

# AI-enhanced seasonal predictions of Mediterranean cyclones

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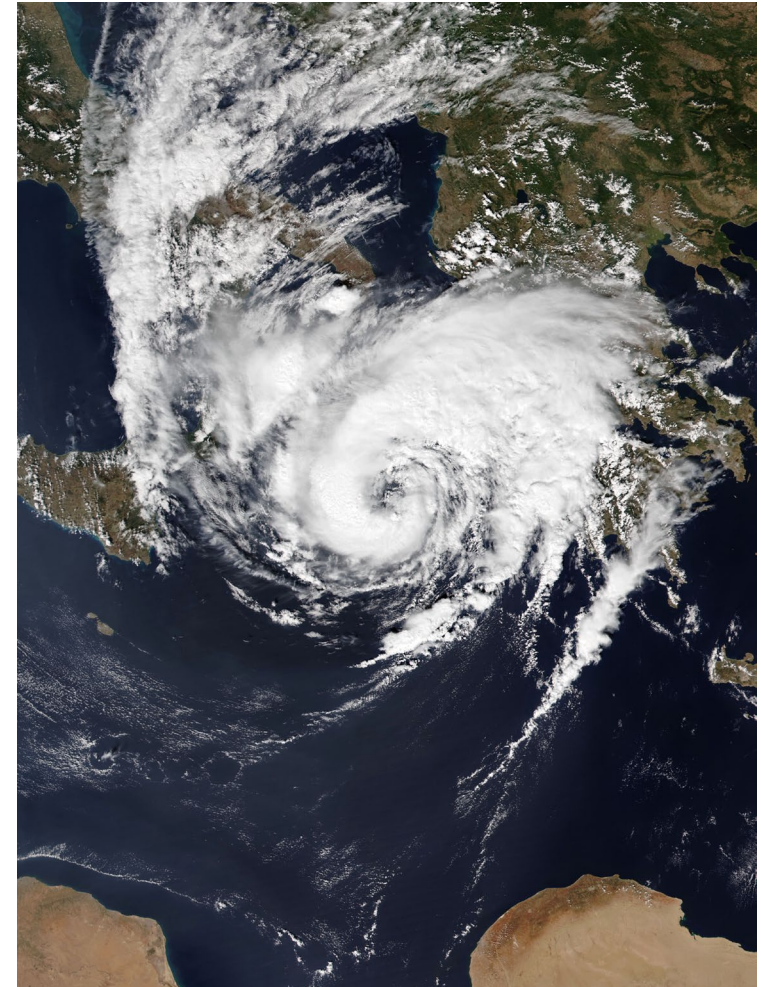
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ATMOS 2024, Bologna

4-7-2024

# Background

- Cyclones form frequently in the Mediterranean basin due to region location and the complex topography
- Even though smaller and shorter lived than cyclones forming in other ocean basins Med cyclones cause severe damage in the highly populated coasts of the region
- A number of different dynamical mechanisms for cyclone genesis and intensification play a role, resulting in the occurrence of different types of low pressure systems, ranging from mid-latitude to tropical-like cyclones

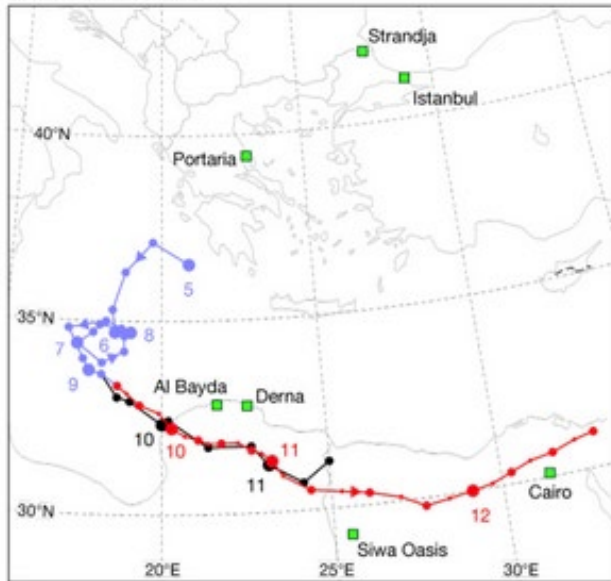


Ianos (September 2020)

