Artificial Intelligence for Tropical Meteorology: Challenges and Opportunities

Tom Beucler, Frederick Tam, Milton Gomez (UNIL)

TROPICANA Workshop – June 24th, 2024

∂^3 AWN

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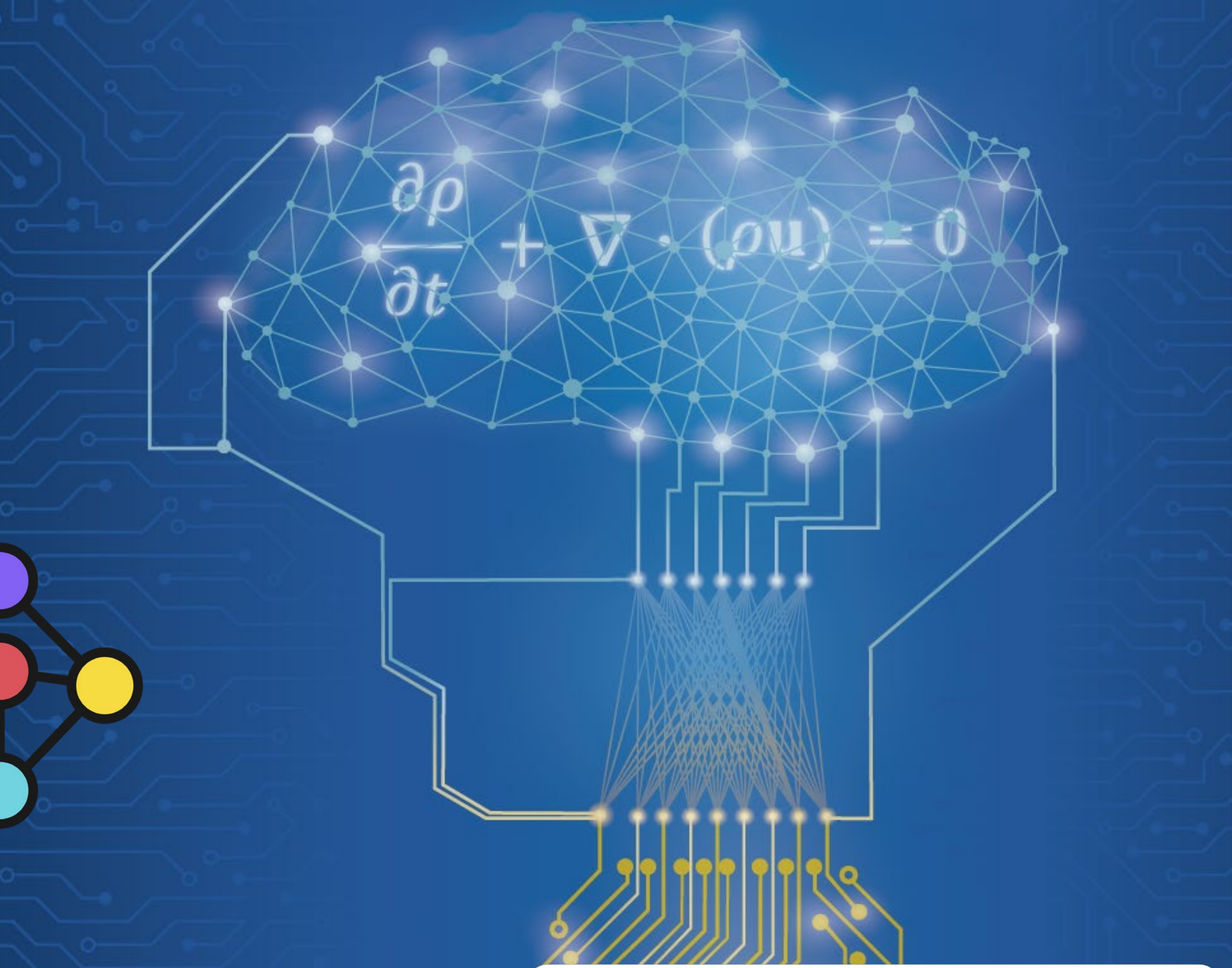
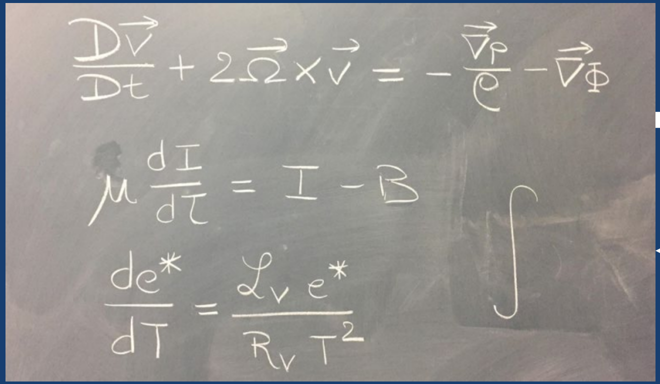
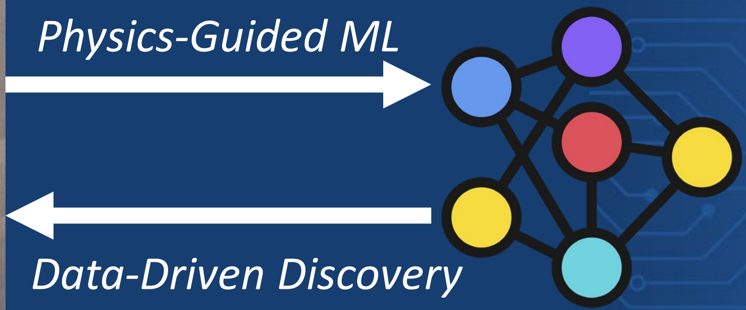
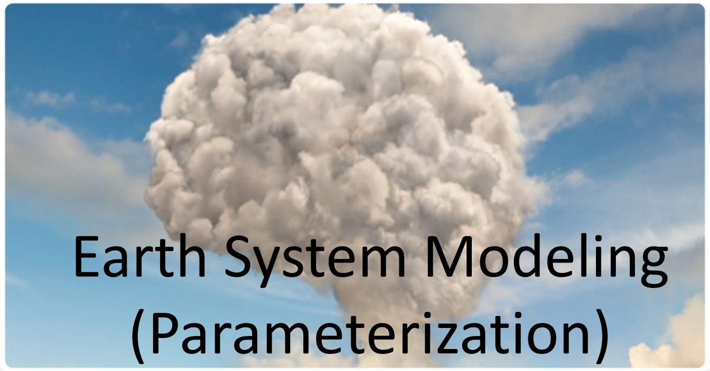
UNIL | Université de Lausanne
Expertise Center for
Climate Extremes (ECCE)

Atmospheric Physics + ML









Artificial Intelligence for Tropical Meteorology: Challenges and Opportunities

1. Process understanding in tropical meteorology with ML
2. Causal discovery for tropical cyclone forecasting
3. Post-processing of neural weather models

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CIRA
Connecting Models and Observations

Artificial Intelligence Risk Communication Environmental Science

Extreme Weather Events
Forecasting,
Post-Processing,
Understanding

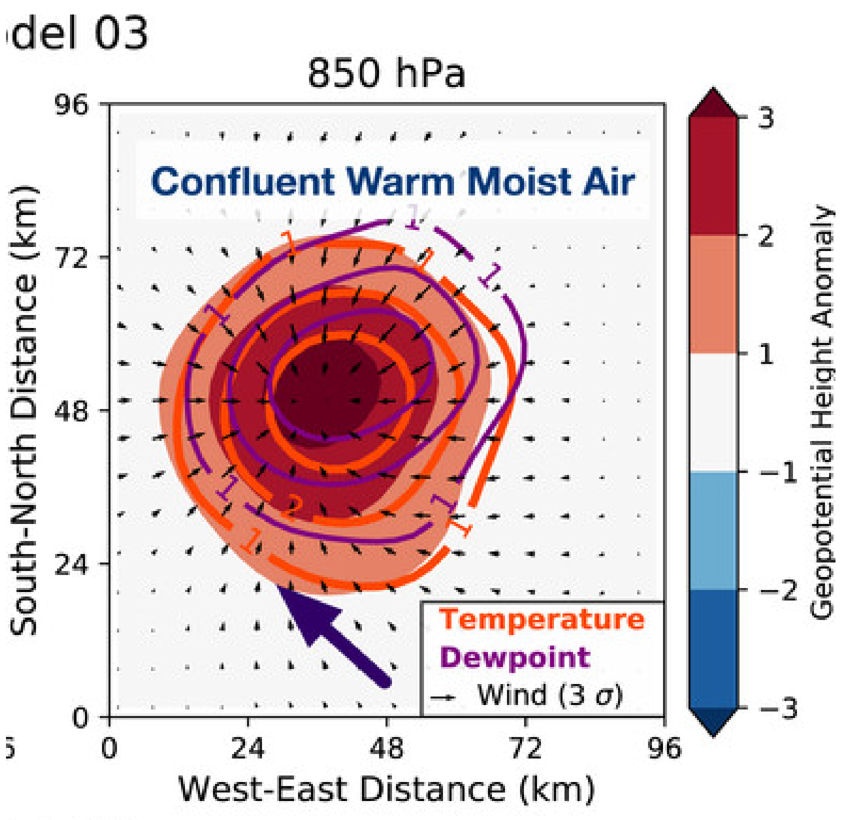
Tam, F. I-H., T. Beucler, & Ruppert, J. H. Jr. (2024), Identifying Three-Dimensional Radiative Patterns Associated with Early Tropical Cyclone Intensification. *Submitted to JAMES, in review.*

1. Process understanding in tropical meteorology with ML

Exploiting the feature detection properties of ML to understand a complex physical system

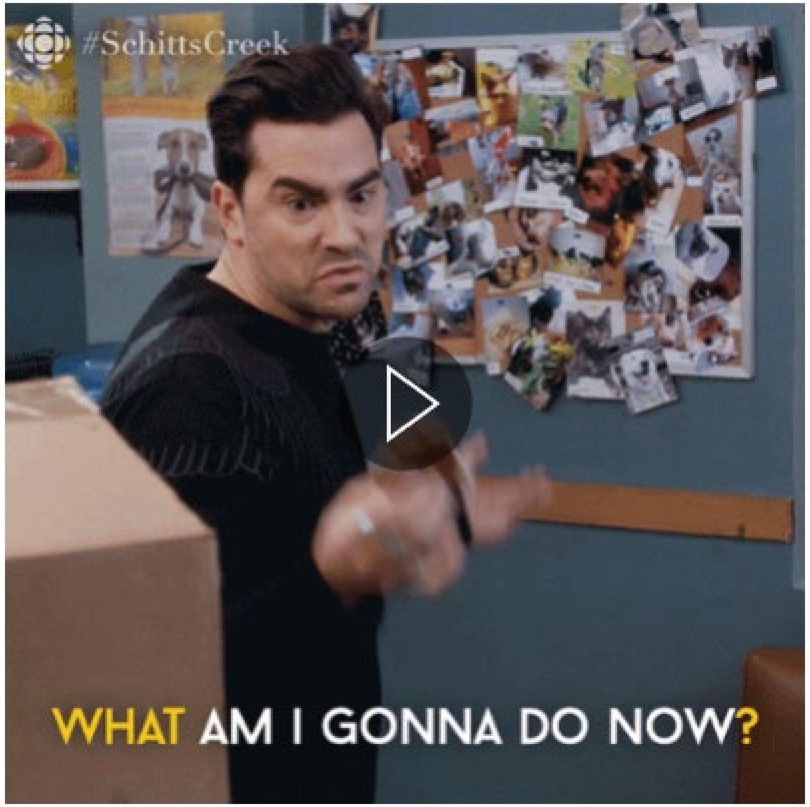
Gagne et al. (2019)

Identifying & Understanding Patterns = critical



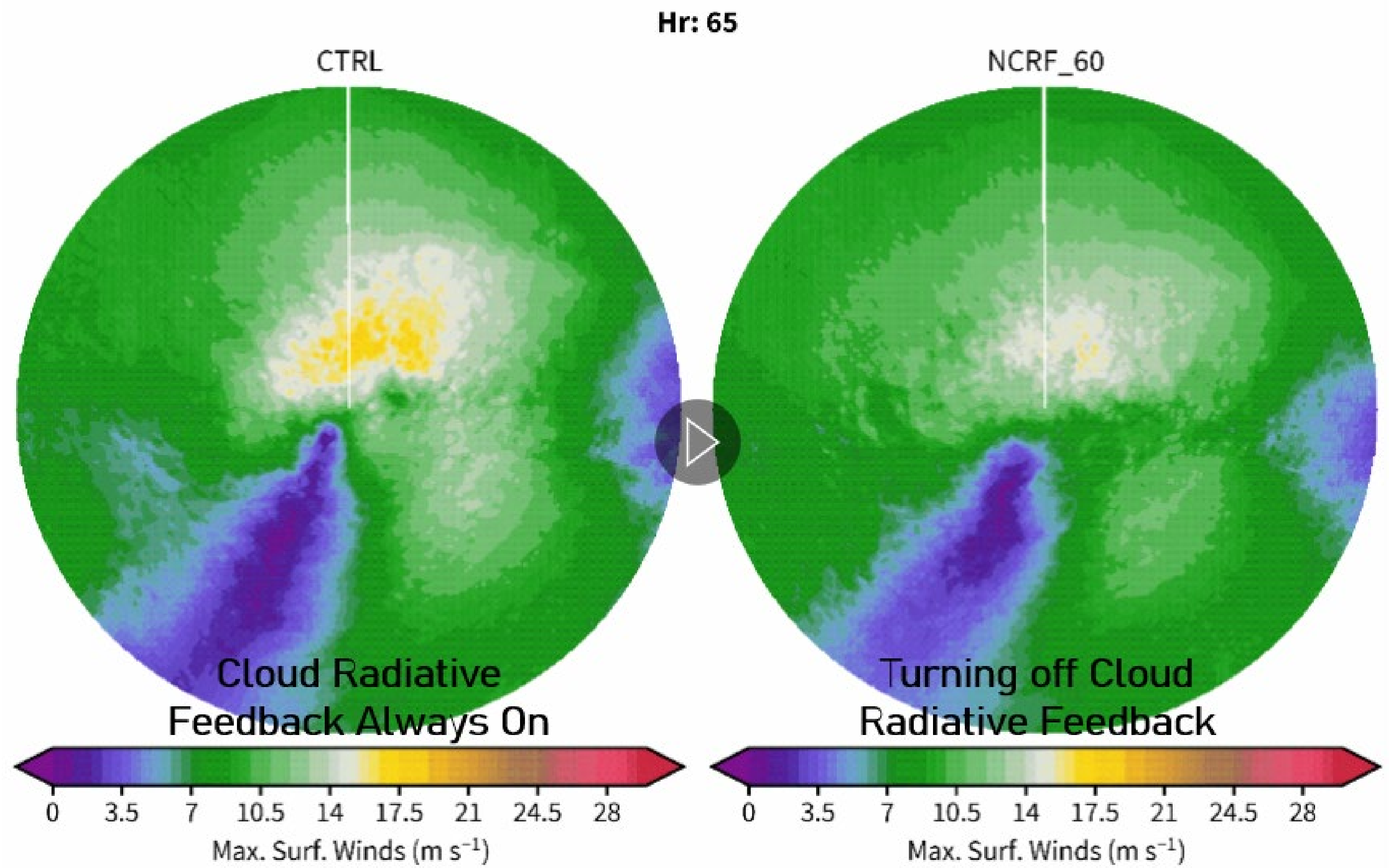
With patterns, we can better understand the physical processes behind extreme weather

How do we objectively discover these patterns?

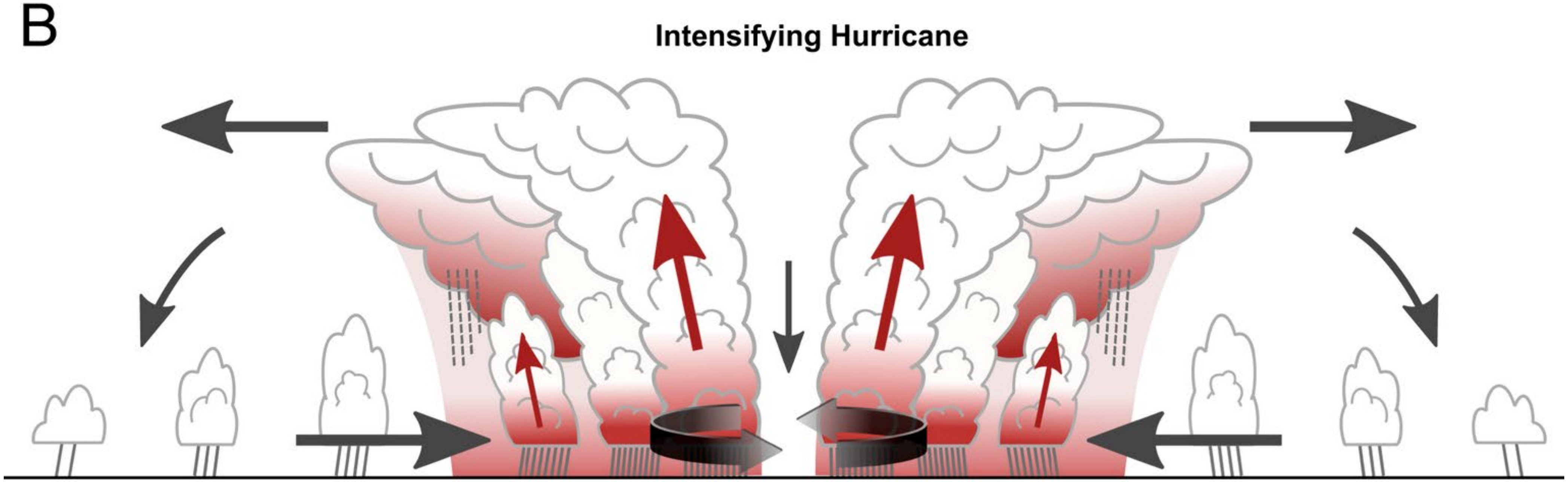


Our proposal: Machine learning can help!

Scientific Question: Cloud-radiative feedback asymmetries and Tropical Cyclogenesis



Scientific Question: Cloud-radiative feedback asymmetries and Tropical Cyclogensis

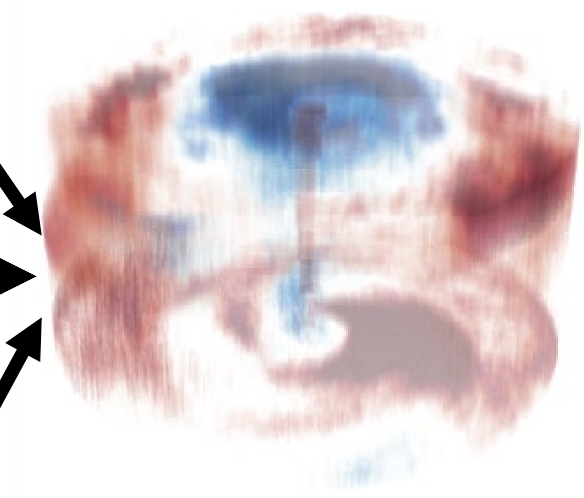


Will asymmetric cloud radiative forcing bring additional/less intensification v.s. axisymmetric forcing?

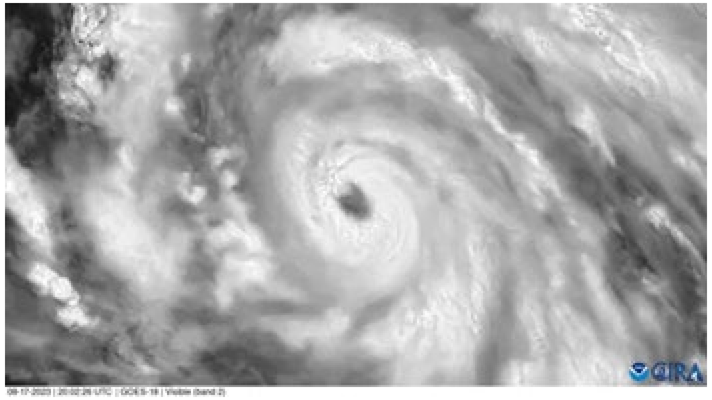
Ruppert et al. (2020)

Interpretable AI to extract TCG radiative patterns from complex data

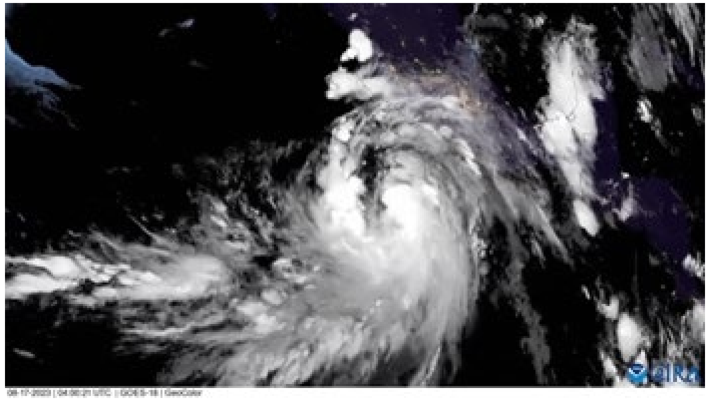
Sparse representation of radiation data



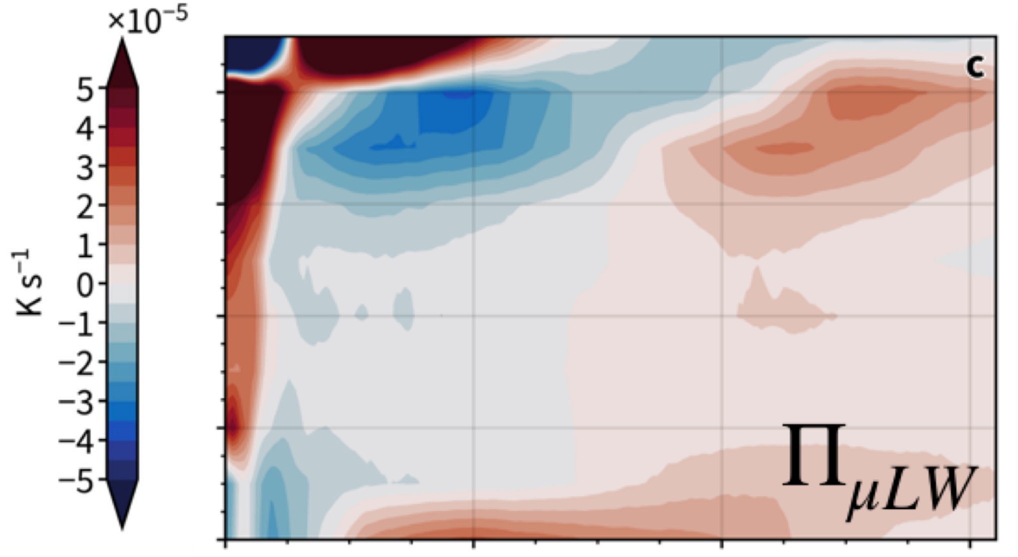
II. <u>Supervised</u> learning based on prediction task



