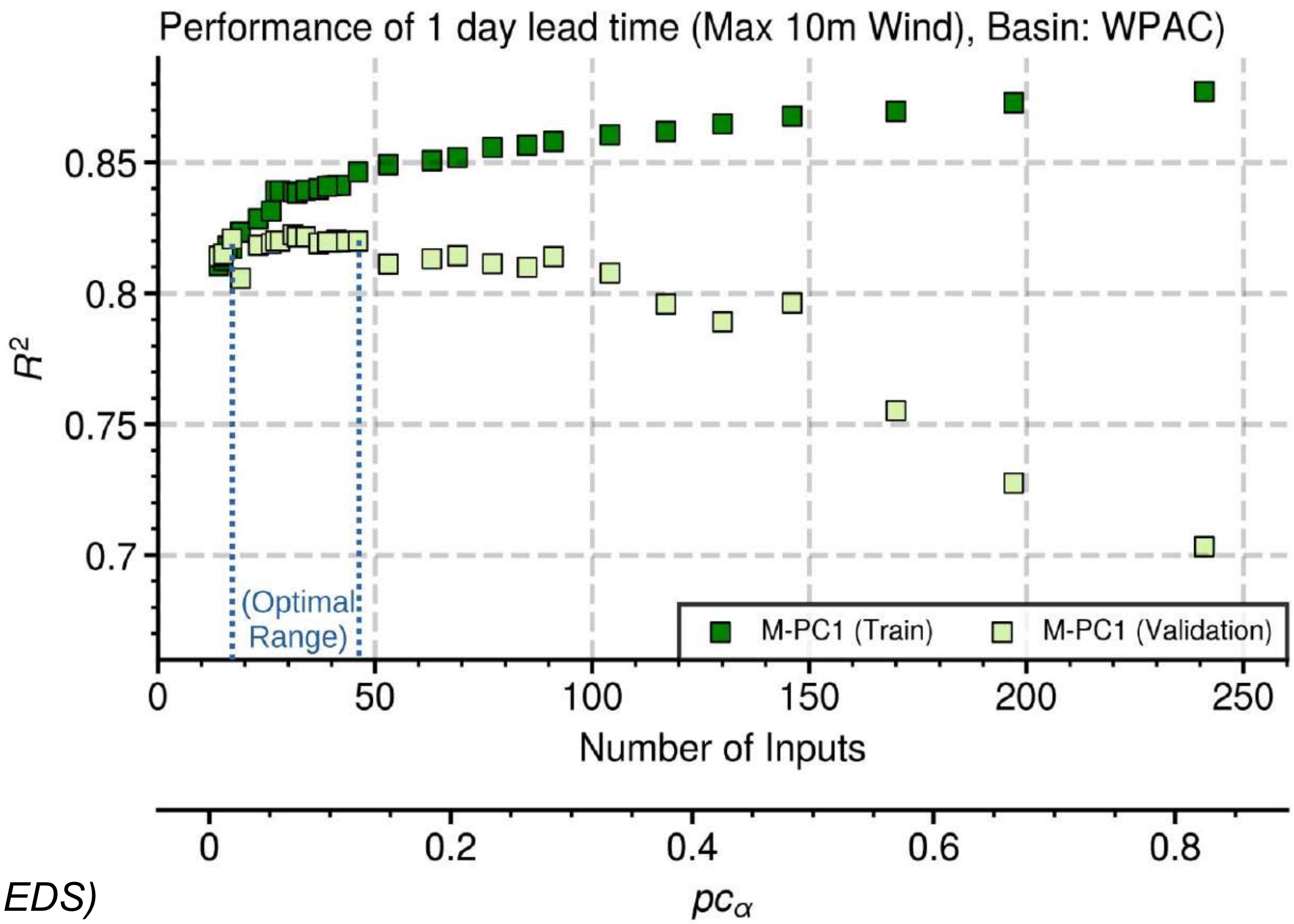
Step I. Pre-processing &
Dimensionality Reduction

Credits: *Saranya Ganesh S. (UNIL)*

The optimal set of predictors is validated using an independent validation set (50 separate TCs)