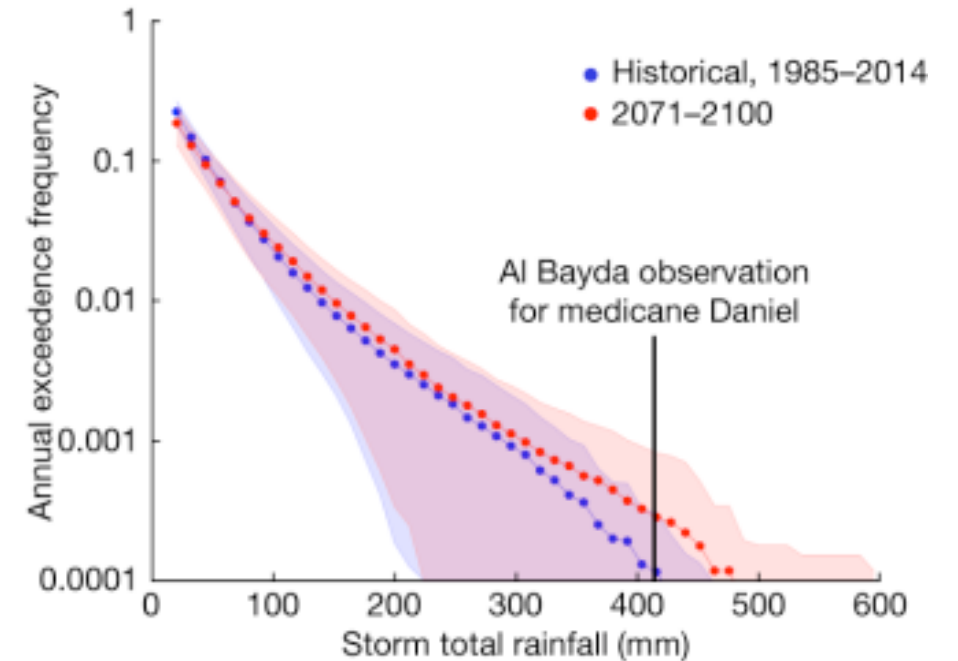
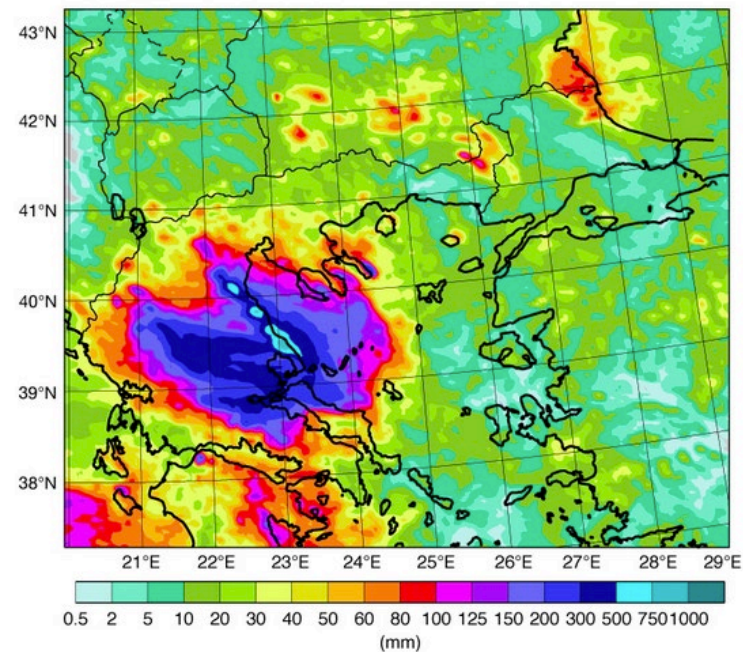
# Storm Daniel

- *Storm Daniel in September 2023 was the costliest cyclone outside the North Atlantic (> 20 B US\$)*
- *The deadliest cyclone globally since 2013 (10.000 fatalities estimated)*