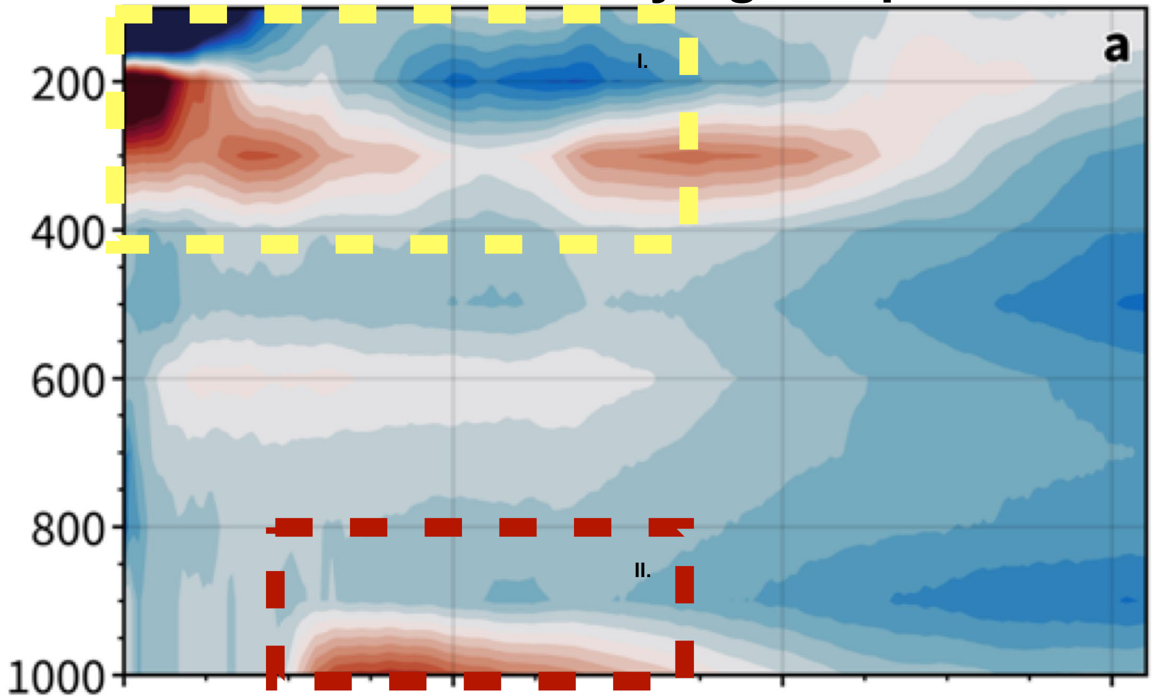
24-hr TC intensification rates



Extracted radiative structure encodes critical cloud processes



Fast-intensifying sample

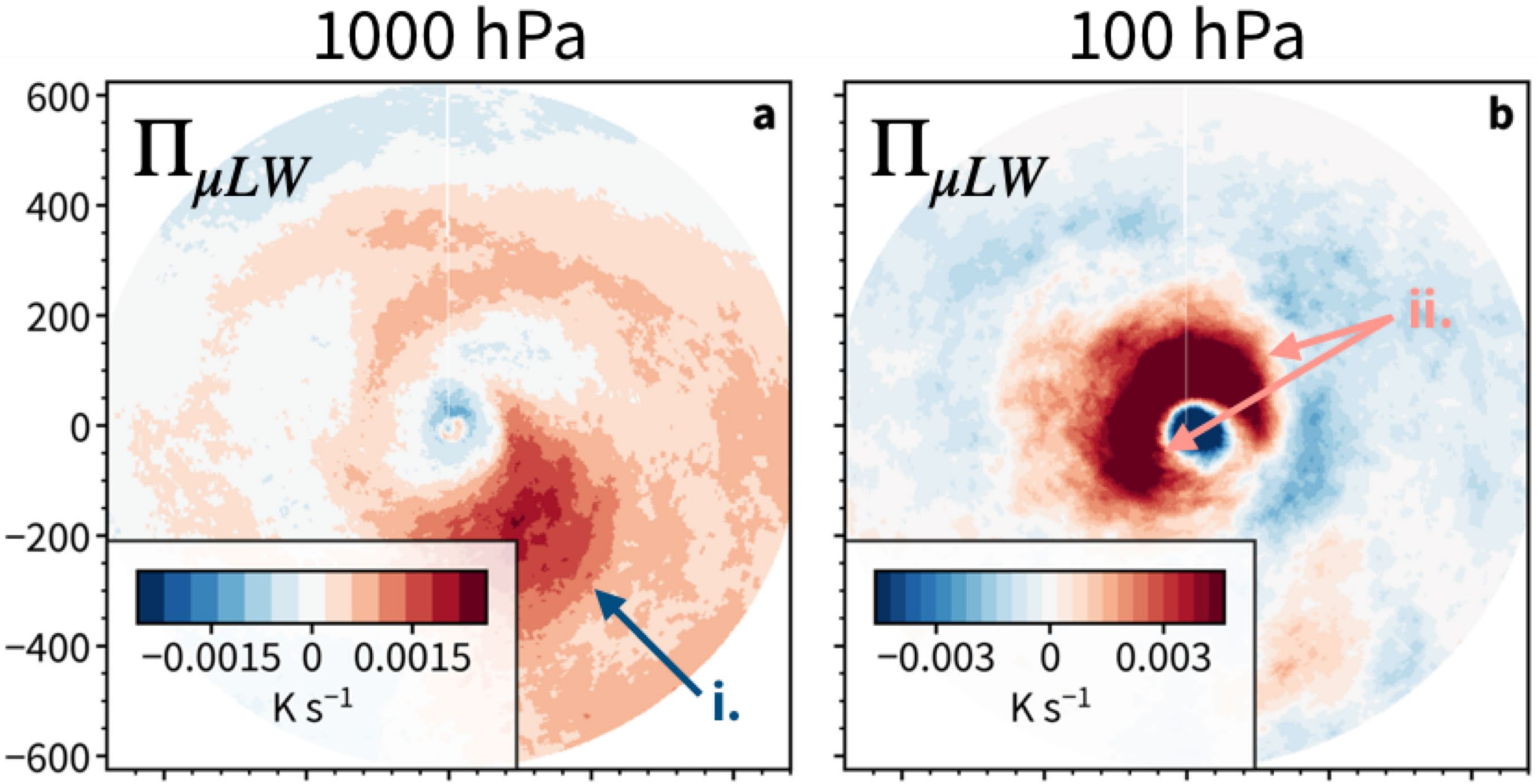


(I) Deep convective development, rising outflow in the inner core

(II) Shallow cloud radiative signature

(Upper-level) Trabing et al. (2019); Ramsay (2013)
(Low-level) Wang (2014)

The shallow clouds & deep convection signatures are asymmetric



Selecting robust features for machine-learning applications using multidata causal discovery

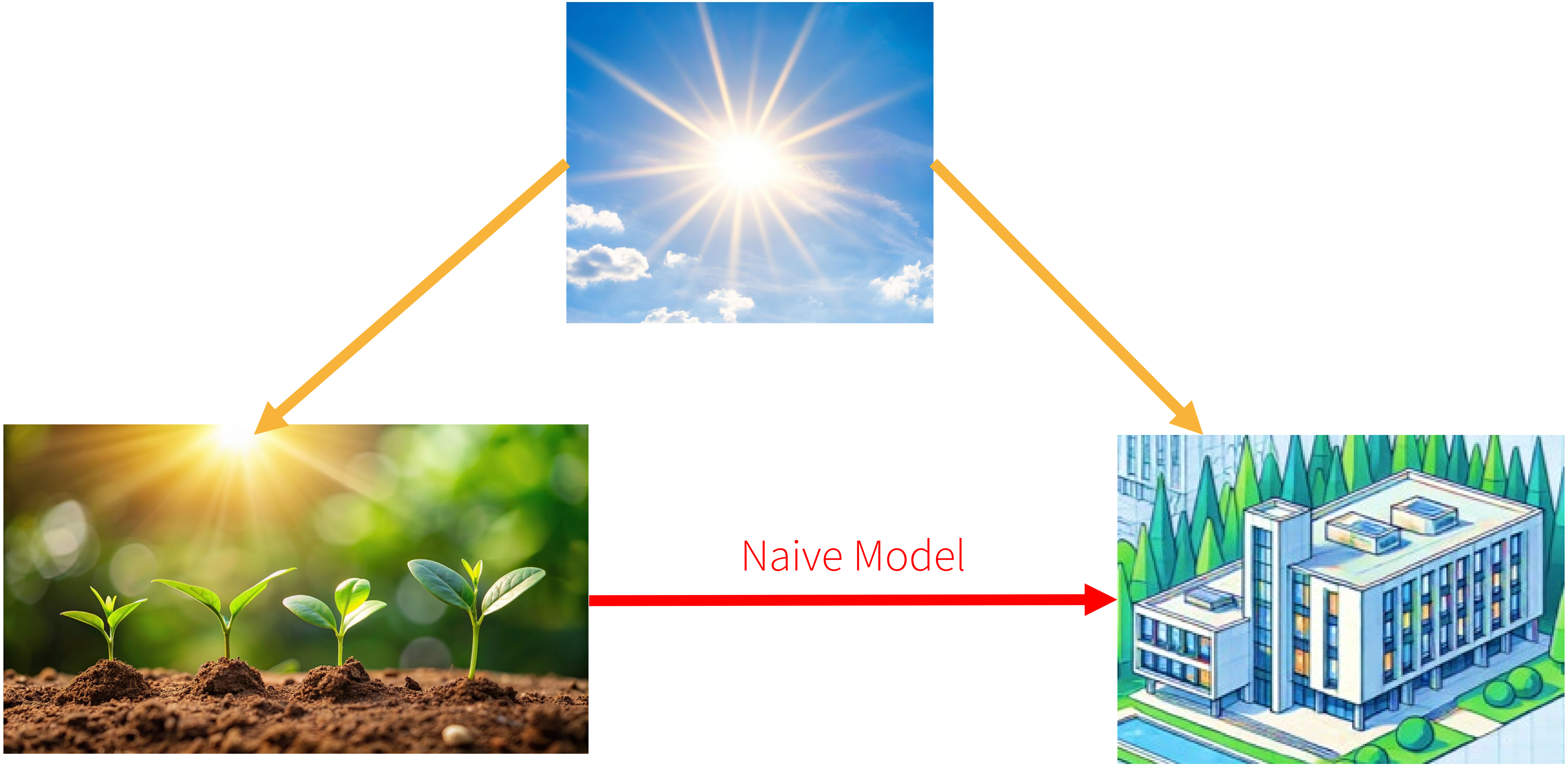
Saranya Ganesh S.[1], Tom Beucler[1], Frederick Iat-Hin Tam[1], Milton S. Gomez[1], Jakob Runge[2,3] and Andreas Gerhardus[2]

ENVIRONMENTAL DATA SCIENCE

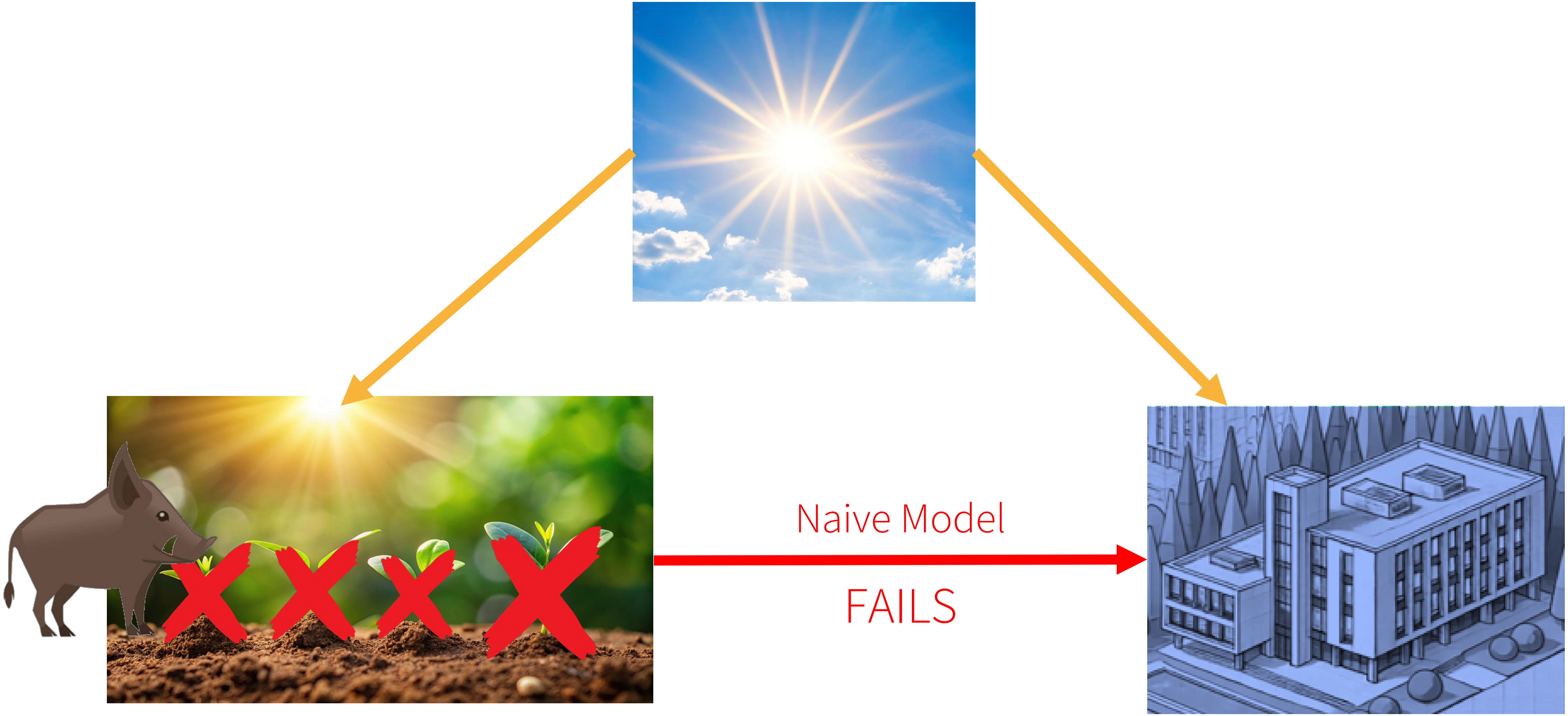
2. Causal Discovery for Tropical Cyclone Forecasting

Can Causal Discovery Improve Statistical Forecasting?

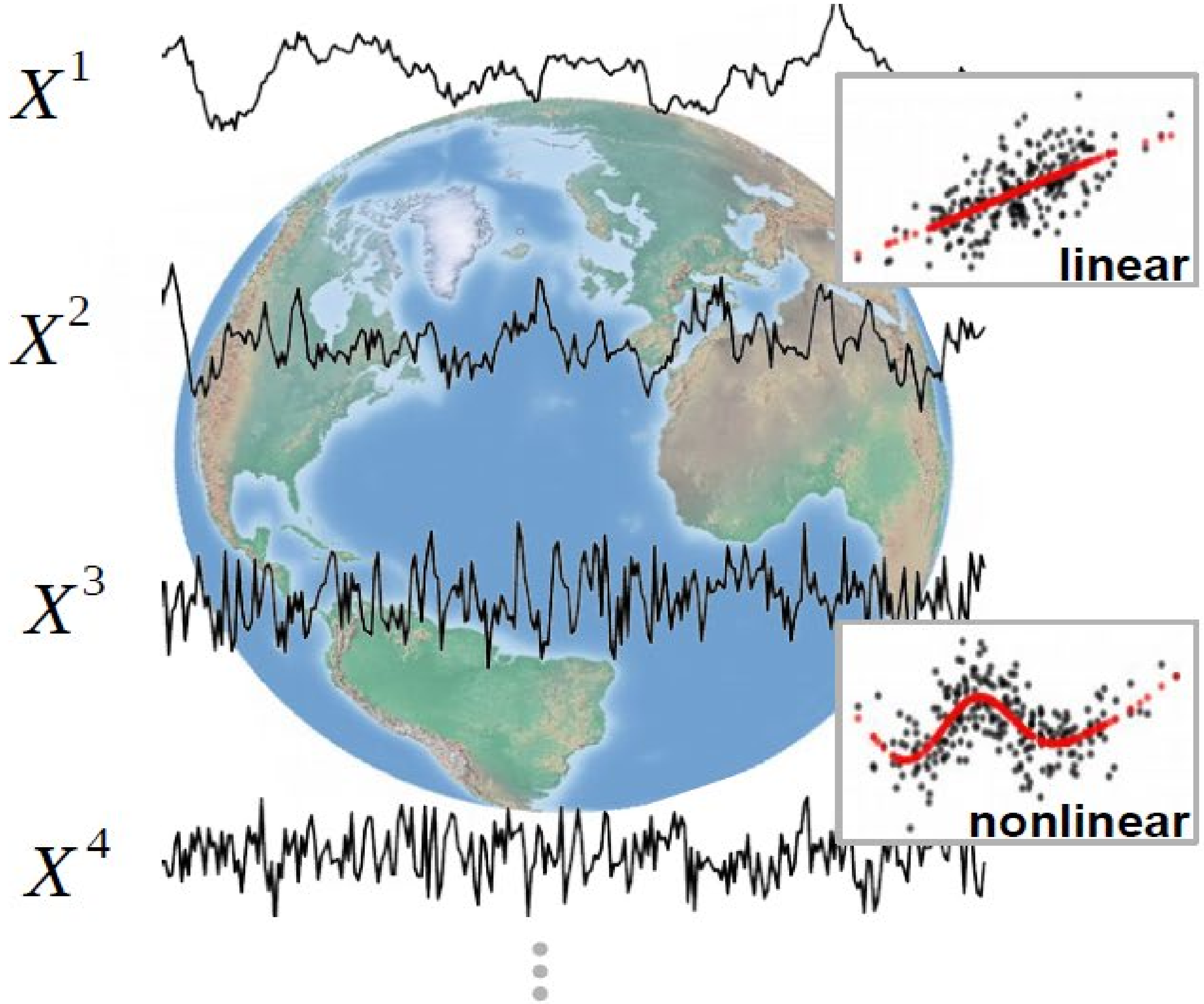
Can Causal Discovery Improve Statistical Forecasting?



Can Causal Discovery Improve Statistical Forecasting?

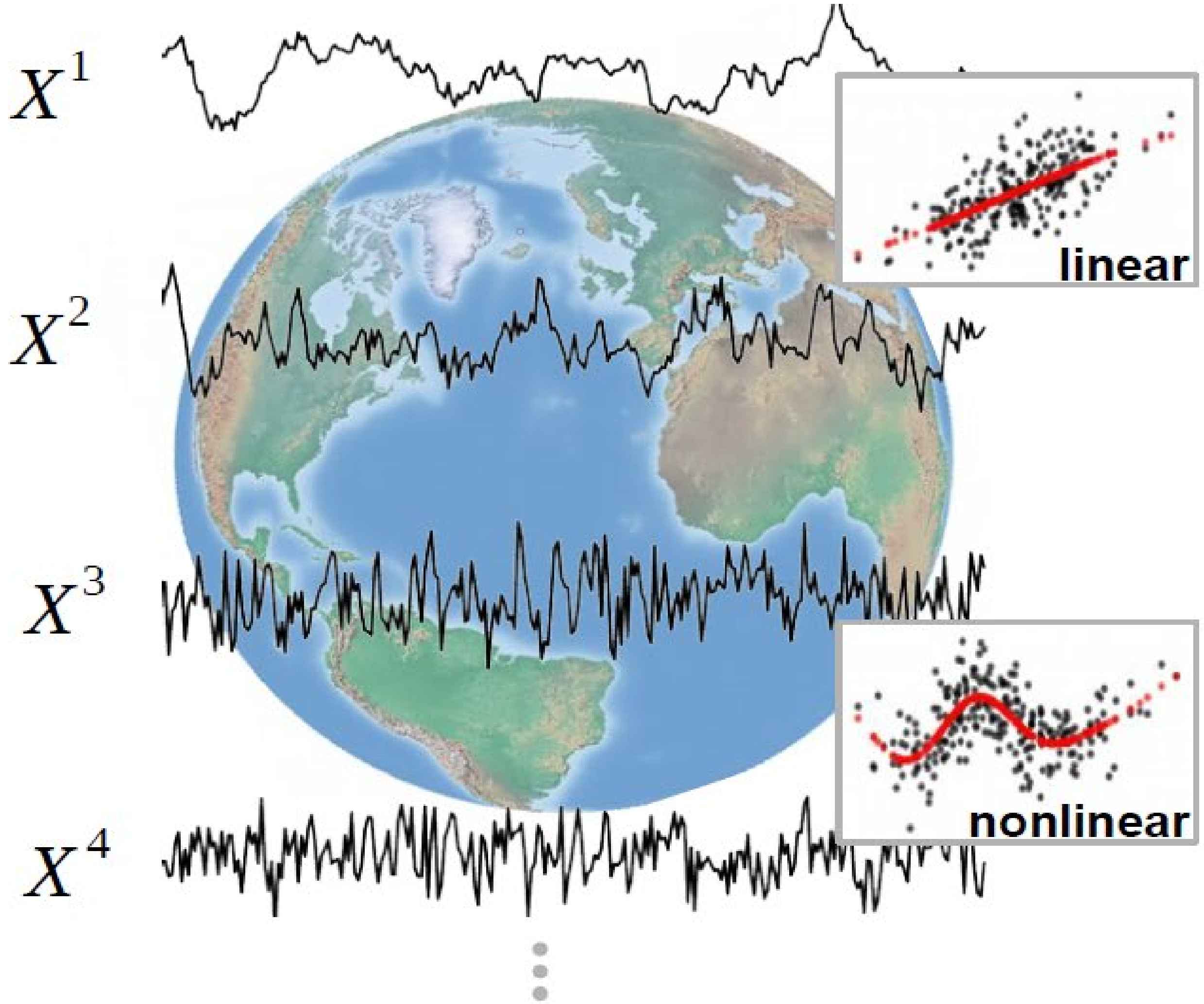


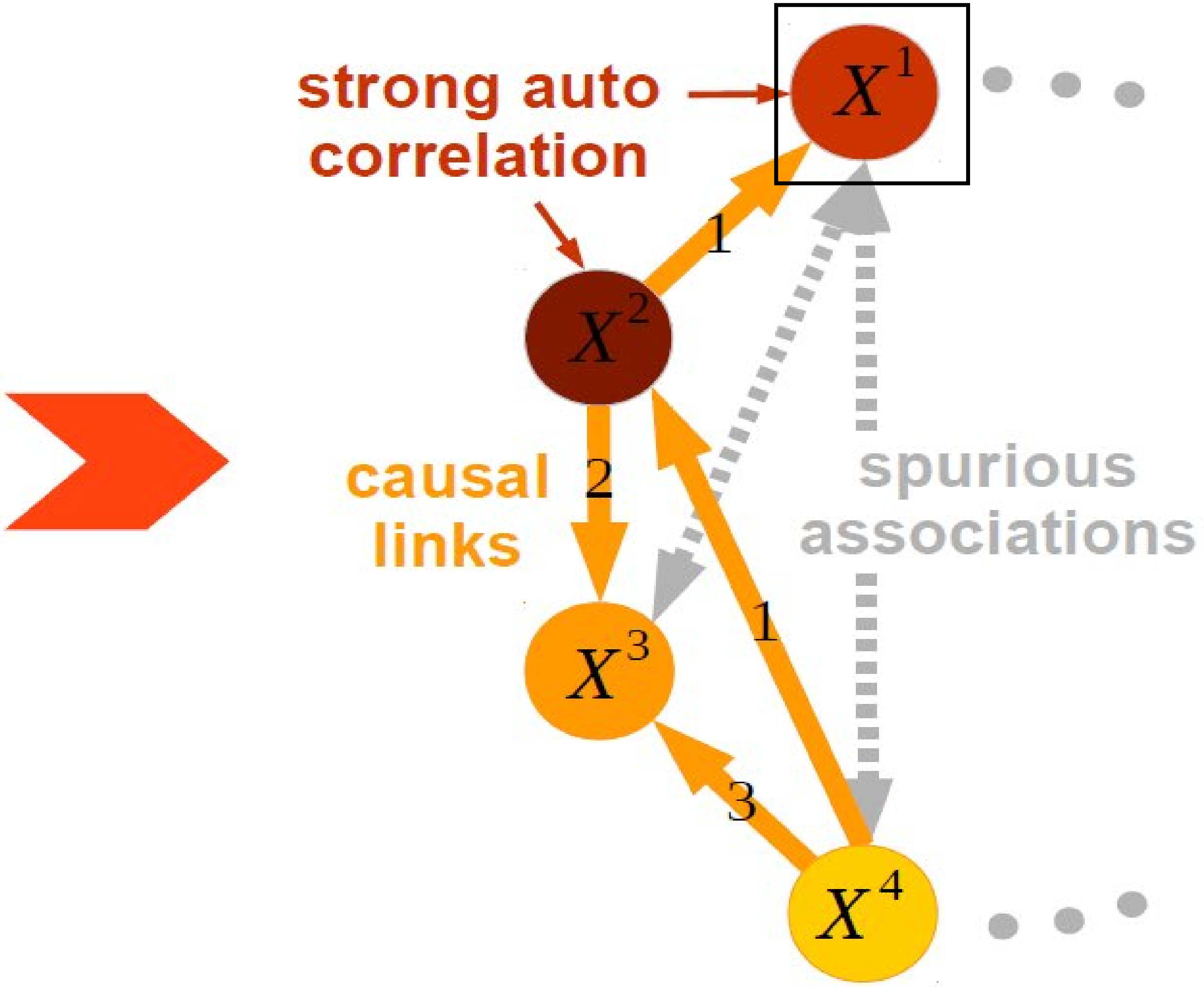
Can Causal Discovery Improve Statistical Forecasting?