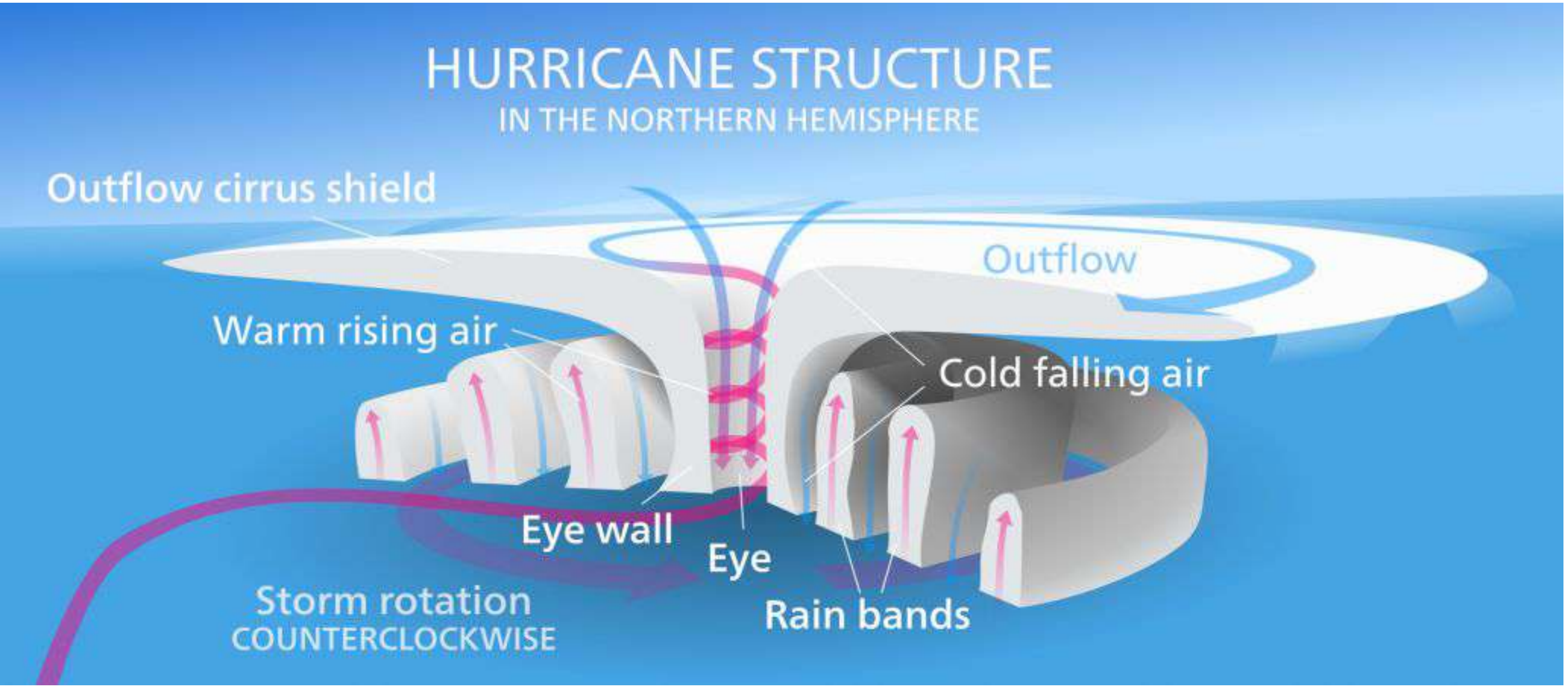
Multidata causal feature selection outperforms:

1. Random feature selection
2. XAI-based feature selection (Random forest)
3. Lagged correlation-based feature selection

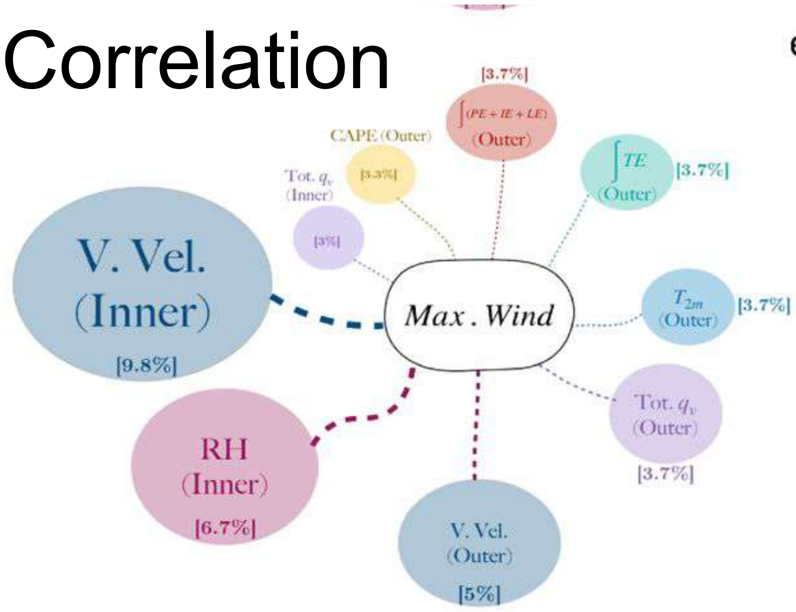


Preprint coming soon: Ganesh S. et al. (2023, EDS)

Causal feature selection not only removes spurious links, but also suggests new predictors for TC intensity



Correlation



Preprint coming soon: Ganesh S. et al. (2023, EDS)

Opportunities brought by Machine Learning

1) Improvement in prediction quality (algorithms, optimization)

2) Improvements in understanding (new spatiotemporal connectivities, nonlinearities, predictors, etc.)