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

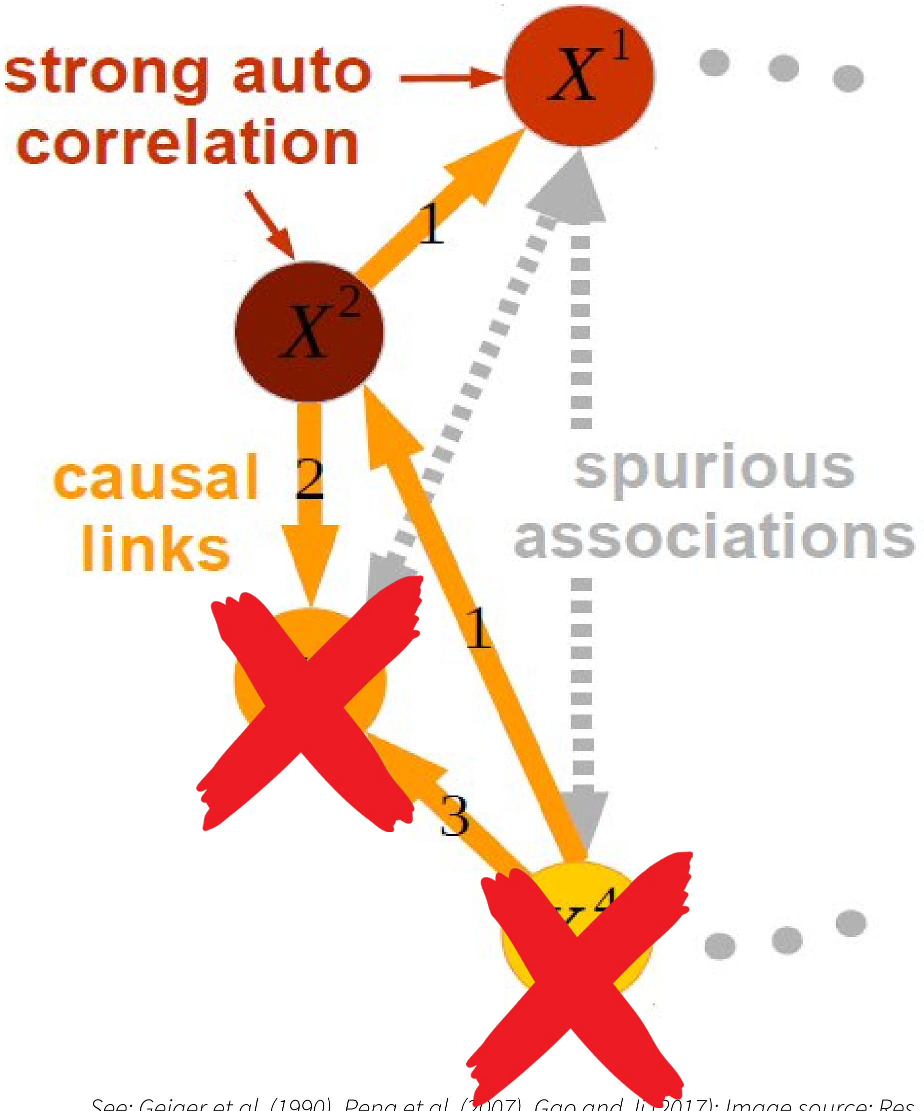
Can Causal Discovery Improve Statistical Forecasting?





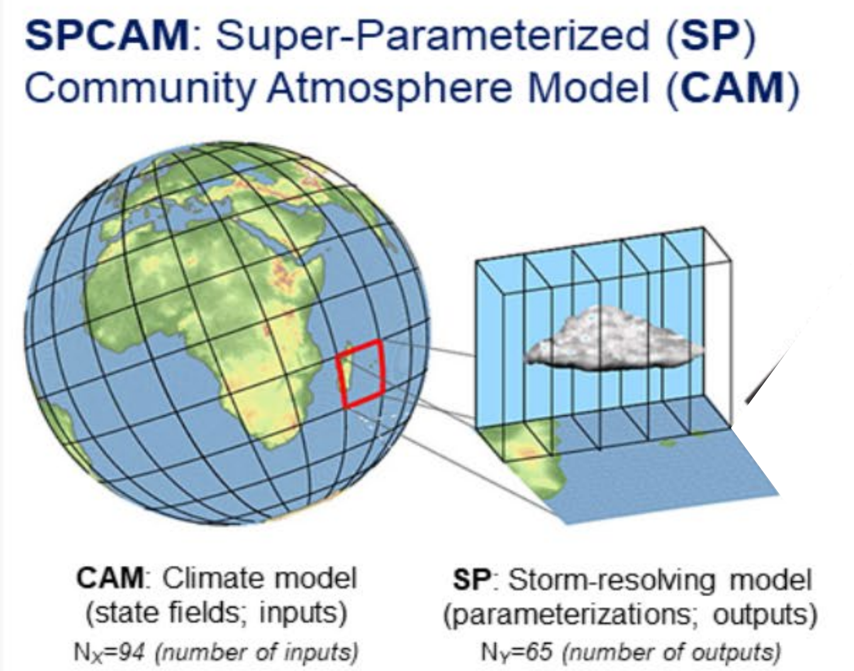
Source: Runge et al. (2019), See: Kretschmer et al. (2016), Runge et al. (2019), Spirtes & Glymour (1991)

Causal feature selection => removing non-causal predictors

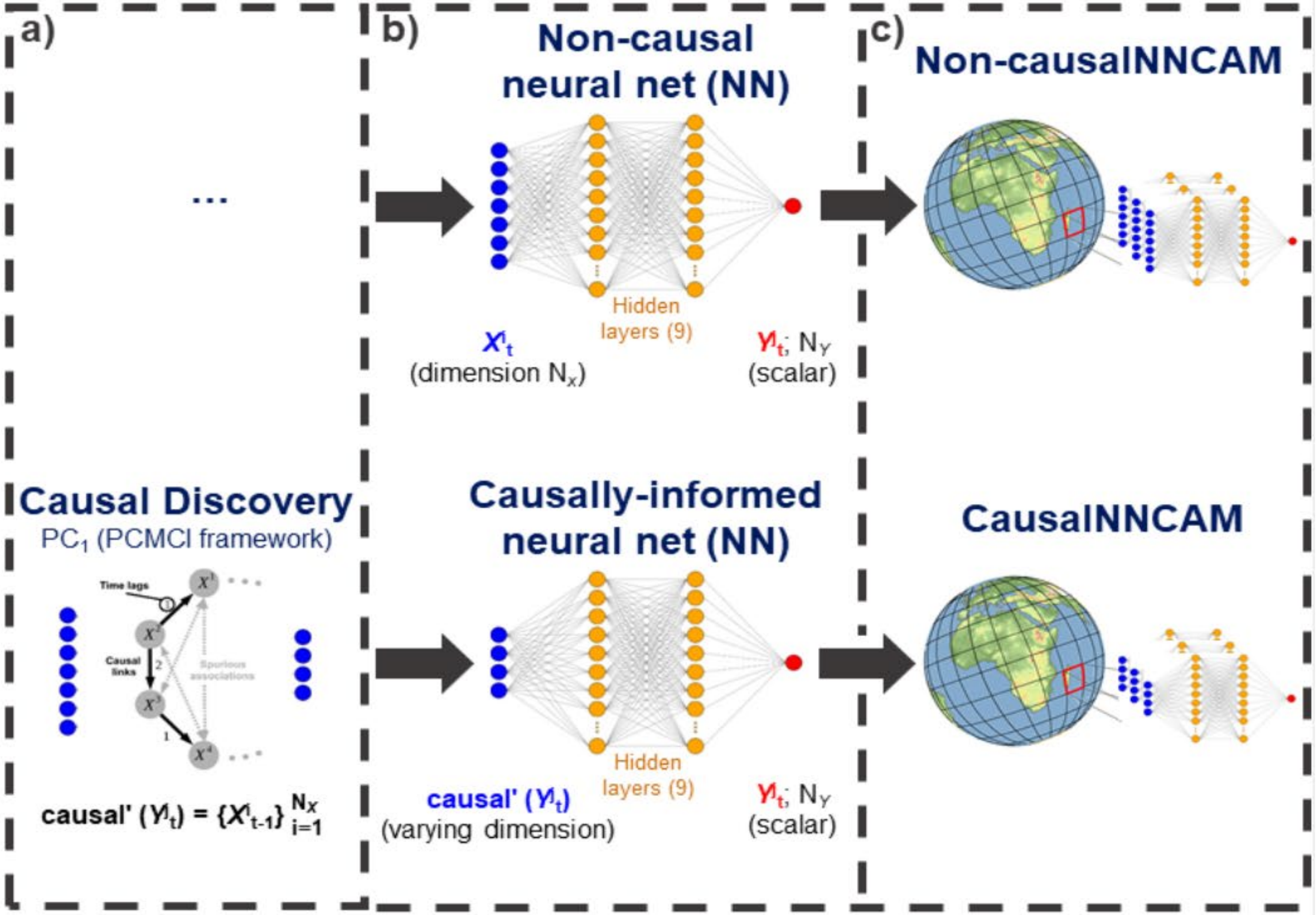


See: Geiger et al. (1990), Pena et al. (2007), Gao and Ji (2017); Image source: Res

Causal feature selection improves the robustness & stability of hybrid climate-AI simulations

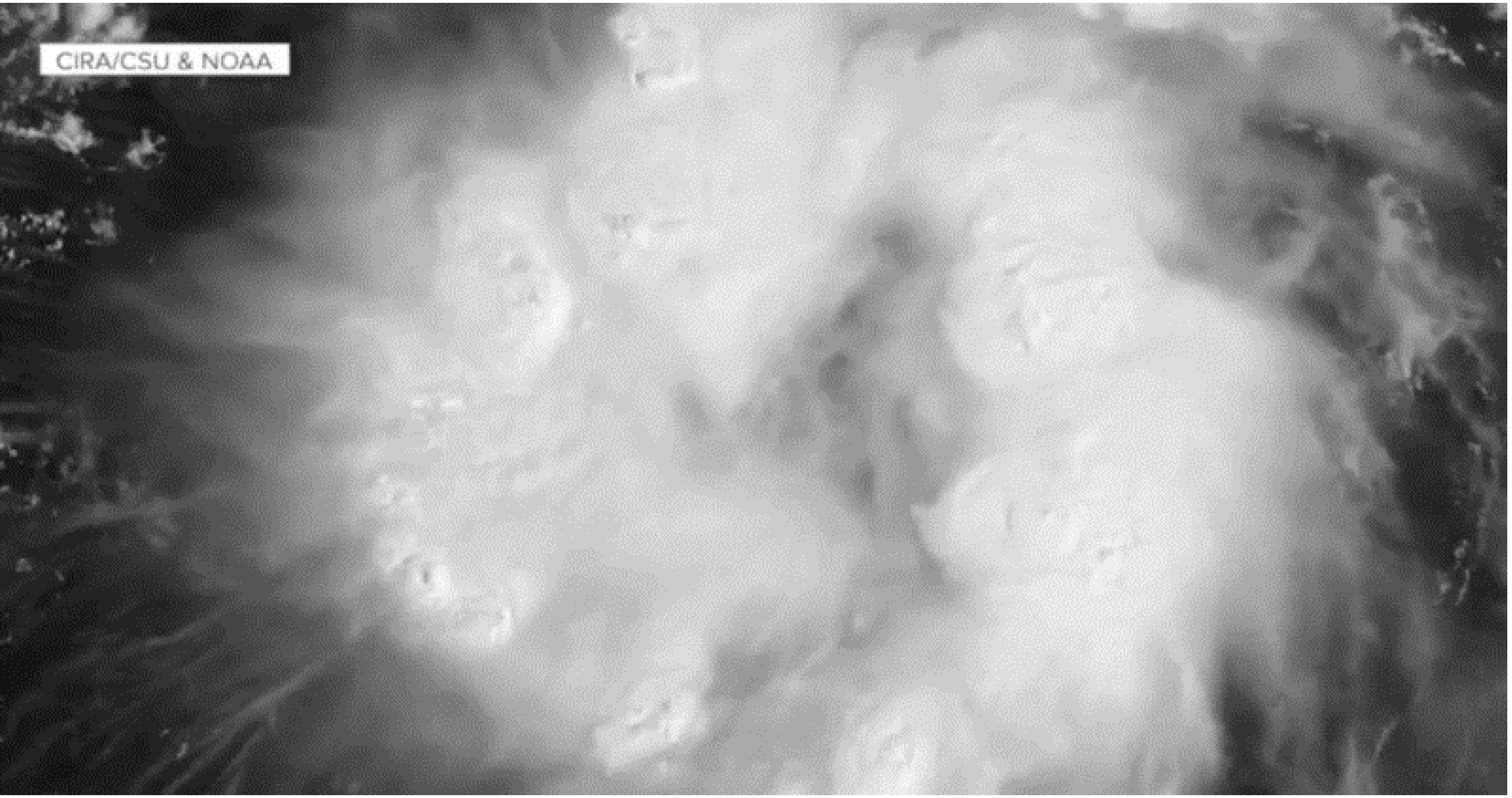


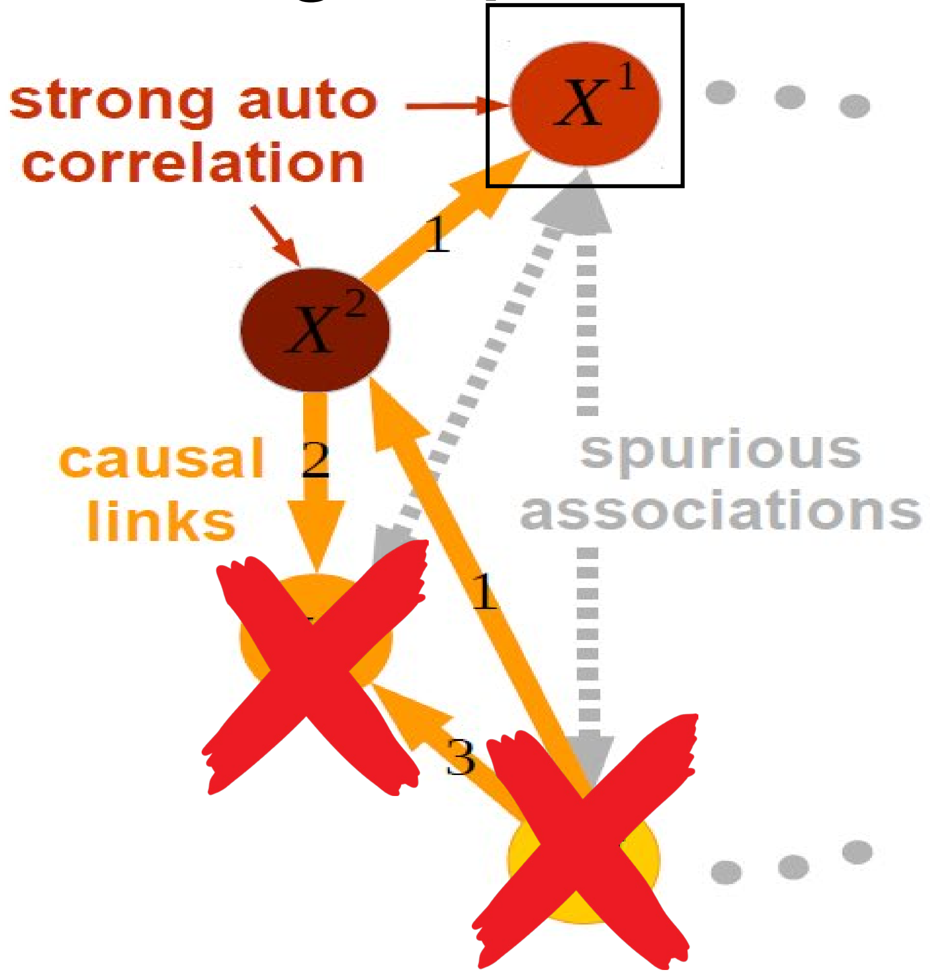
AMERICAN METEOROLOGICAL SOCIETY
AMS 2022
102nd ANNUAL MEETING



See: *Iglesias-Suarez et al. (2024)*

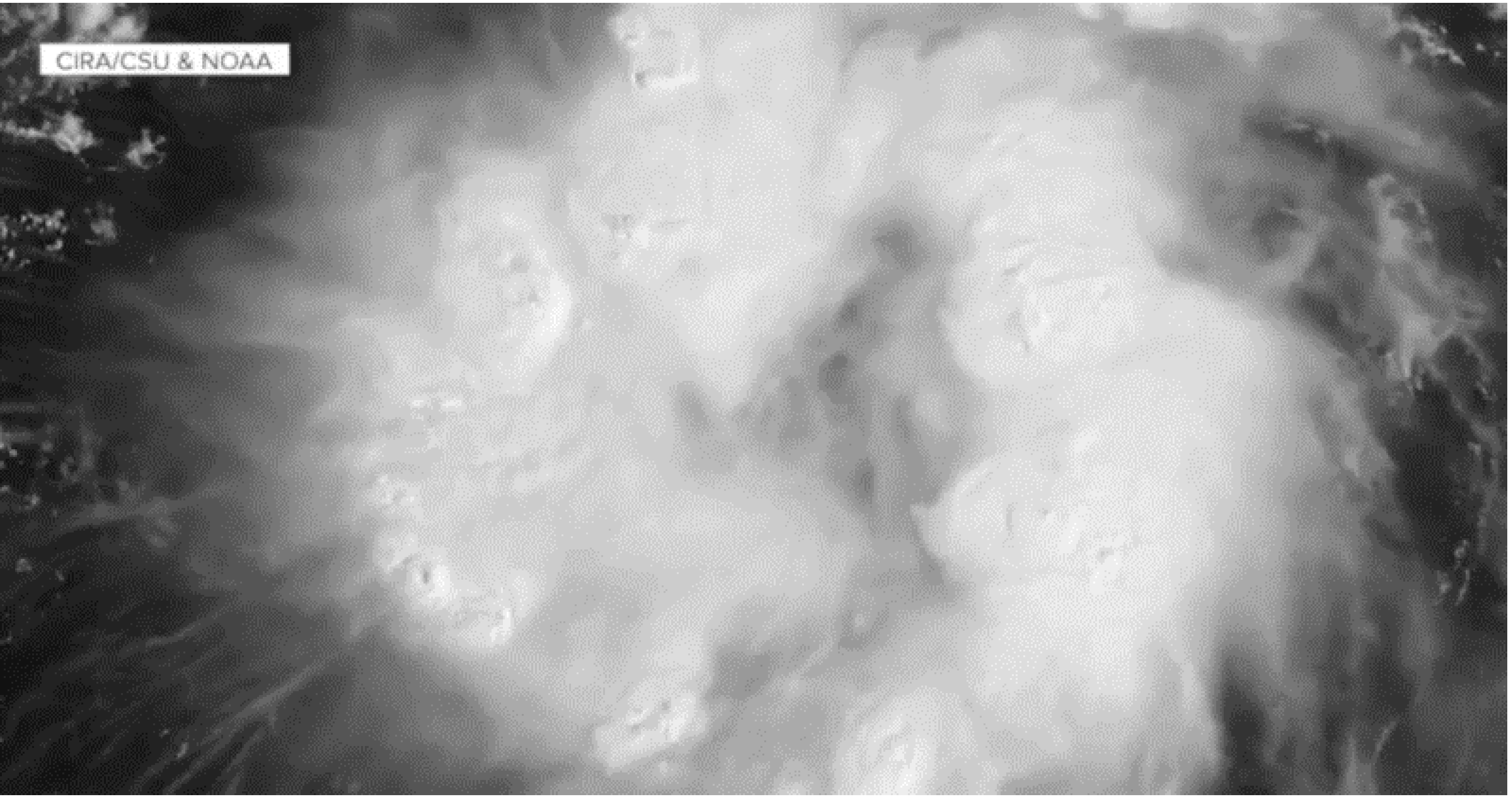
Causal feature selection improves the robustness & interpretability of tropical meteorological predictions





See: Geiger et al. (1990), Pena et al. (2007), Gao and Ji (2017); Image source: Res; Video source: Denver7, CIRA & NOAA

Causal feature selection improves the robustness & interpretability of tropical meteorological predictions

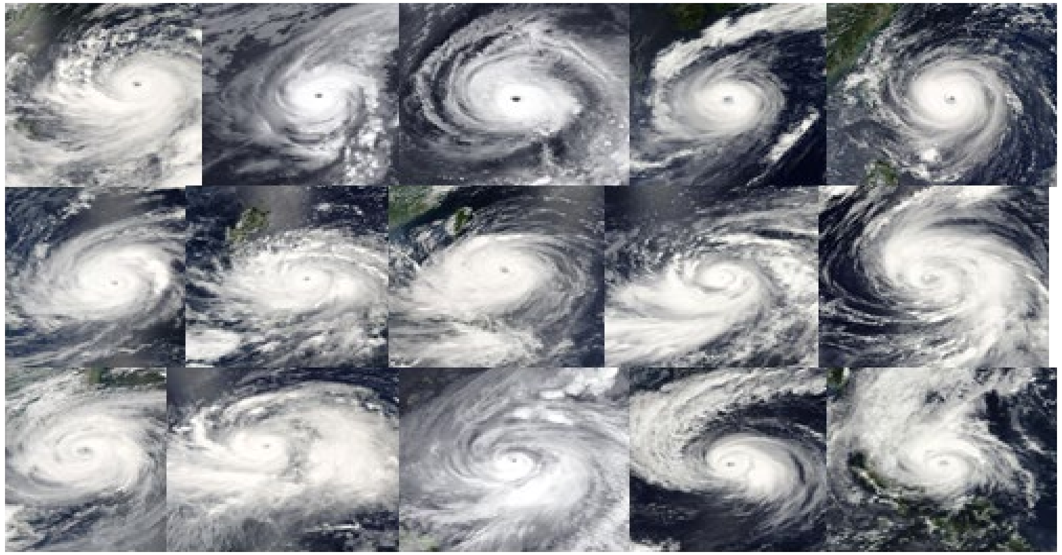


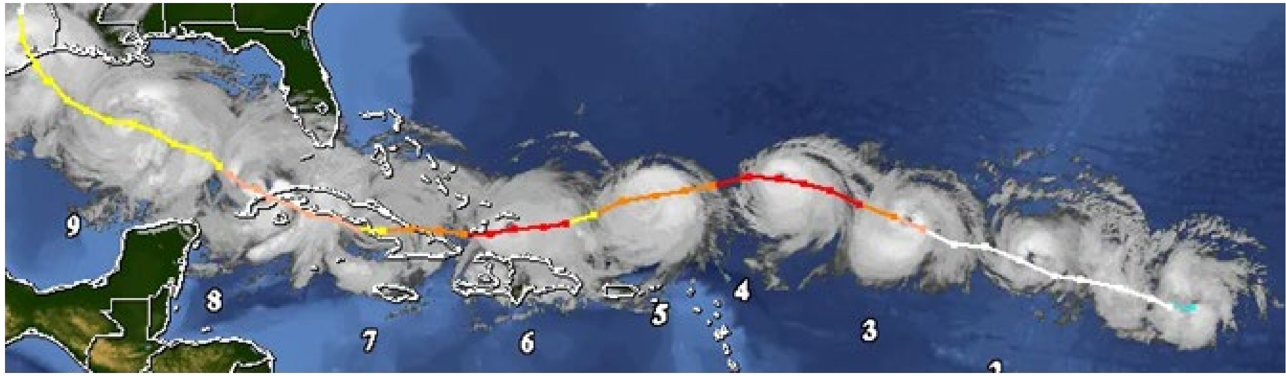
1. Causal forecasting schemes outperform non-causal baselines
   ✶*Multidata Causal F.S.*

2. Causal discovery can enrich existing schemes, improving generalization
   ✶*Stat. Hurricane I.P.S.*

<u>See</u>: Geiger et al. (1990), Pena et al. (2007), Gao and Ji (2017); <u>Image source</u>: Res; <u>Video source</u>: Denver7, CIRA & NOAA

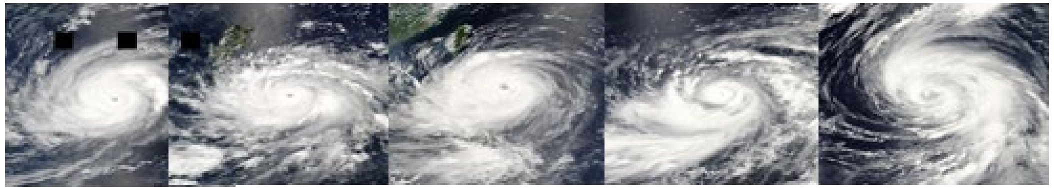
Motivation 1: Using causal discovery to find new TC intensity predictors



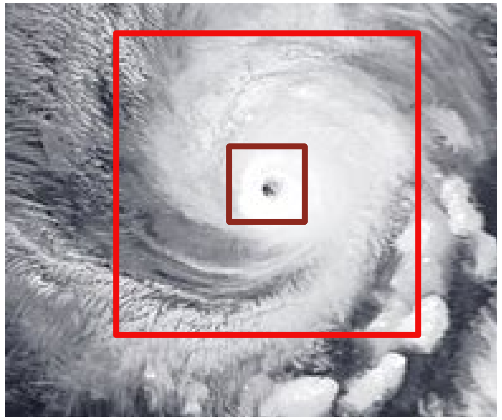


Best tracks from IBtrACS

$\vec{\nabla} \cdot \boldsymbol{u_h}$, w , ζ , RH , z , θ_e , $\partial_z U$, IWP...

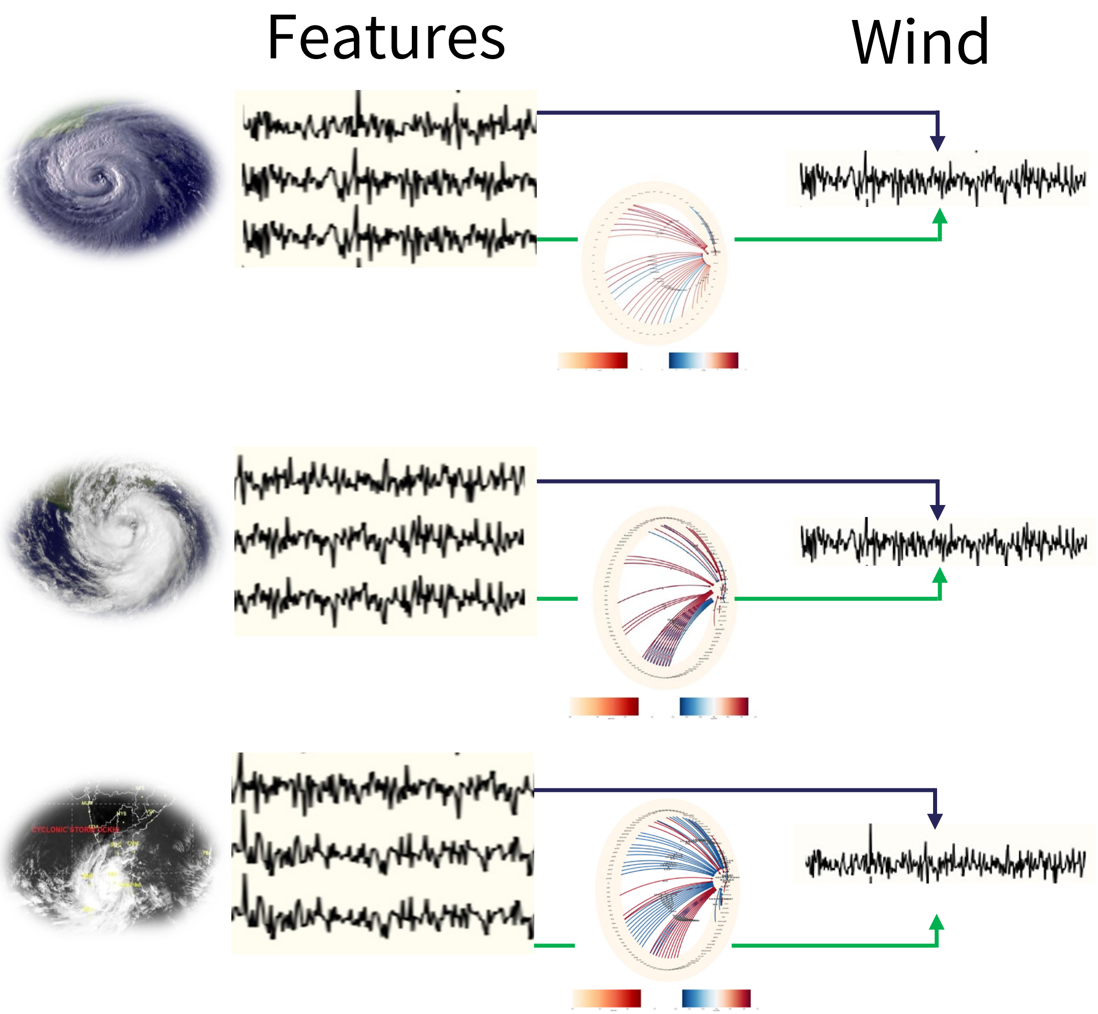


260 cases in the Northwest Pacific Basin (2001-2020) from ERA5

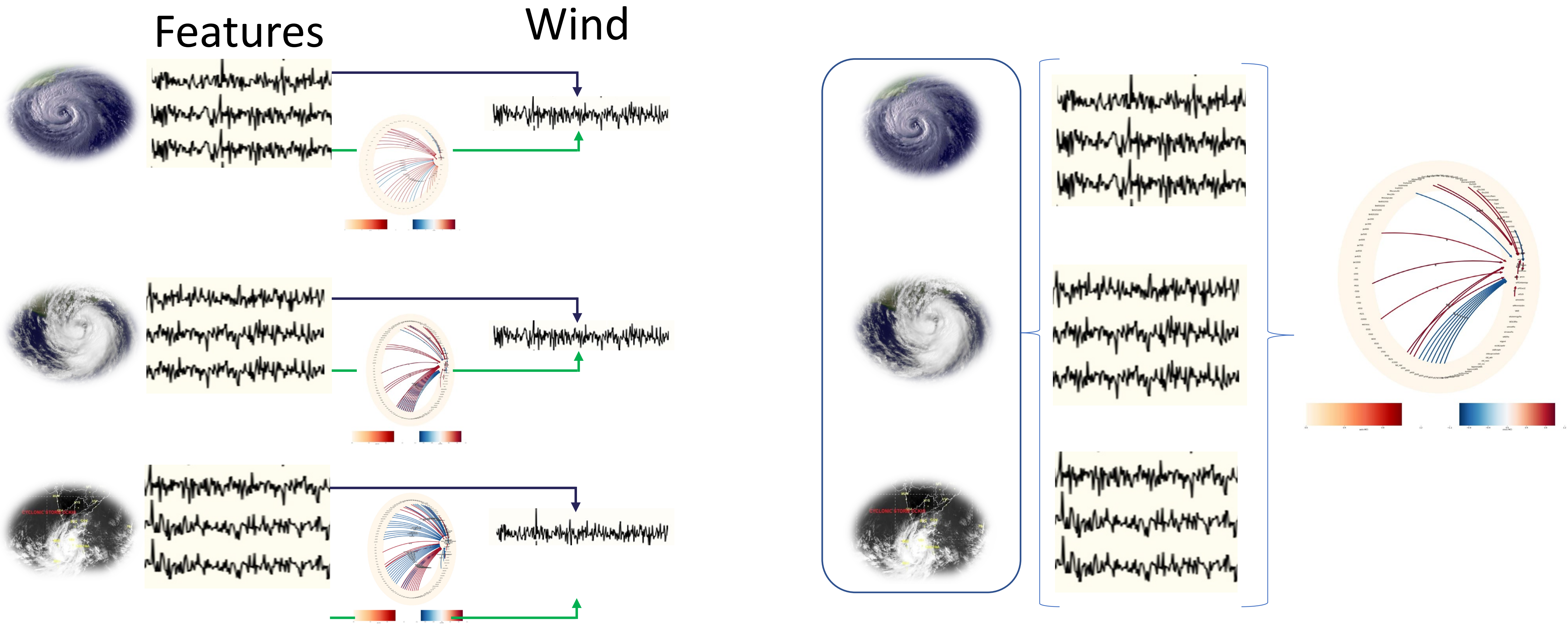


Area-average:
0-200km “Inner”
200-800km “Outer”

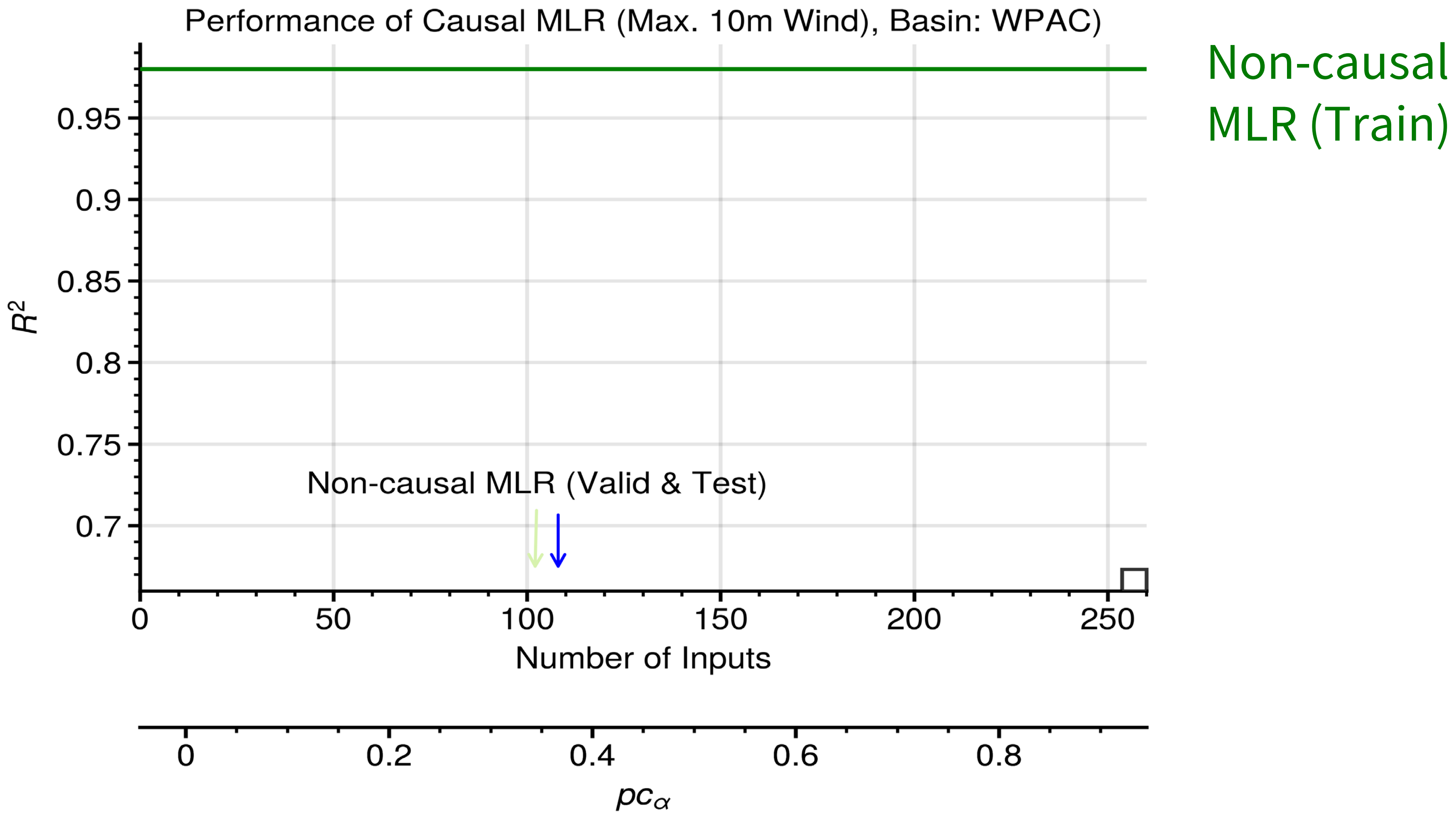
The time series are used to train ML models that predicts max. surface wind speeds with a lead time of 48 hours



Multidata causal discovery to discover a single set of causal drivers for *all TCs (in the training set)*



ML models using causal features generalize better to unseen cases



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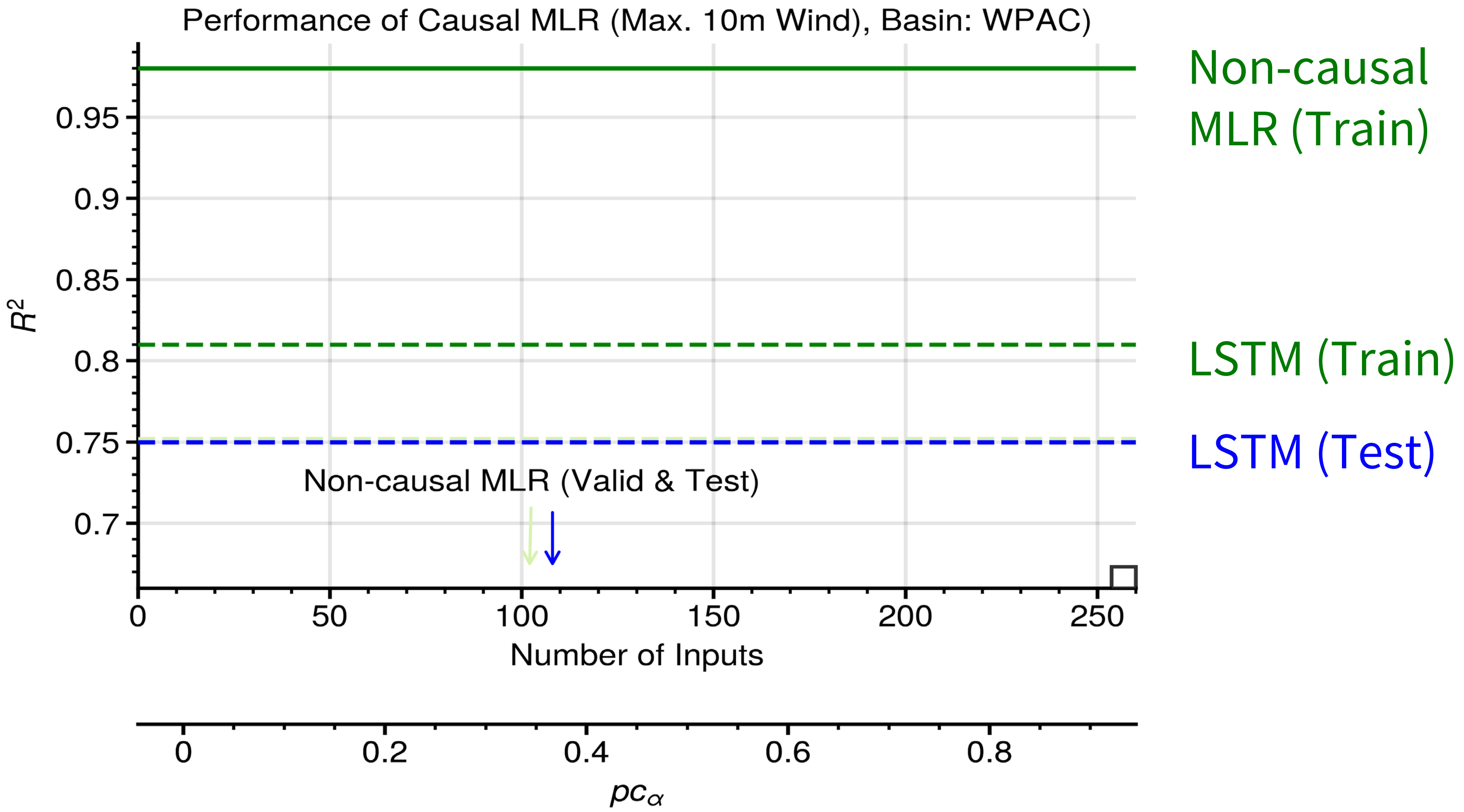
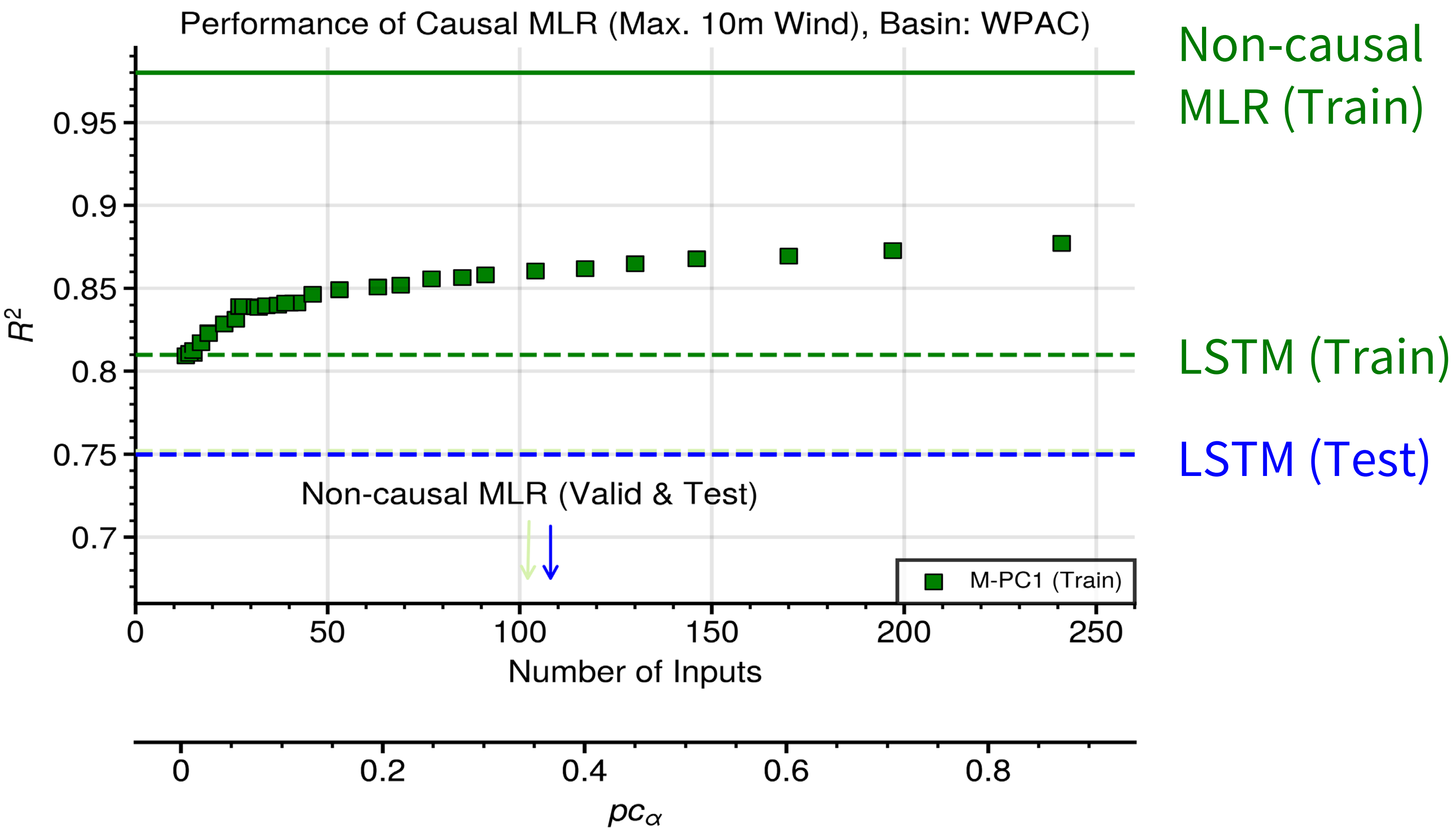
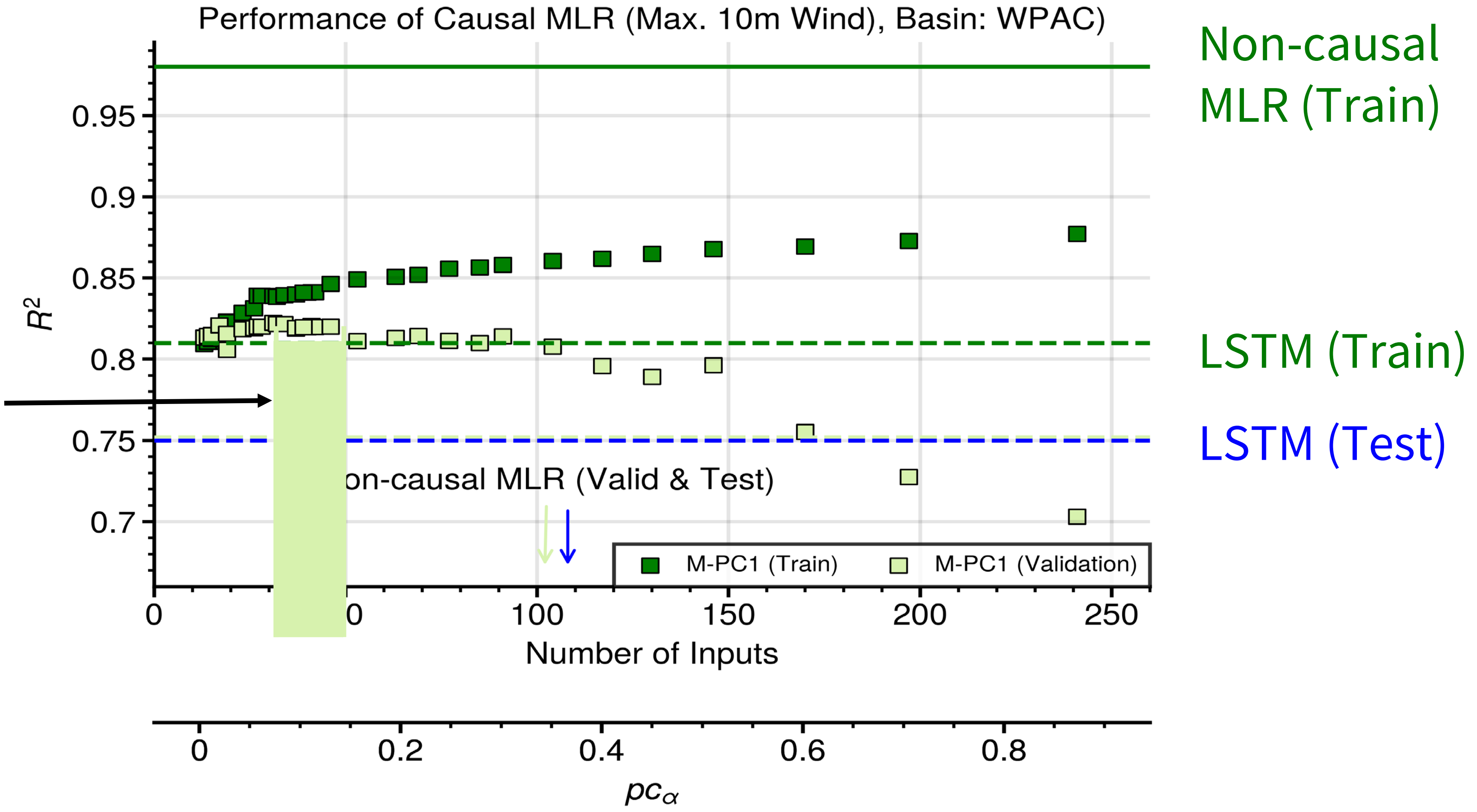