3) Can we learn more?

Can we use machine learning to create additional datasets for tropical meteorology?

Microwave Imagery (i.e., AMSR-E, AMSR2)	**Visible and Infrared Imagery (GOES, Himawari)**
Can help with intensity estimation, center fixing, storm motion, and storm structures	Used to estimate TC intensity, center, and size
Can “See through” clouds	Limited to cloud top temperatures
Each satellite passes over a location ~ every 12 hours (including all satellites, coverage is about 3-hrly)	Geostationary satellites “look” at the same locations all the time; with GOES, we get a full scan of the CONUS every 10 min

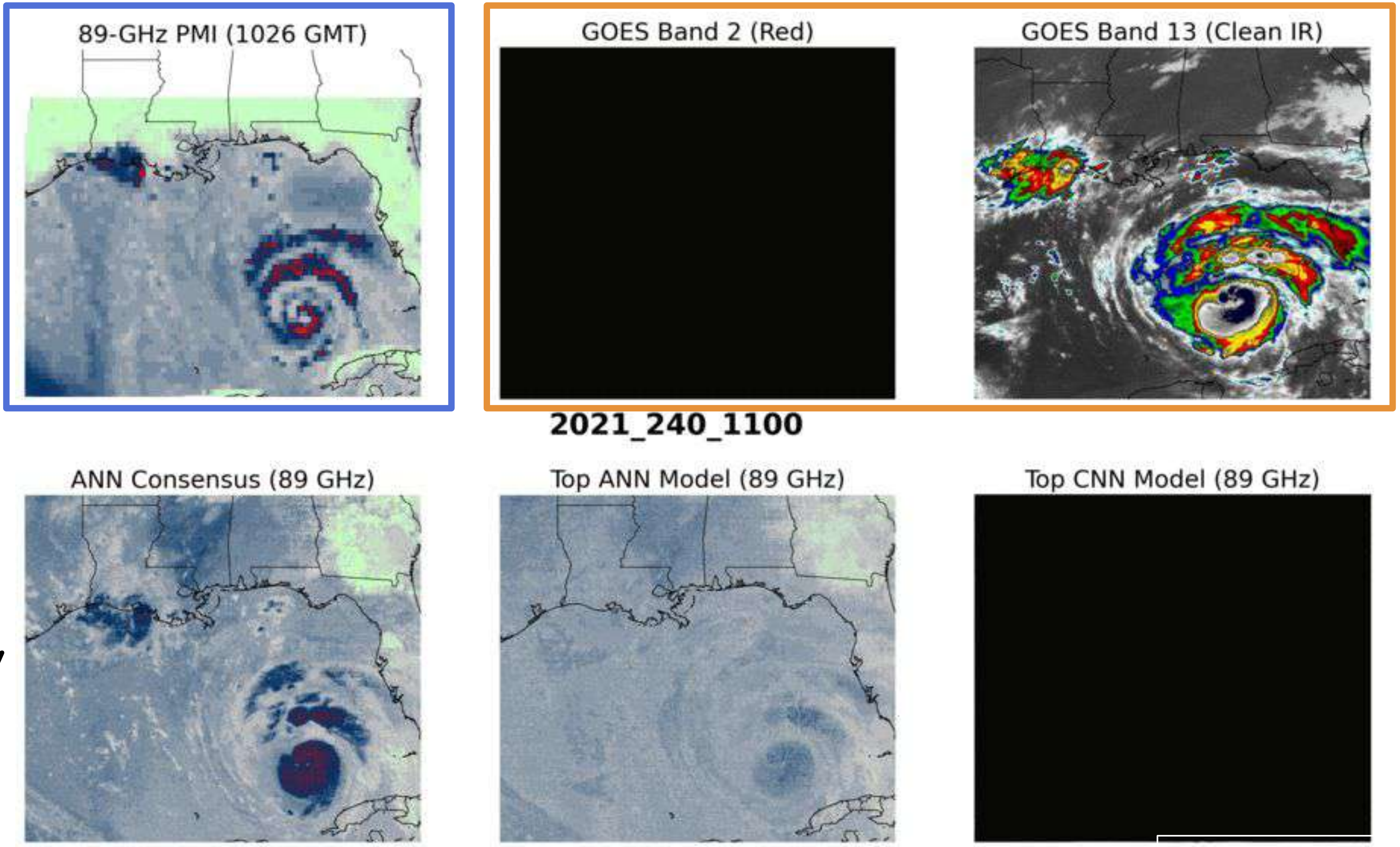
Goal: can we use a neural network, trained on GOES visible and IR imagery, to produce simulated microwave data at high temporal frequencies?

Opportunities for **improved forecasting** and **TC physics study**

Promising early results using neural networks to create simulated microwave data from visible/IR.

Observed microwave (available every few hours or less)

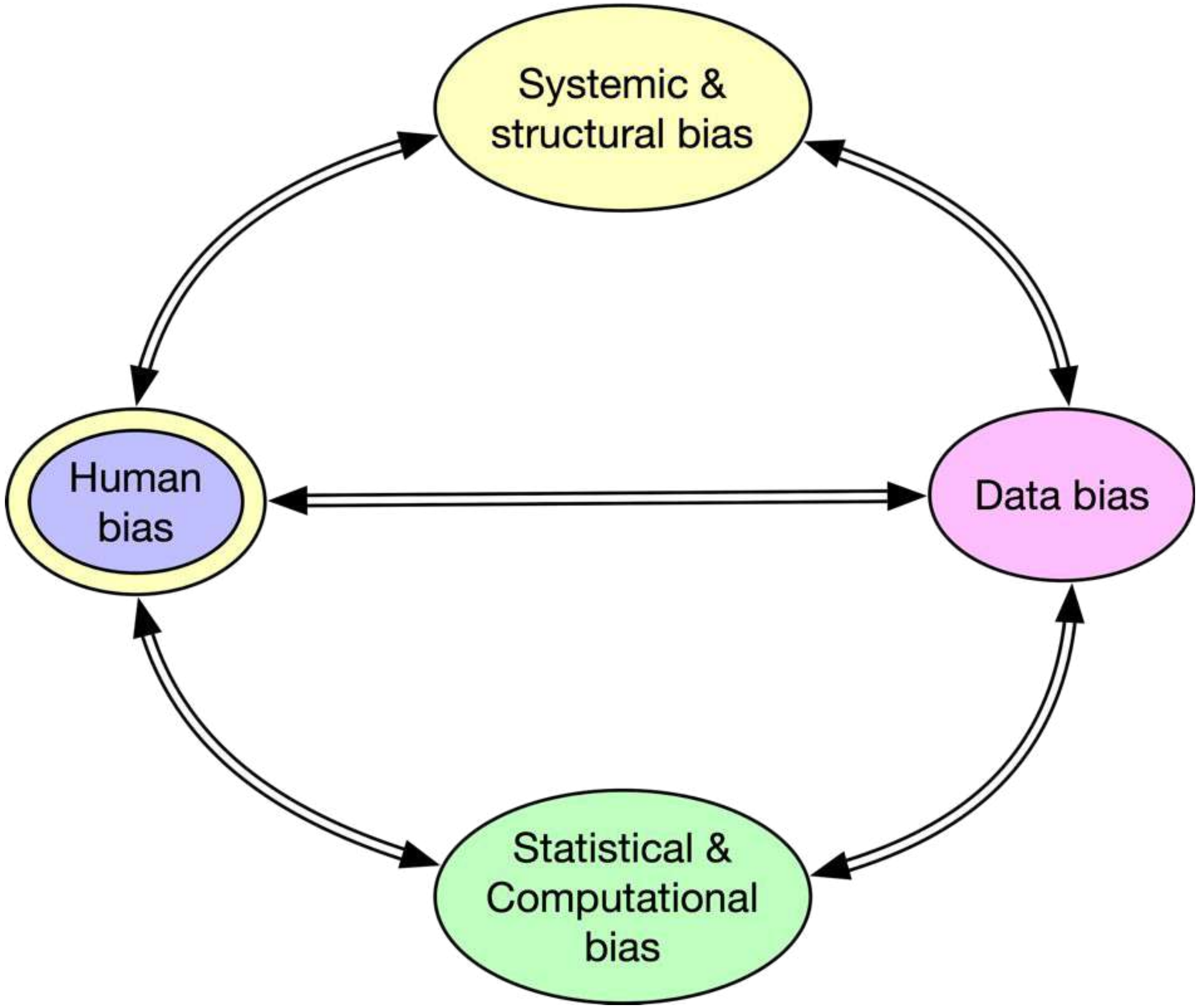
GOES inputs (available every 10 min)



Simulated microwave produced by neural networks

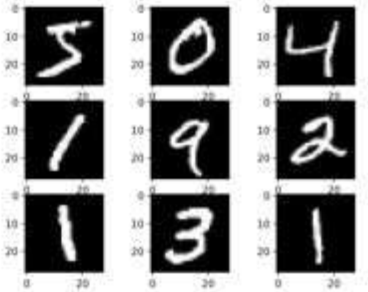
Credit: Kathy Haynes, CIRA

Addressing biases in artificial intelligence and earth sciences.