ML models using causal features generalize better to unseen cases

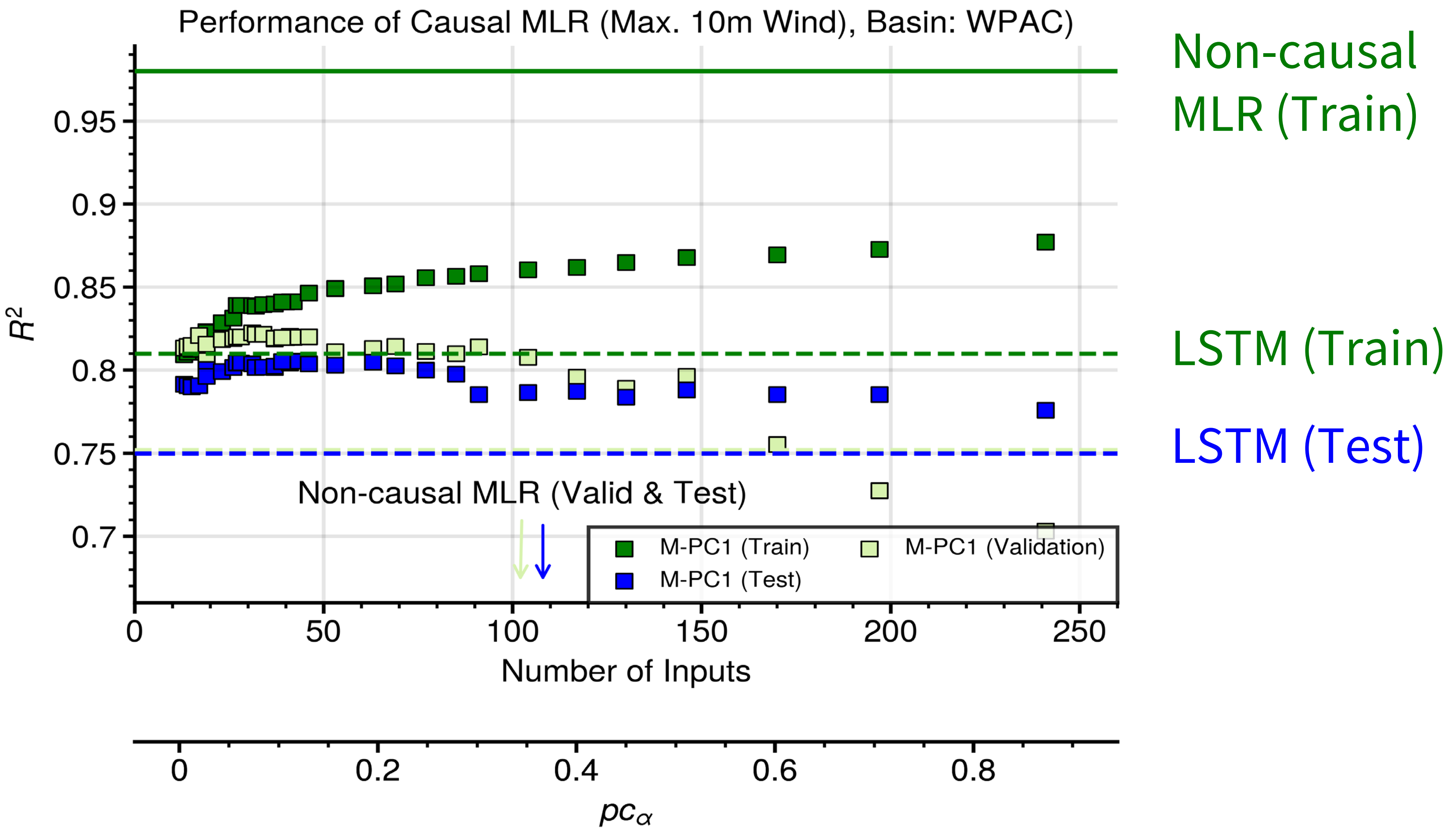


Schemes using causal features generalize better to unseen cases

Causal predictors yielding best generalization



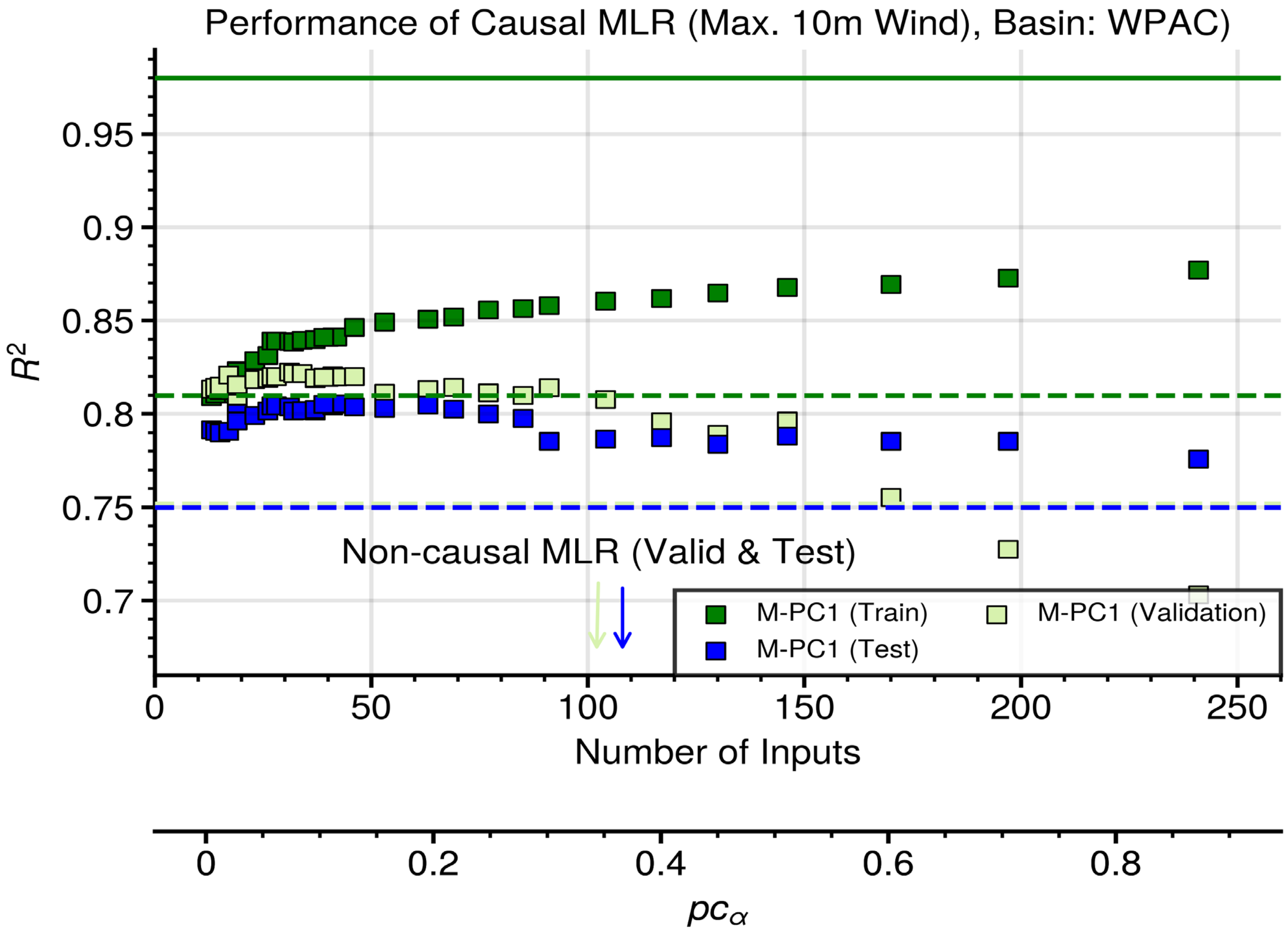
Schemes using causal features generalize better to unseen cases



Schemes using causal features generalize better to unseen cases

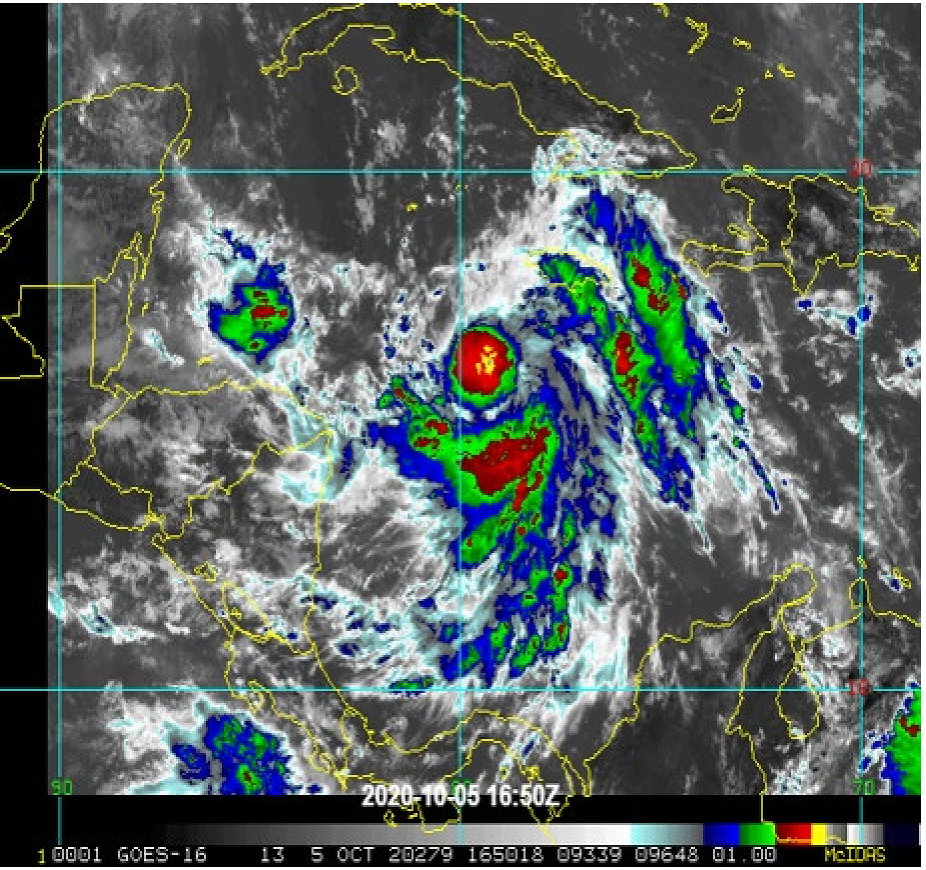
Multidata causal feature selection outperforms:

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



See: Ganesh S. et al. (2023, EDS)

Motivation 2: Can we use multidata causal features selection to improve the generalizability of existing schemes?



Statistical Hurricane Intensity Prediction Scheme:

- Statistical-dynamical guidance product based on multiple linear regressions
- Most skillful in the early 2000s
- Still used today in the consensus forecast
- ≈ 30 (thermo)dynamical/climatological drivers

How to add/remove predictors using multidata causal feature selection?

Image source: https://rammb-data.cira.colostate.edu/tc_realtime/ ; See: DeMaria et al. (2021), DeMaria et al. (2022), IWTC (2023)

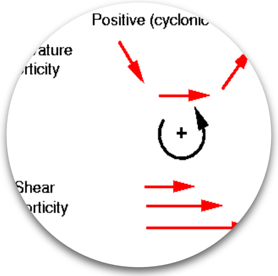
Experiment 2.2: Performing causal feature selection on an ERA5 replication of the SHIPS developmental dataset suggests new predictors

Ideal Case

Causal ML Pipeline ↕ SHIPS dvp. Dataset

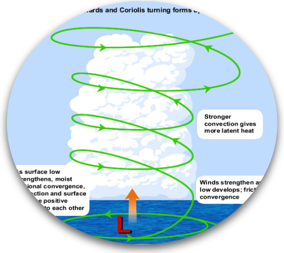
Reality

Causal ML Pipeline ↕ ERA5 Reanalysis → New SHIPS dvp. Dataset ↕ Causal ML Pipeline



Relative Vorticity
Inner+1000hPa

Relative Humidity
Inner+600hPa, Outer+950hPa



Mass-weighted w
0-500km

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Causal Feature Selection for Tropical Cyclone Forecasting

AMS 2024

Causal discovery can select drivers that are causally-related to the forecasted variable:

- Eliminating confounded vars, improving generalizability
- Enriching empirical schemes by suggesting new drivers

→ Broader applicability of causal discovery/inference for robust statistical forecasting

3) Post-processing Medium-Range, Neural Weather Forecasts of TCs

Tom Beucler[1]

Louis Poulain--Auzéau[2]

Alexis Berne[2]

Monika Feldmann[3]

Milton Gomez[1]

1: Université de Lausanne
2: Institut Polytéchnique Federale de Lausanne
3: Universität Bern

The Advent of Neural Weather Models (NeWMs)

Advancements in AI have led to machine learning models that by some metrics compete with or outperform deterministic NWP models[1].

FourcastNetV2	Graphcast	PanguWeather	AIFS
Spherical Neural Operators	Interaction Graph Neural Networks	Transformers	GNNs + Transformers
NVIDIA	Google	HUAWEI	ECMWF

[1] Rasp, S., Hoyer, S., Merose, A., Langmore, I., Battaglia, P., Russell, T., ... & Sha, F. (2024). WeatherBench 2: A benchmark for the next generation of data-driven global weather models. *Journal of Advances in Modeling Earth Systems*, *16*(6), e2023MS004019.

Logos from Wikimedia Commons

What do NeWMs actually do?

FourCastNetv2[2]

Can we learn a grid-invariant filters to map the states of the atmosphere?

GraphCast[1]

Can we evolve the state of the atmosphere in a latent graph space?

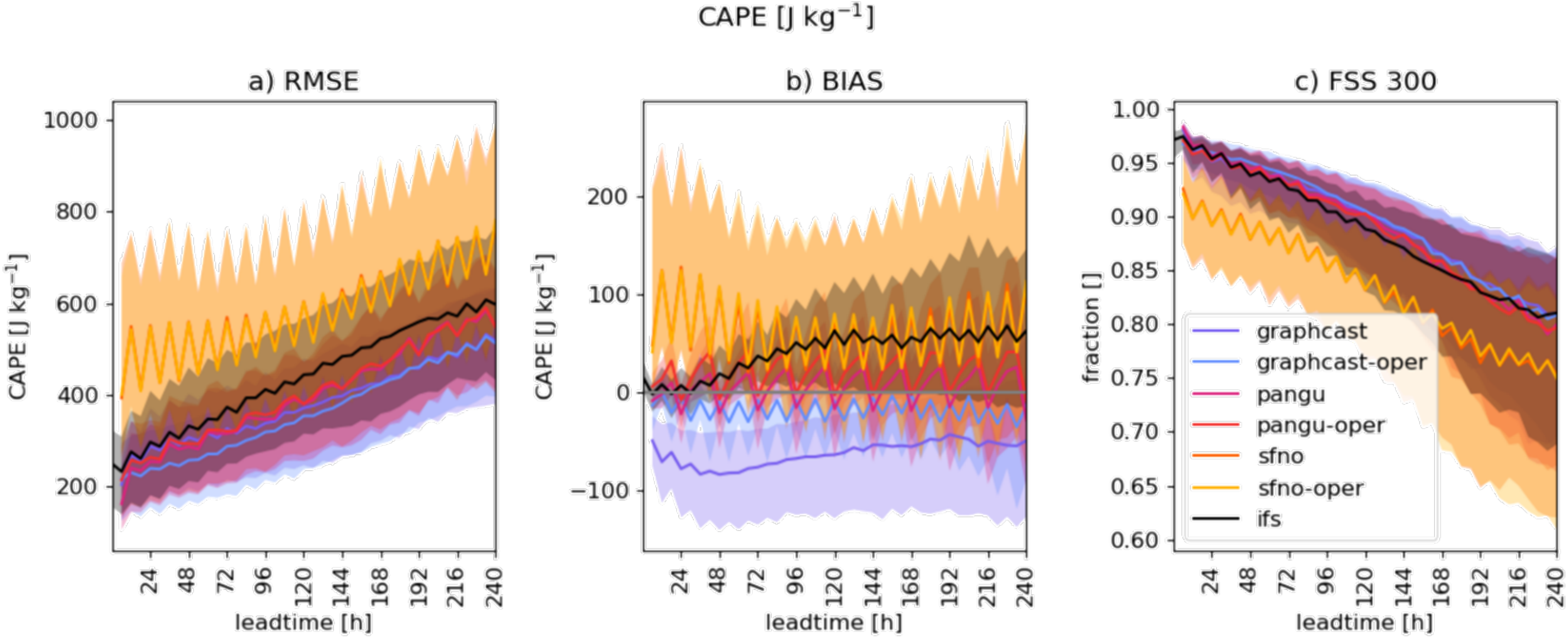
PanguWeather[3]

Can we learn how to predict the state of the atmosphere from a series of queries, keys, and values generated from its current state?

[1] Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., ... & Battaglia, P. (2023). Learning skillful medium-range global weather forecasting. *Science*, *382*(6677), 1416-1421.
[2] Bonev, B., Kurth, T., Hundt, C., Pathak, J., Baust, M., Kashinath, K., & Anandkumar, A. (2023, July). Spherical fourier neural operators: Learning stable dynamics on the sphere. In *International conference on machine learning* (pp. 2806-2823). PMLR.
[3] Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, *619*(7970), 533-538.

How well do they do?