Credit: Amy McGovern (OU) and co-authors

- Potential of artificial intelligence for tropical meteorology is clear…
- … but hindered by lack of unified training data & evaluation protocols



IMAGENET

WeatherBench

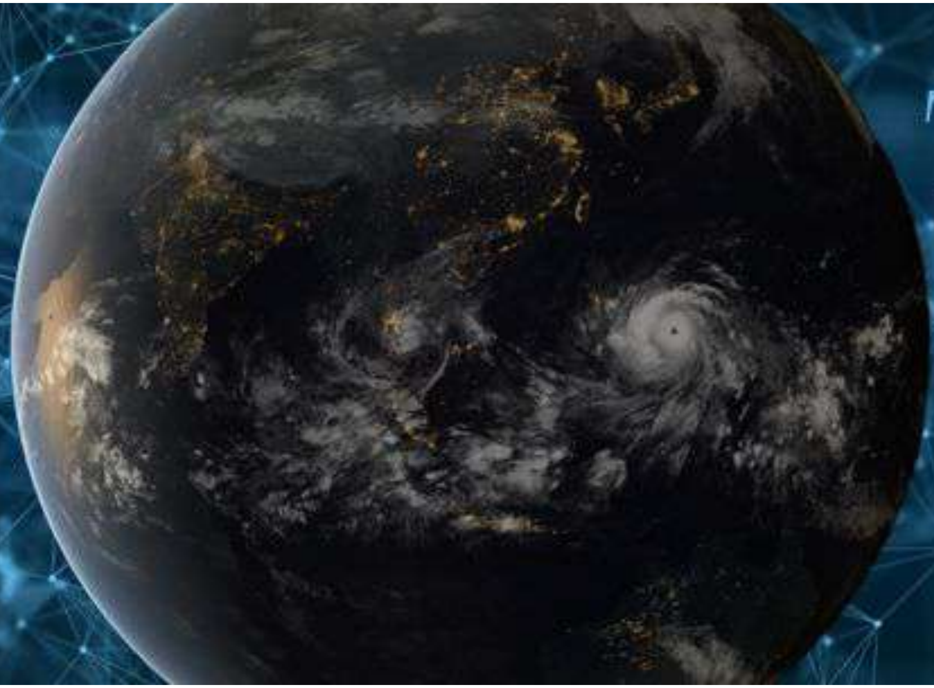
MAELSTROM
Empowering weather and climate forecast

ClimateBench v1.0: A Benchmark for Data-Driven Climate Projections

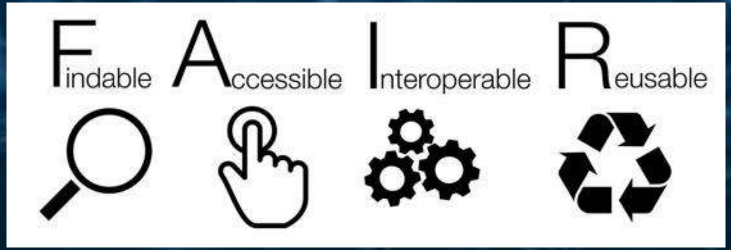
D. Watson-Parris, Y. Rao, D. Olivié, Ø. Seland, P. Nowack, G. Camps-Valls, P. Stier, S. Bouabid, M. Dewey, E. Fons, J. Gonzalez, P. Harder, K. Jeggle ... See all authors

First published: 15 September 2022 | https://doi.org/10.1029/2021MS002954

- AI-ready datasets for TC prediction at different timescales
- Collaborative design of evaluation



TCBench



See: MNIST (1998, LeCun), CIFAR (2009, Krizhevsky), ImageNet (2009, Deng et al.), WeatherBench (2020, Rasp et al.), Maelstrom datasets (2021, Dueben et al.), ClimateBench (2022, Watson-Parris et

Thank you!

ML can improve:

1) predictions of TCs across life stages,
2) understanding of physical processes

...as long as we keep data limitations and biases in mind

Marie McGraw (CIRA) & Tom Beucler (UNI Lausanne)

AI for Good – March 8th, 2023

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