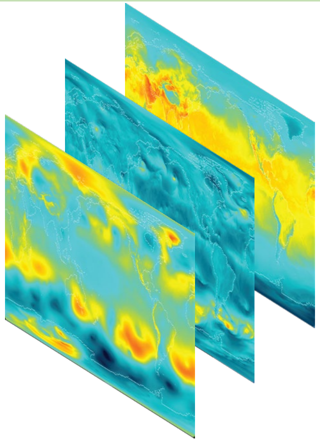
arXiv
2406.09474

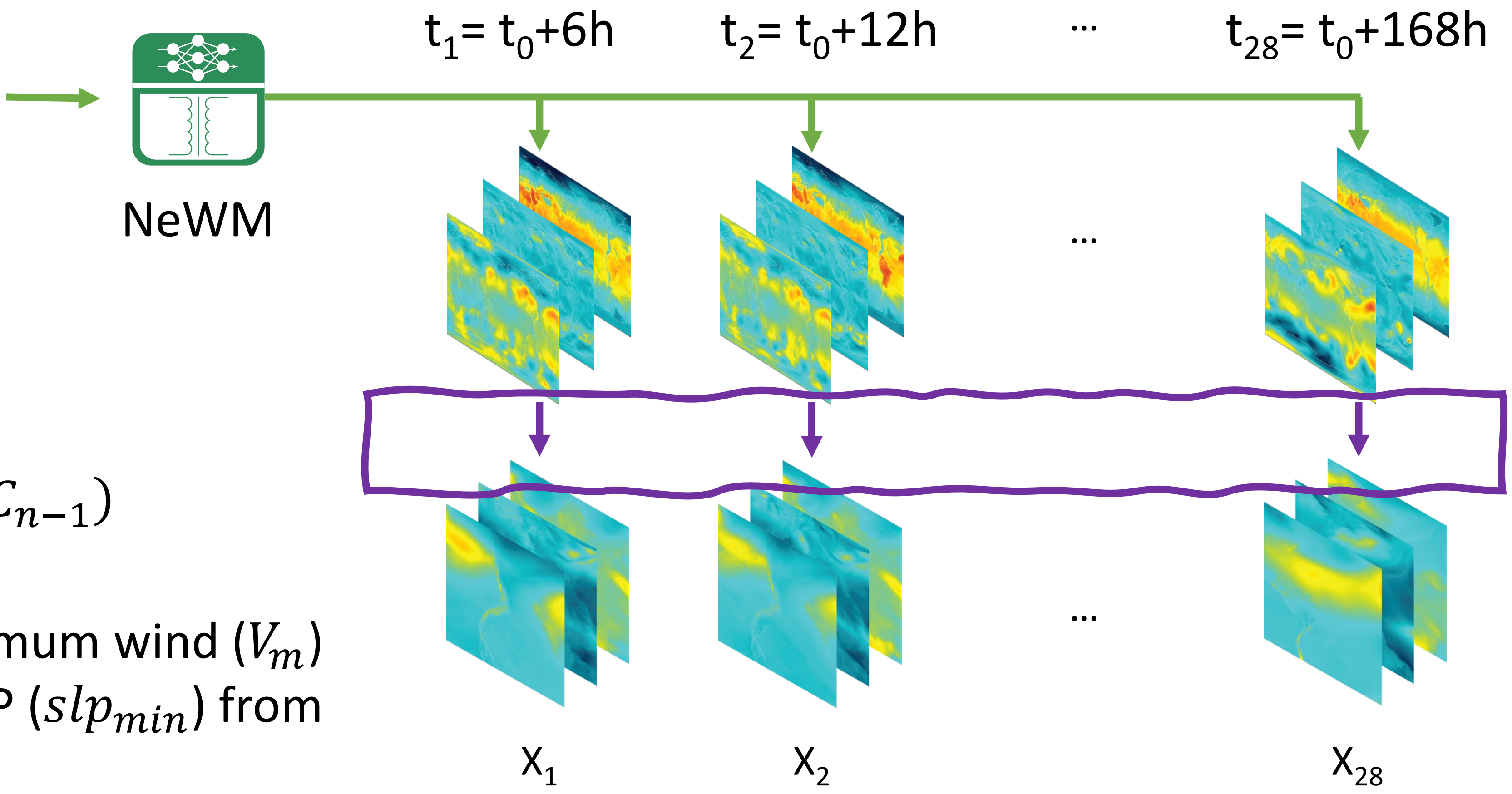


"…deriving CAPE and DLS in neural weather models already provides useful information for severe convective outlooks, which are key for severe weather warnings."[1]

[1] Feldmann, M., Beucler, T., Gomez, M., & Martius, O. (2024). Lightning-Fast Thunderstorm Warnings: Predicting Severe Convective Environments with Global Neural Weather Models. *arXiv preprint arXiv:2406.09474*.

Can we post-process the outputs for TCs?





$$IC_0 = ERA5_{t_0}$$

$$IC_n = NeWM(IC_{n-1})$$

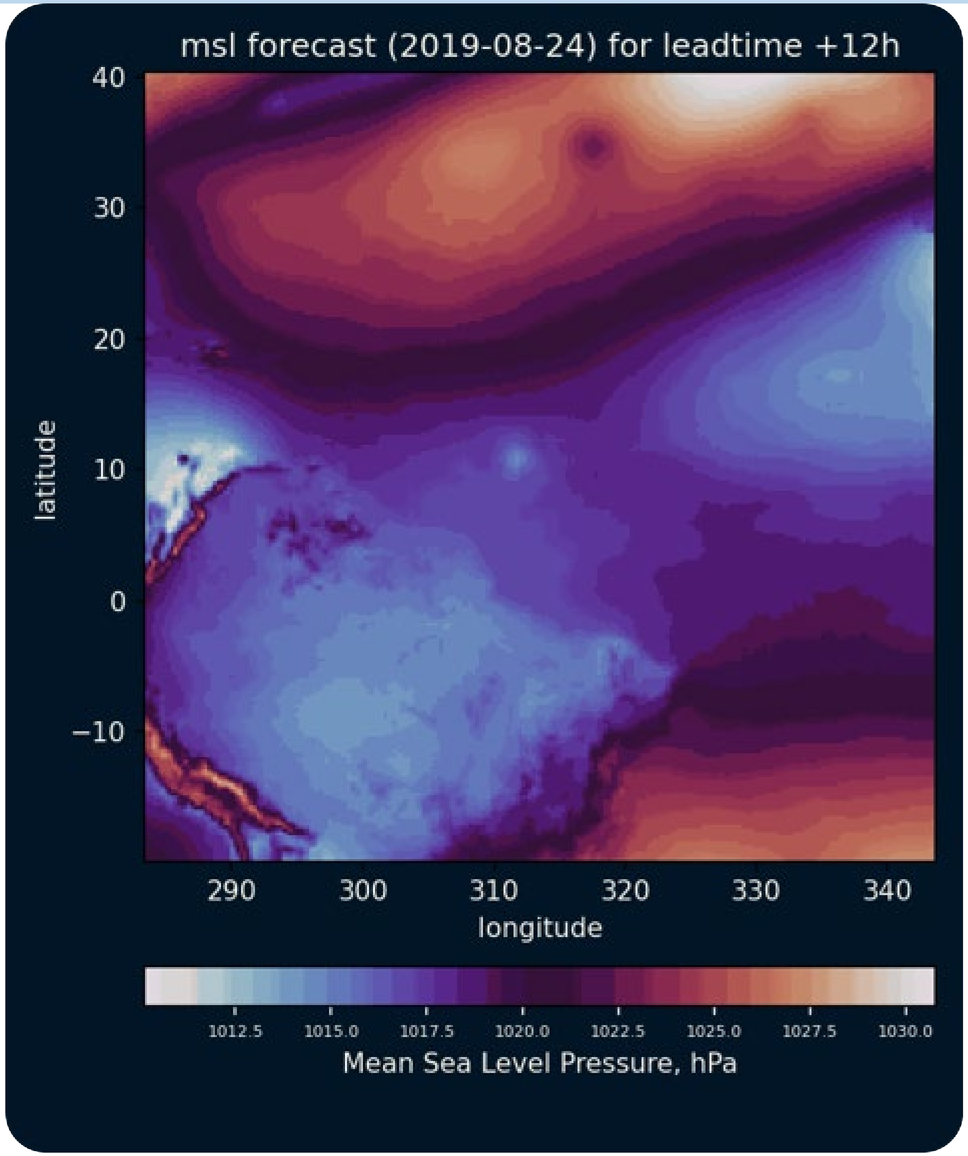
Clip +/- 30° around IBTrACS TC position @ t_0 (IBT_{t_0})

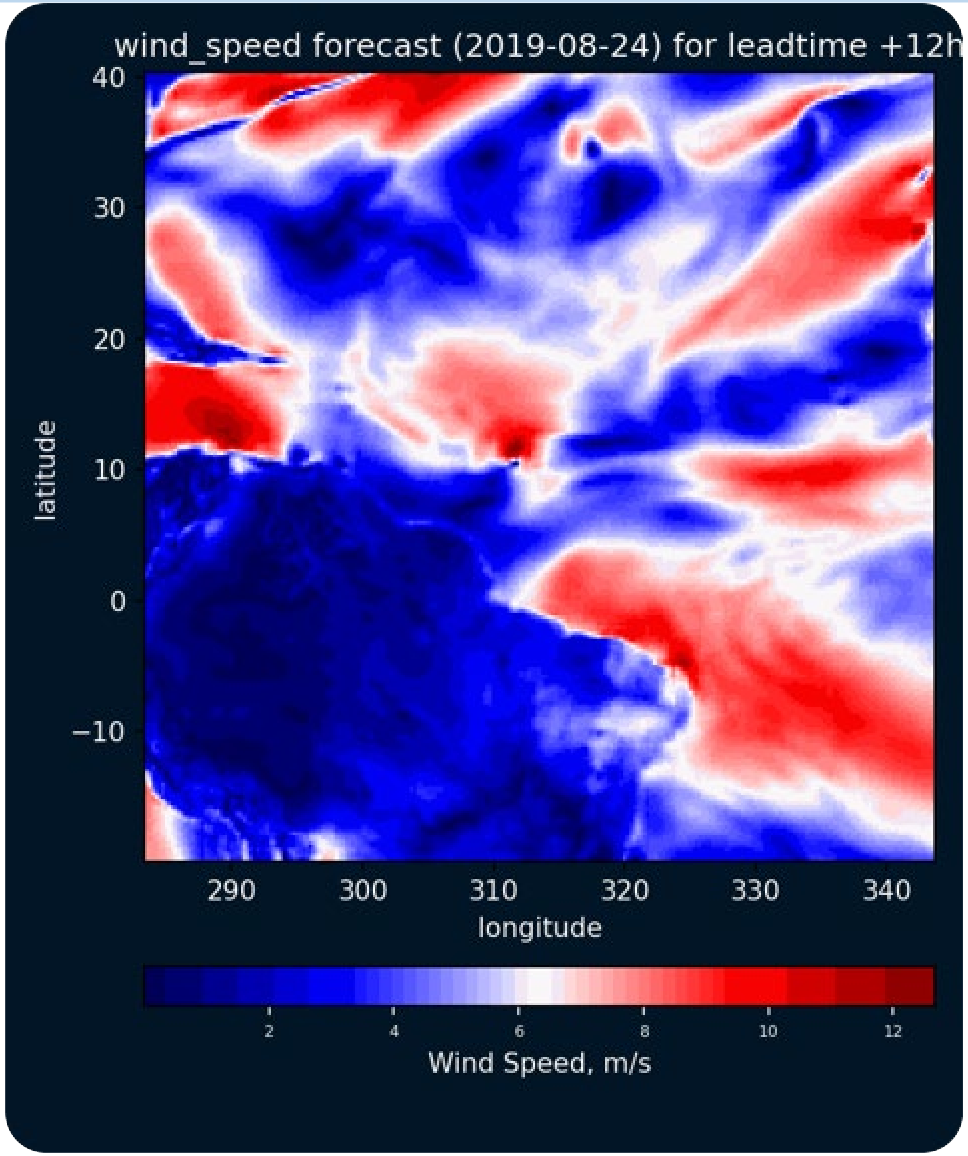
Intensity as maximum wind (V_m) and minimum SLP (slp_{min}) from IBTrACS

$$\begin{matrix} V_m\ (t_n) \\ slp_{min}\ (t_n) \end{matrix} = \mathcal{F}(X_n),\ n > 0\ \mid\ \left(NeWM(IC_{n-1}),\ IBT_{t_0}\right) \rightarrow X_n$$

Dorian (2019) according to PanguWeather

Clip +/- 30° around IBTrACS TC position @ t_0 (IBT_{t_0})

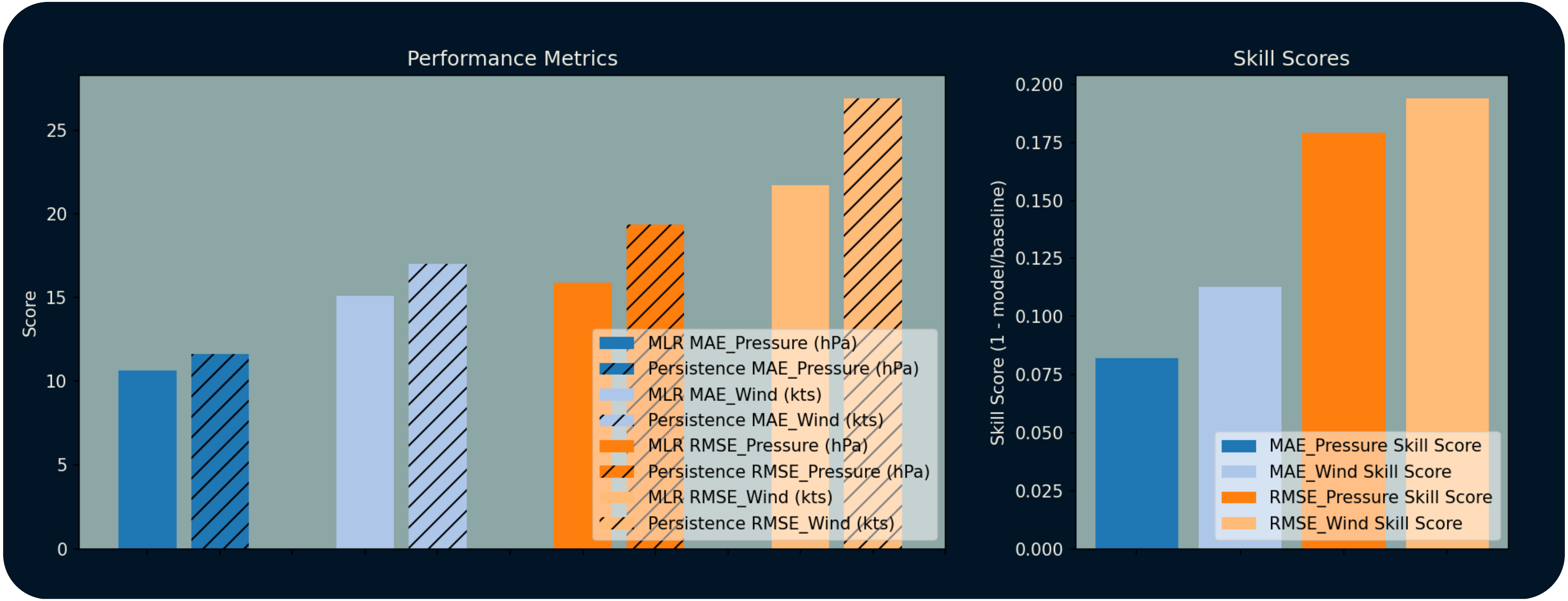




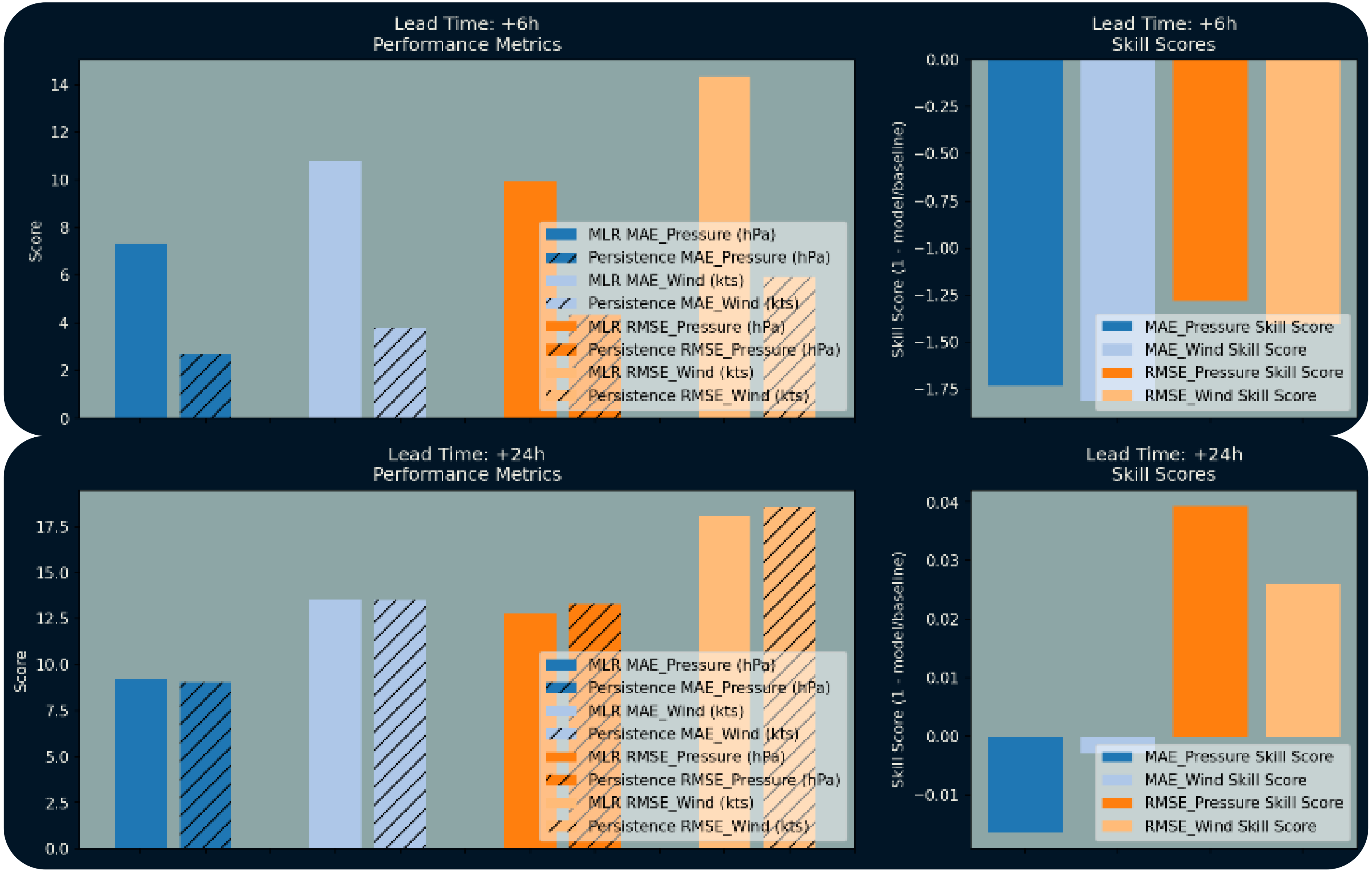
Can we post-process the outputs for TCs?

Preliminary results say indicate we can

Do NeWMs provide additional information?
MLR based on V_m, $mslp_{min}$ found in the cropped region used to evaluate against persistence, based on PanguWeather

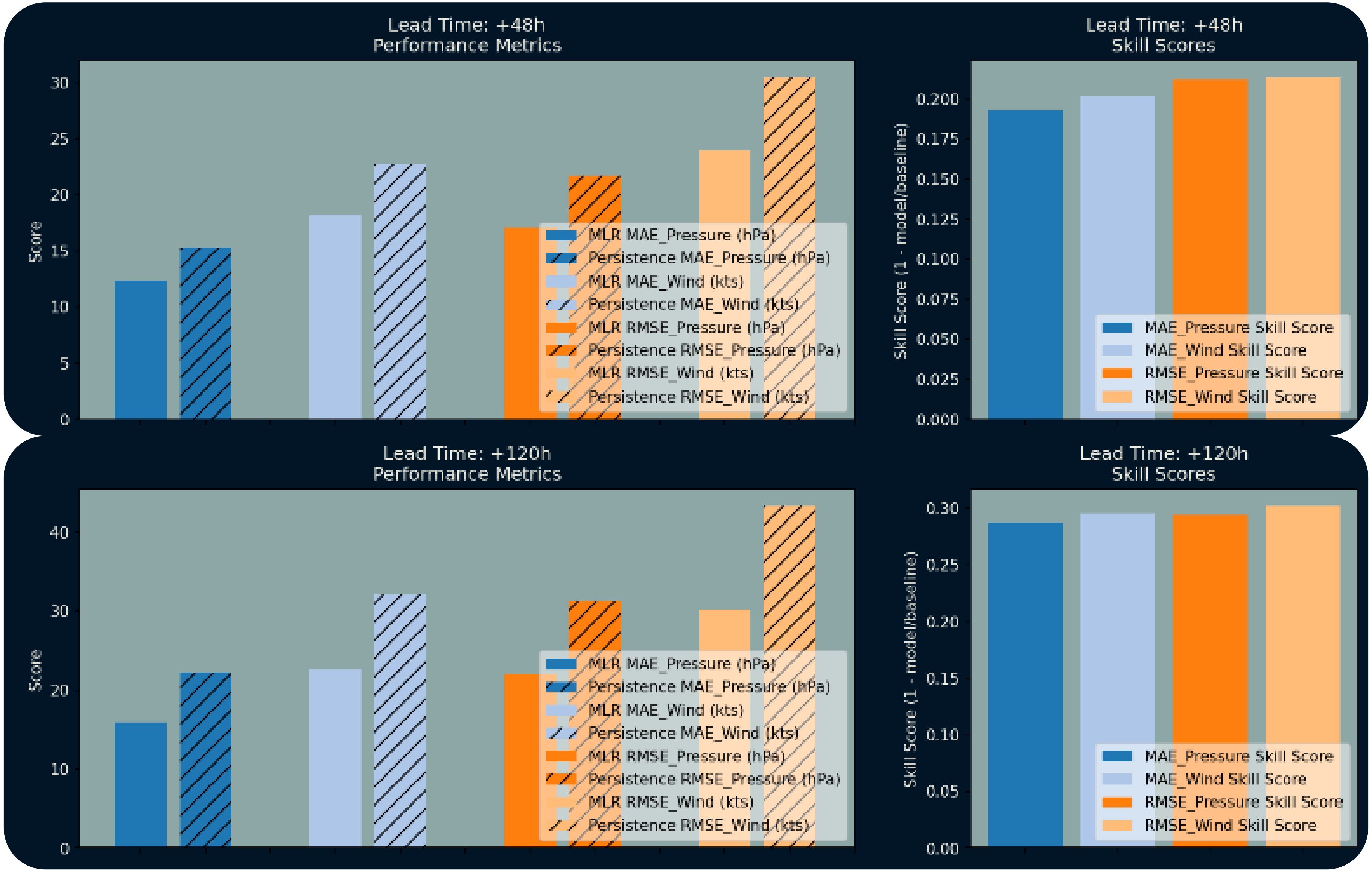


Yes, they do



Lead Time: +6h
Performance Metrics
Score
MLR MAE_Pressure (hPa)
Persistence MAE_Pressure (hPa)
MLR MAE_Wind (kts)
Persistence MAE_Wind (kts)
MLR RMSE_Pressure (hPa)
Persistence RMSE_Pressure (hPa)
MLR RMSE_Wind (kts)
Persistence RMSE_Wind (kts)
Lead Time: +6h
Skill Scores
Skill Score (1 - model/baseline)
MAE_Pressure Skill Score
MAE_Wind Skill Score
RMSE_Pressure Skill Score
RMSE_Wind Skill Score
Lead Time: +24h
Performance Metrics
Lead Time: +24h
Skill Scores

Yes, they do

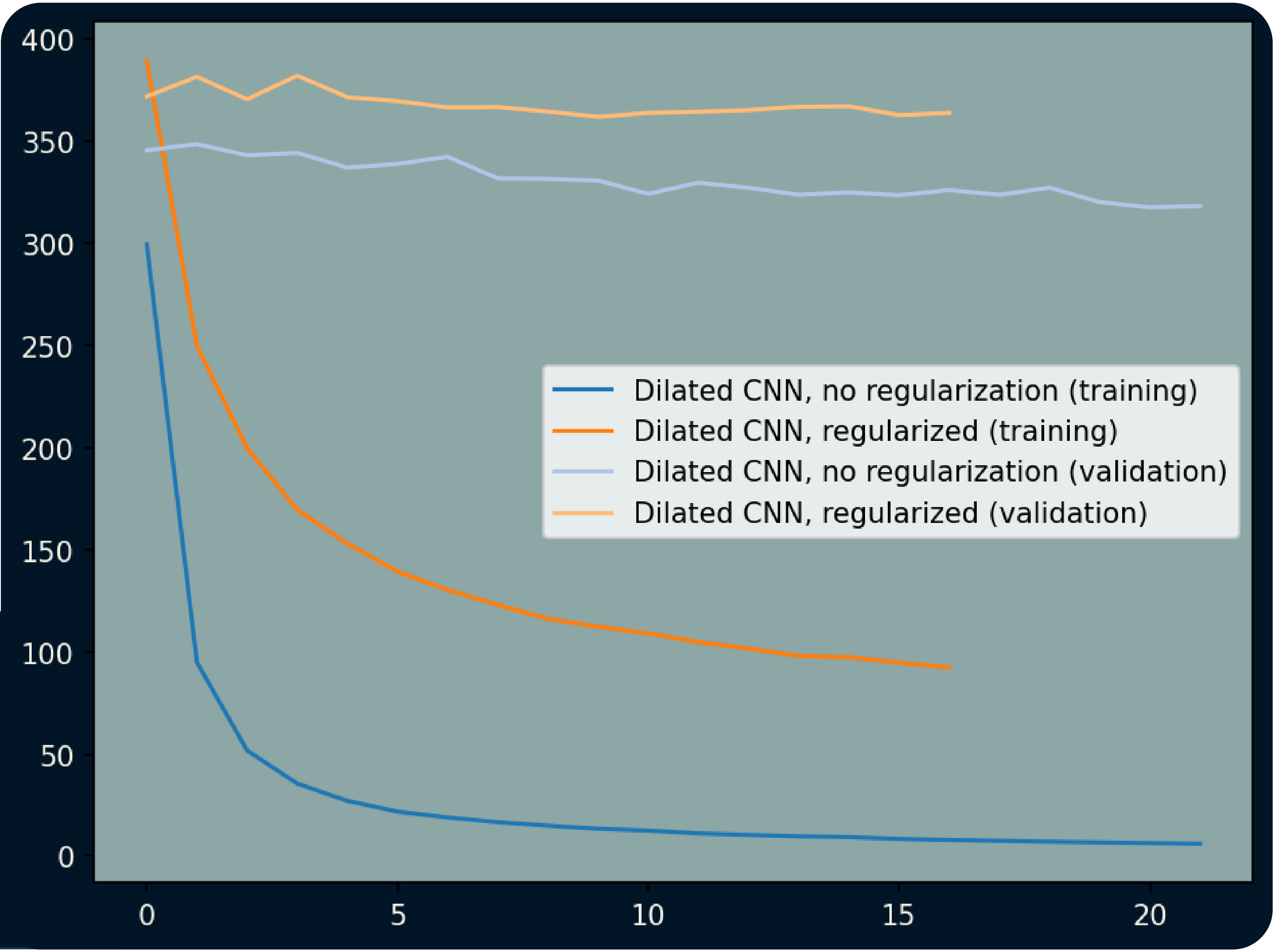


Lead Time: +48h
Performance Metrics
Score
MLR MAE_Pressure (hPa)
Persistence MAE_Pressure (hPa)
MLR MAE_Wind (kts)
Persistence MAE_Wind (kts)
MLR RMSE_Pressure (hPa)
Persistence RMSE_Pressure (hPa)
MLR RMSE_Wind (kts)
Persistence RMSE_Wind (kts)
Lead Time: +48h
Skill Scores
Skill Score (1 - model/baseline)
MAE_Pressure Skill Score
MAE_Wind Skill Score
RMSE_Pressure Skill Score
RMSE_Wind Skill Score
Lead Time: +120h
Performance Metrics
Score
MLR MAE_Pressure (hPa)
Persistence MAE_Pressure (hPa)
MLR MAE_Wind (kts)
Persistence MAE_Wind (kts)
MLR RMSE_Pressure (hPa)
Persistence RMSE_Pressure (hPa)
MLR RMSE_Wind (kts)
Persistence RMSE_Wind (kts)
Lead Time: +120h
Skill Scores
Skill Score (1 - model/baseline)
MAE_Pressure Skill Score
MAE_Wind Skill Score
RMSE_Pressure Skill Score
RMSE_Wind Skill Score

Can we leverage the spatial nature of the information ?

Small CNNs can (over)fit the data

Learning curves showing MSE loss on intensification



Preliminary Conclusions & Work in Progress

Neural Weather Models provide cheap and fast weather forecasts once trained

NeWMs appear to provide information that can be post-processed

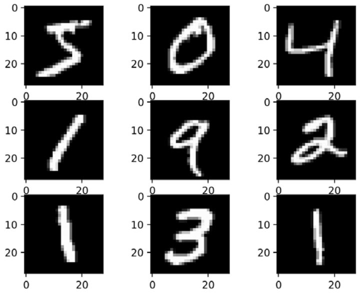
The spatial nature of the NeWM outputs can be exploited

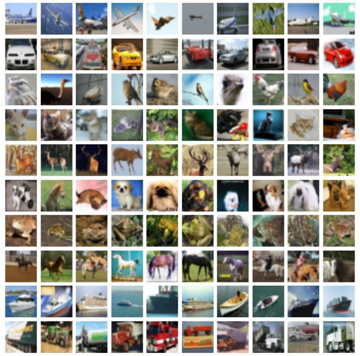
Probabilistic Predictions & Evaluations

Deal with overfitting

Comparison against information from ERA5 initial conditions

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





IMAGENET

WeatherBench

MAELSTROM

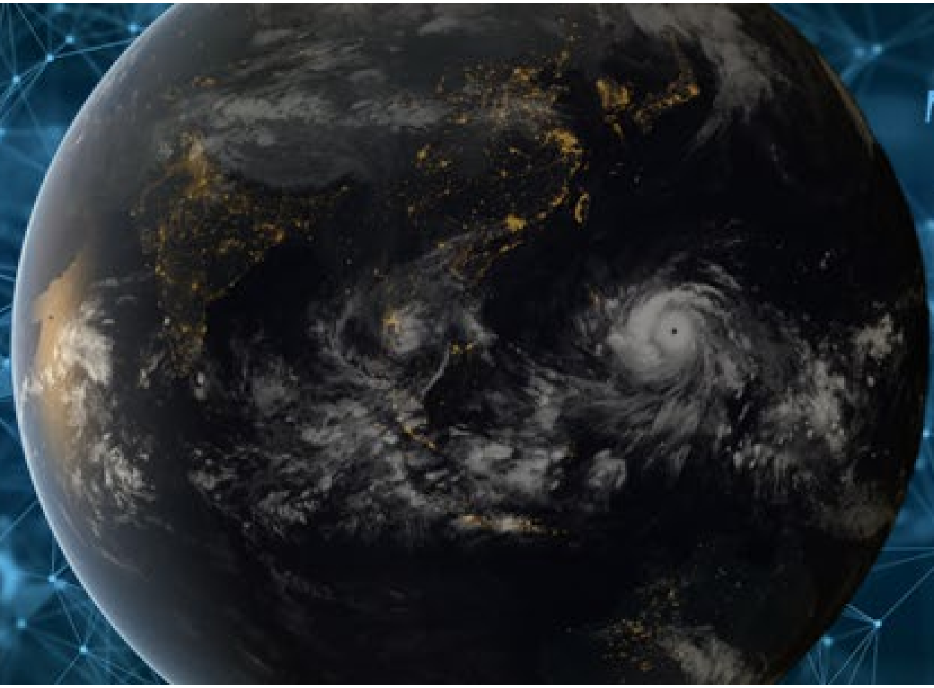
Empowering weather and climate forecast

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

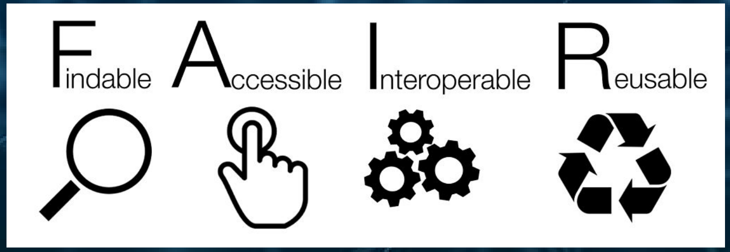
D. Watson-Parris, Y. Rao, D. Olivié, Ø. Seland, P. Nowack, G. Camps-Valls, P. Stier, S. Bouabid, M. Dewey, E. Fons, J. Gonzalez, P. Harder, K. Jeggle ... See all authors

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

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



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 al.)*

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Connecting Models and Observations

Conclusion

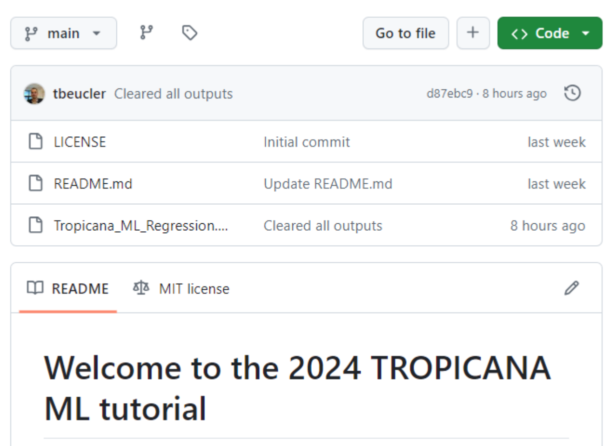
www.unil.ch/dawn

tom.beucler@unil.ch

GitHub

arXiv

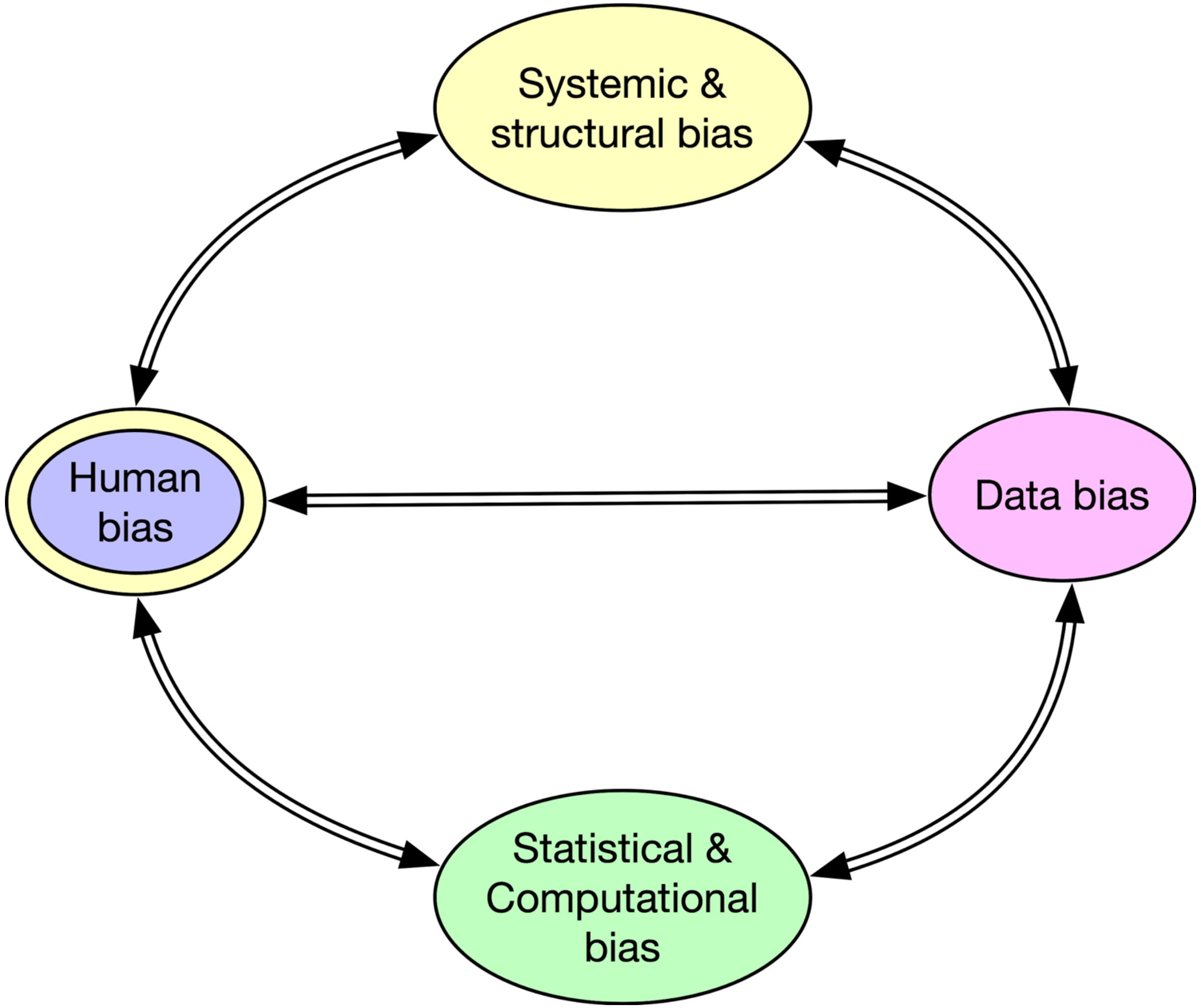
1. ML pattern discovery discovers new scientific insights, useful for hypothesis testing/formulation
2. Causal discovery selects drivers that are causally-related to the forecasted variable, improving generalizability
3. NeWMs show potential for post-processing applications



Bonus Slides

Useful but likely not needed

Addressing biases in artificial intelligence and earth sciences.



<u>Credit</u>: Amy McGovern (OU) and co-authors

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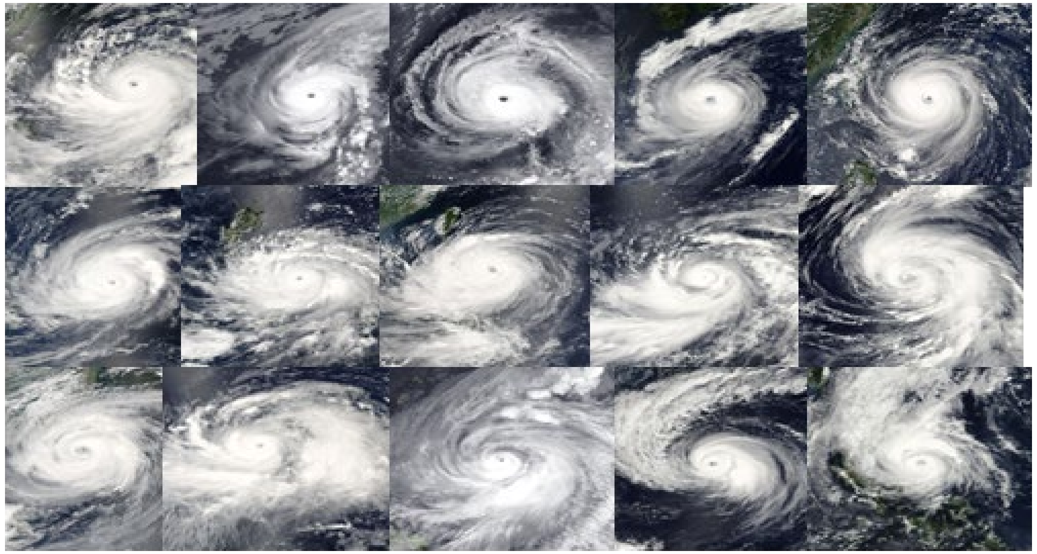
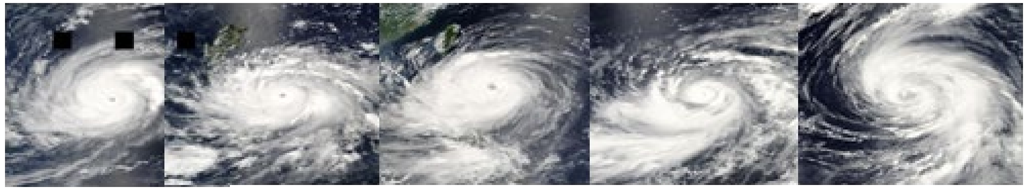
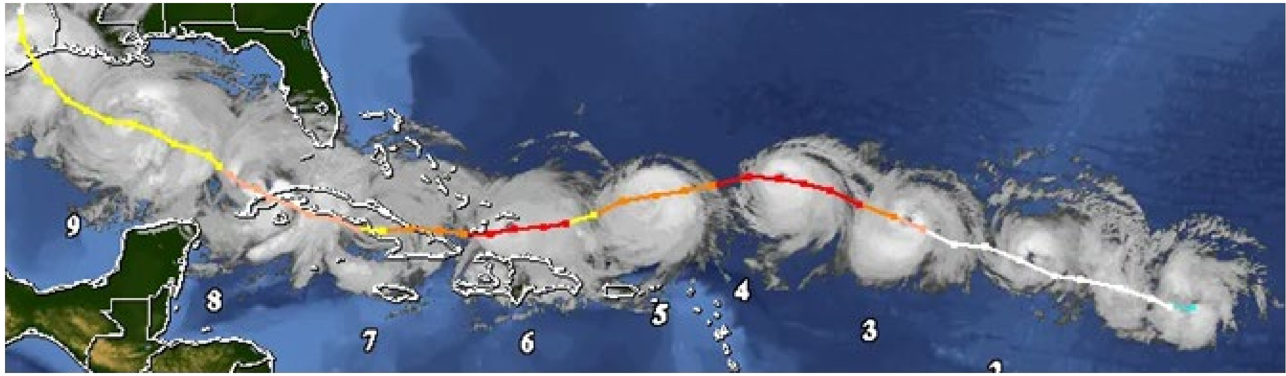
Experiment 2.1: Performing causal feature selection on the SHIPS developmental dataset helps eliminate non-causal predictors

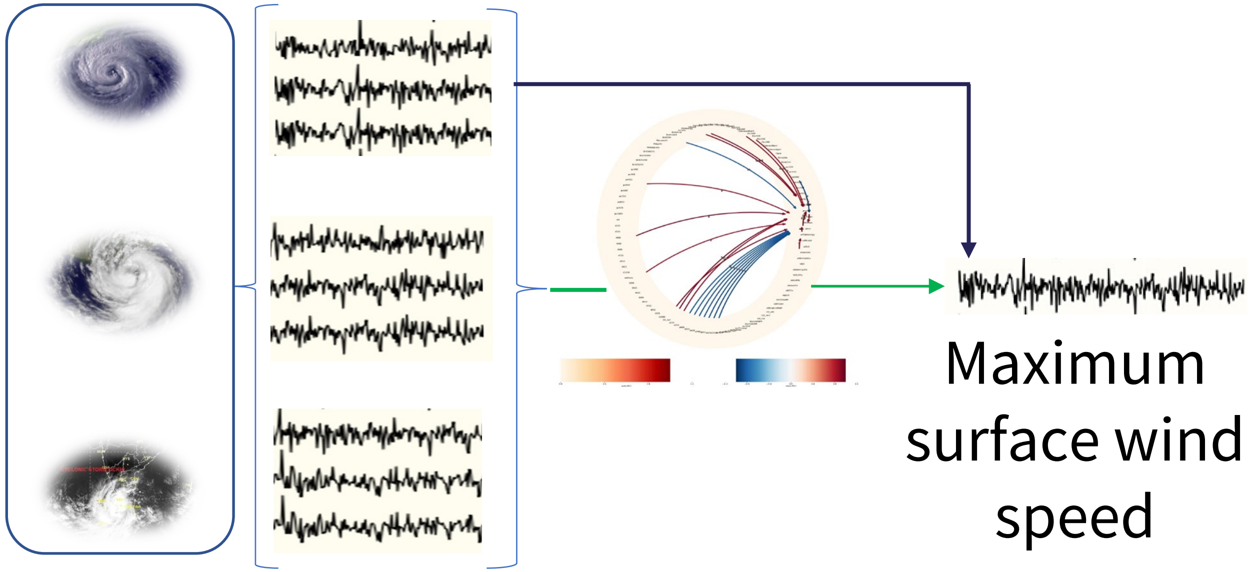




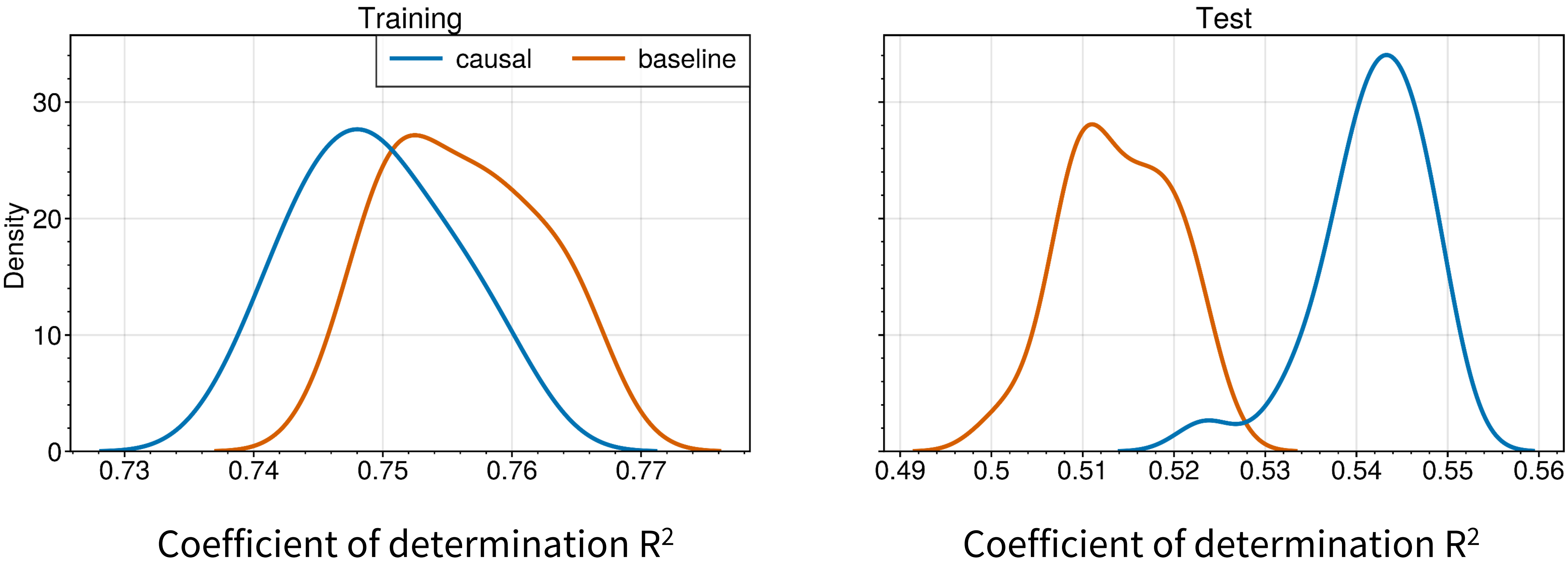
251 cases in the North Atlantic (2000-2022) from SHIPS dvp. data



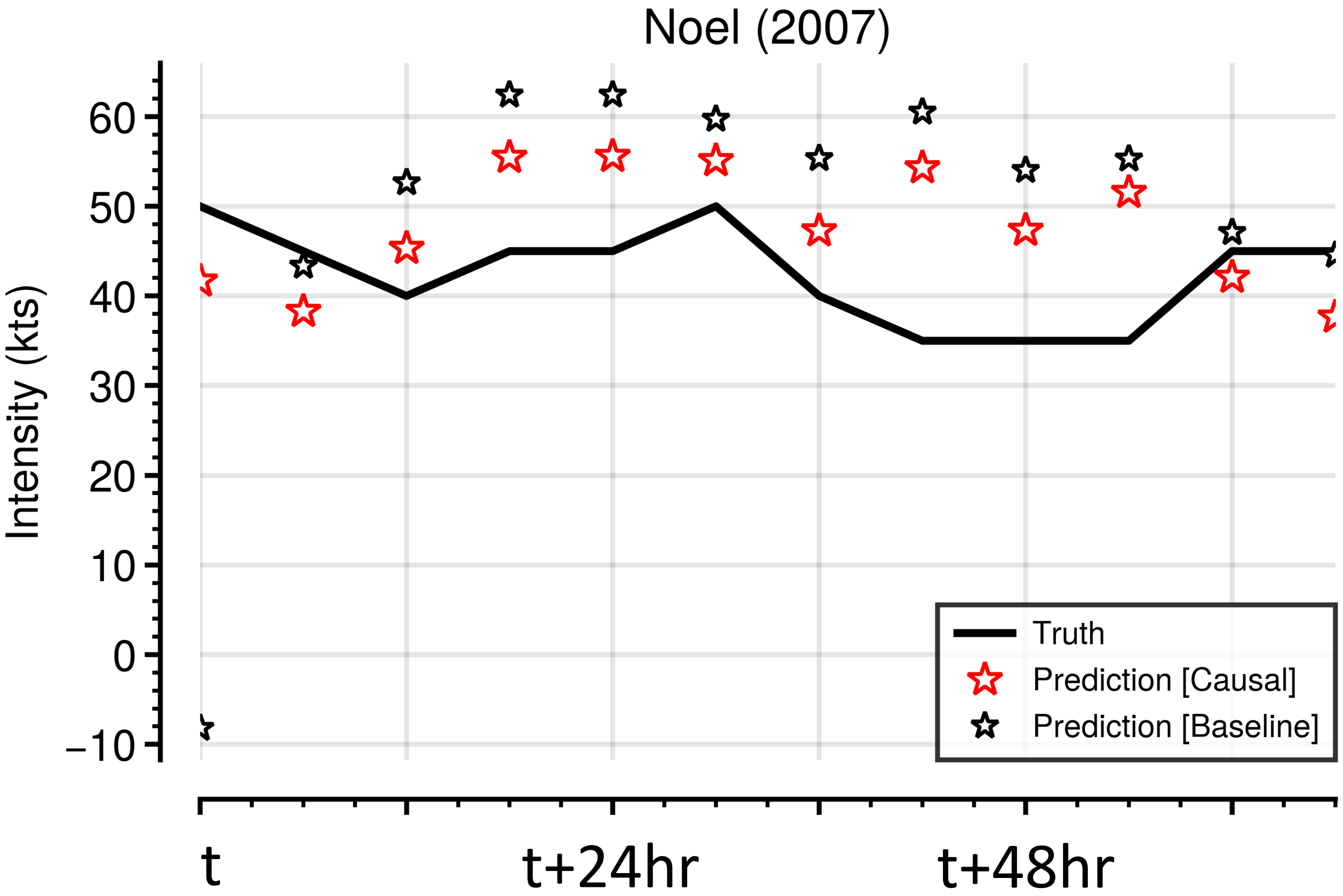
Best tracks from IBtrACS



Causal feature selection helps remove non-causal predictors, improving interpretability & generalizability



Application: Non-causal over-estimation of Hurricane Noel's (2007) 24hr-intensity changes



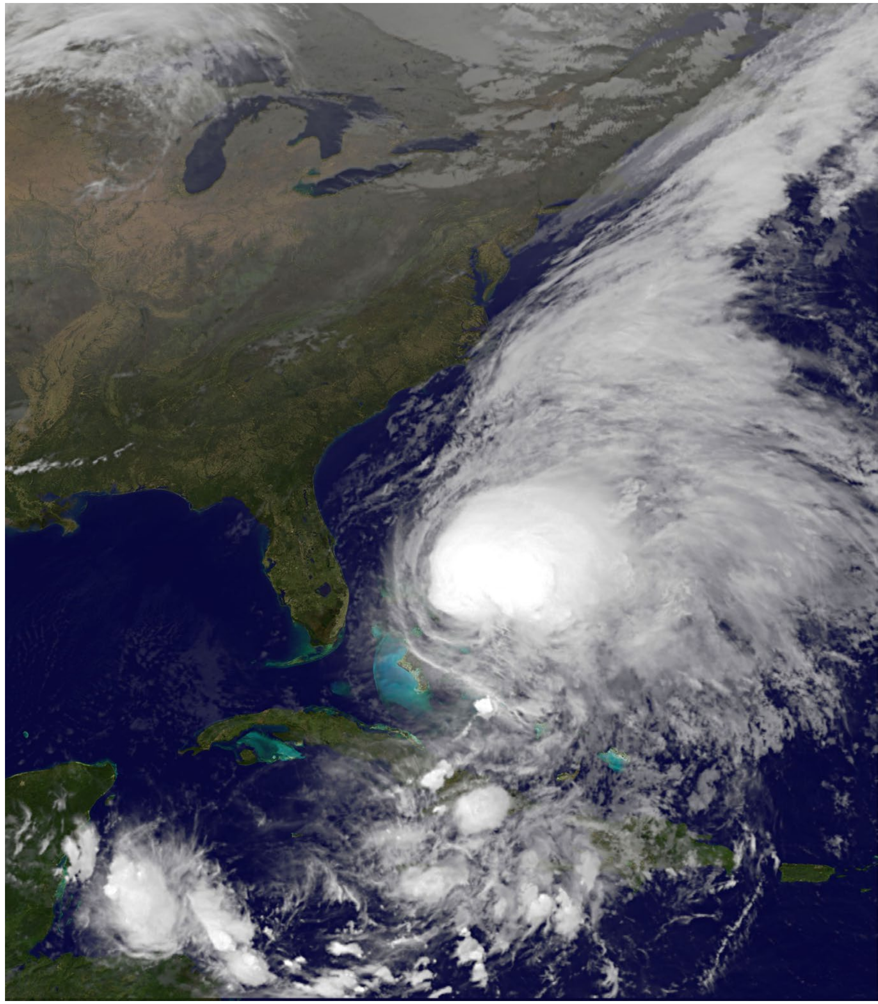
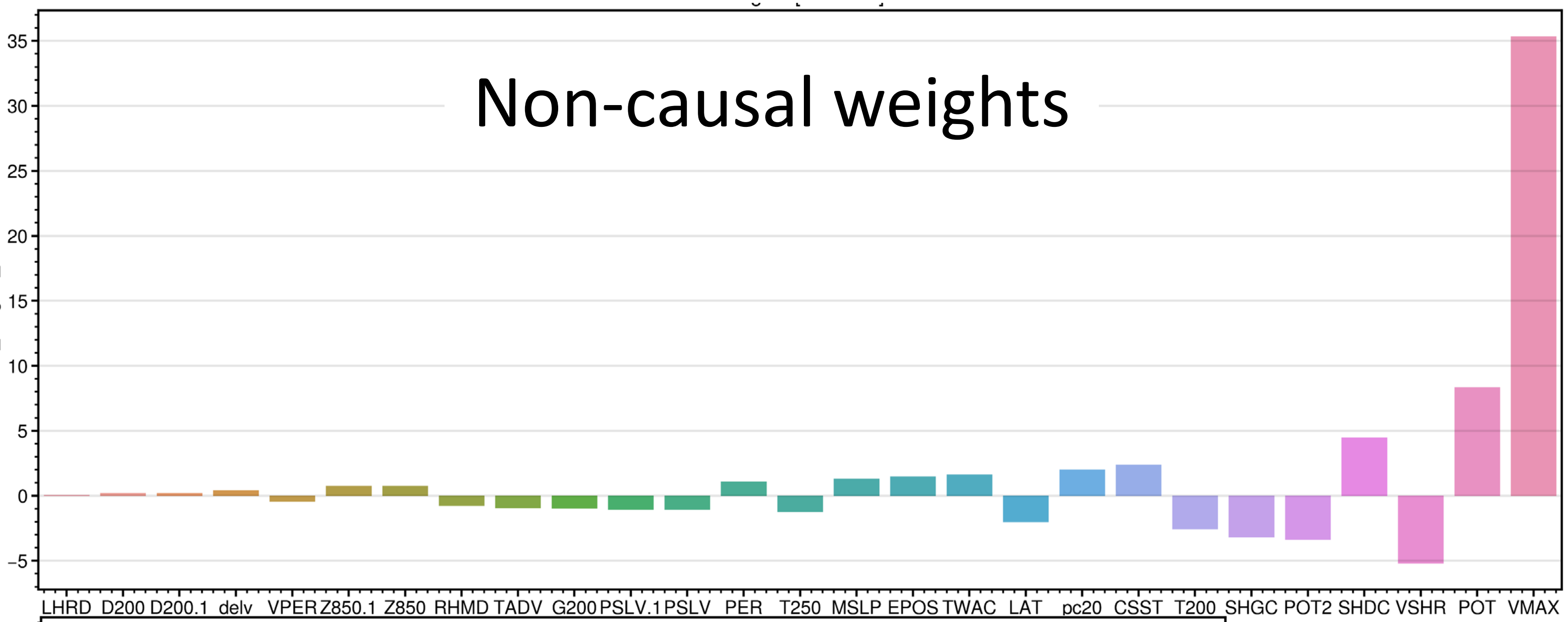
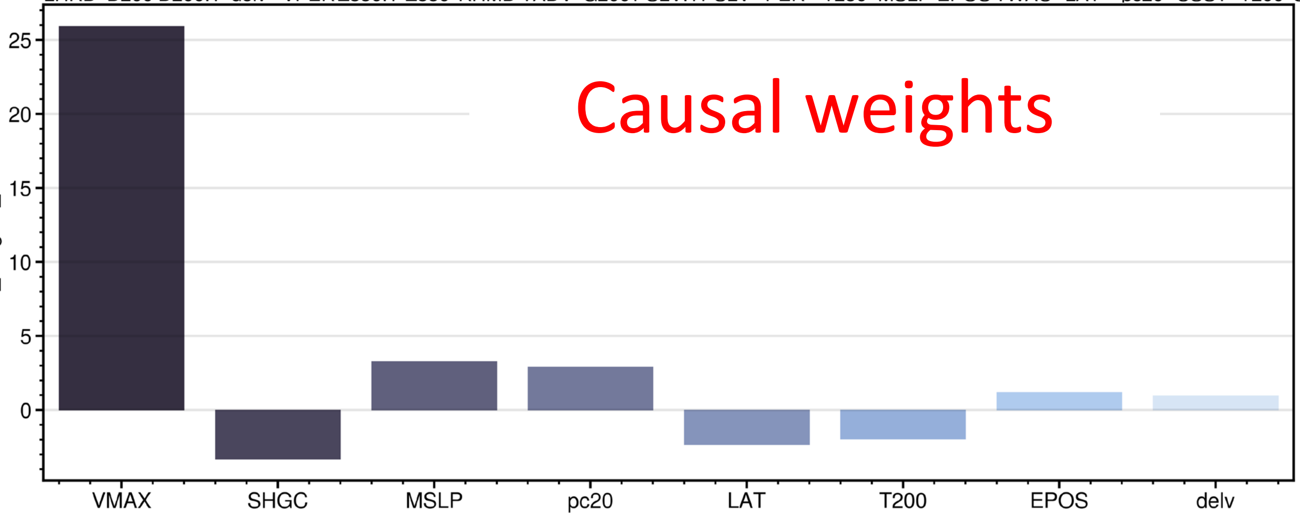


Image source: simple.Wikipedia.org

Application: Non-causal over-estimation of Hurricane Noel's (2007) intensity changes





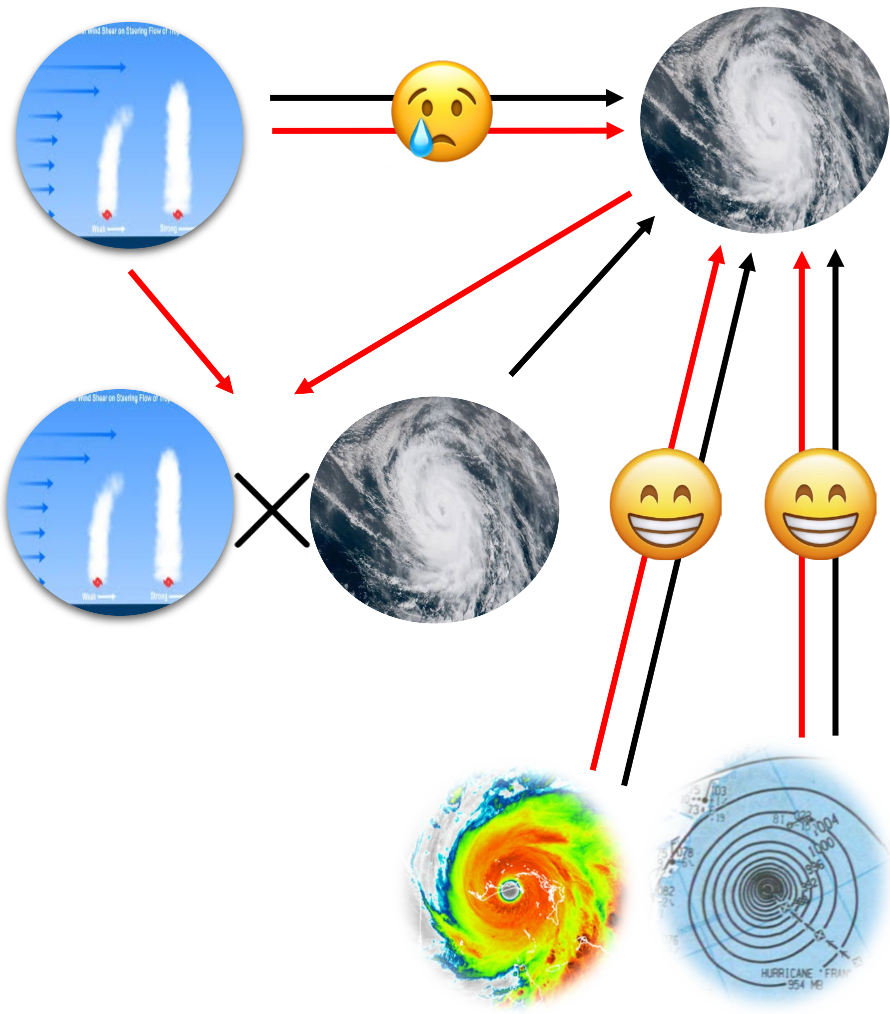


Image source: NOAA NESDIS, NOAA

What do NeWMs actually do?

FourCastNetv2[2]

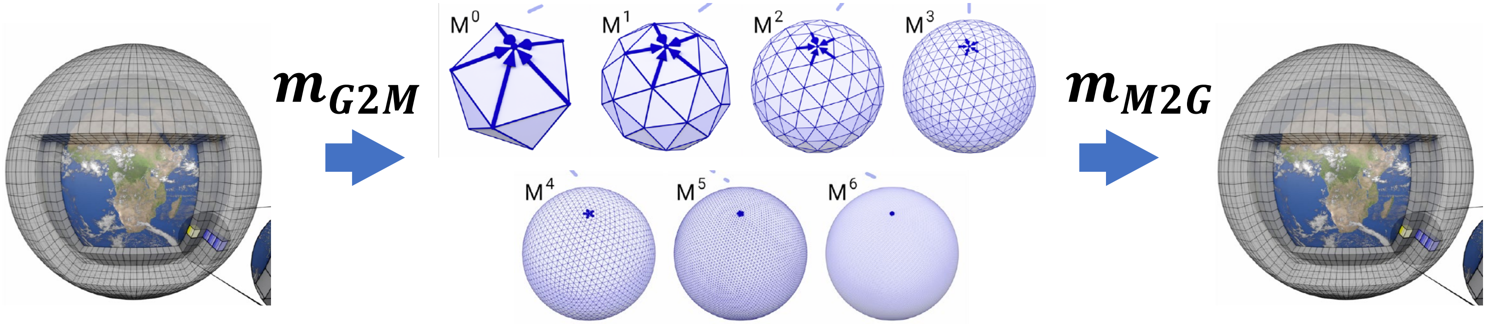
Can we learn a grid-invariant filters to map the states of the atmosphere?

GraphCast[1]

Can we evolve the state of the atmosphere in a latent graph space?

PanguWeather[3]

Can we learn how to predict the state of the atmosphere from a series of queries, keys, and …erated from its …ent state?



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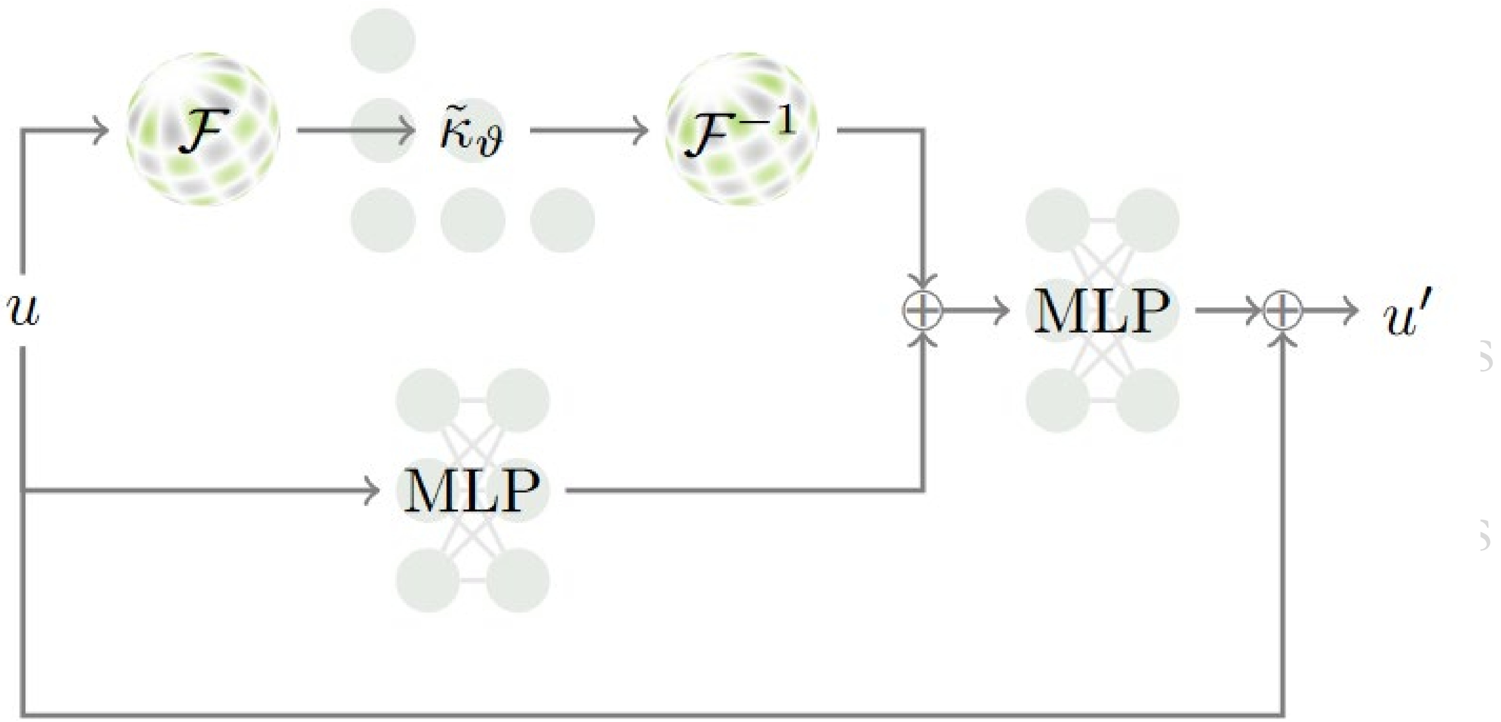
What do NeWMs actually do?

FourCastNetv2[2]

Can we learn a grid-invariant filters to map the states of the atmosphere?



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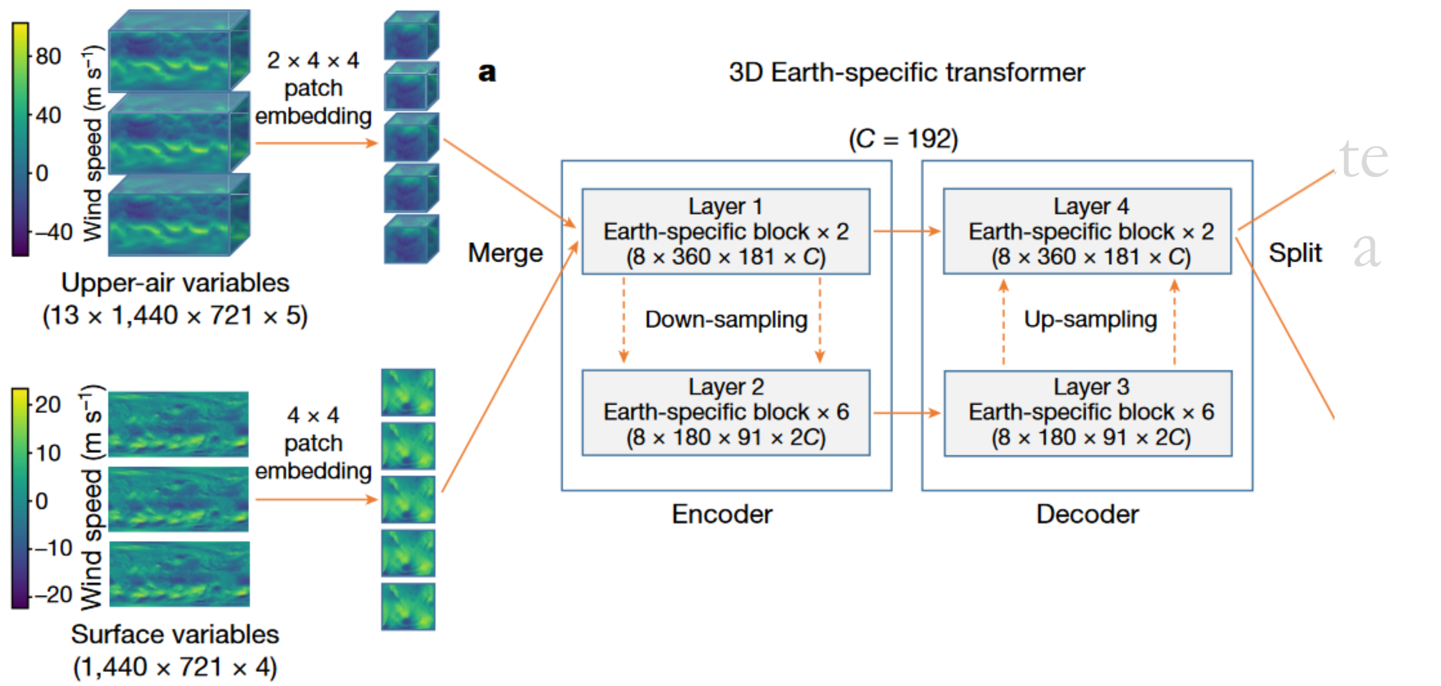

PanguWeather[3]

Can we learn how to predict the state of the atmosphere from a series of queries, keys, and values generated from its current state?

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