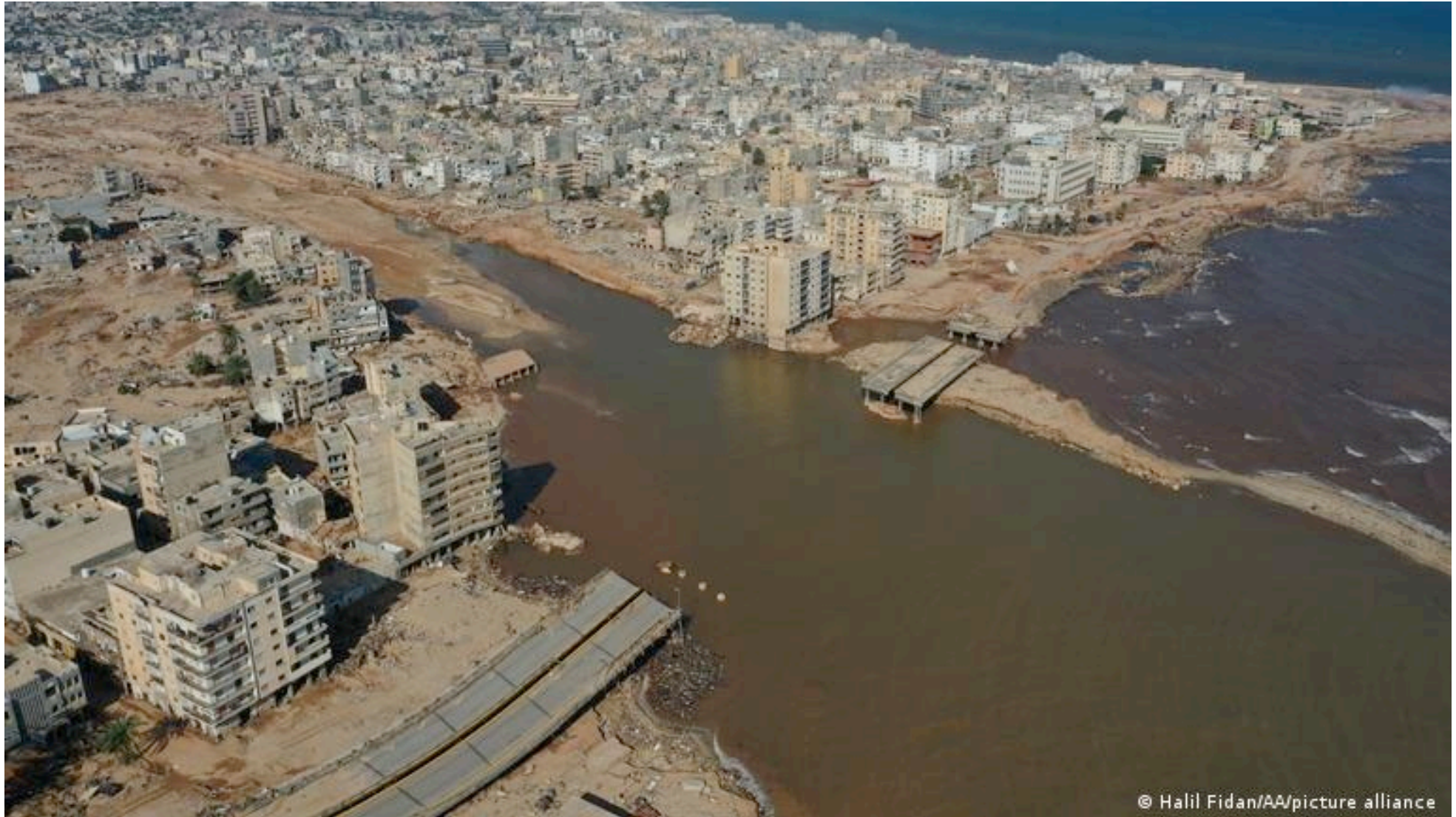
a Full track of Daniel



c DestinE rainfall forecast

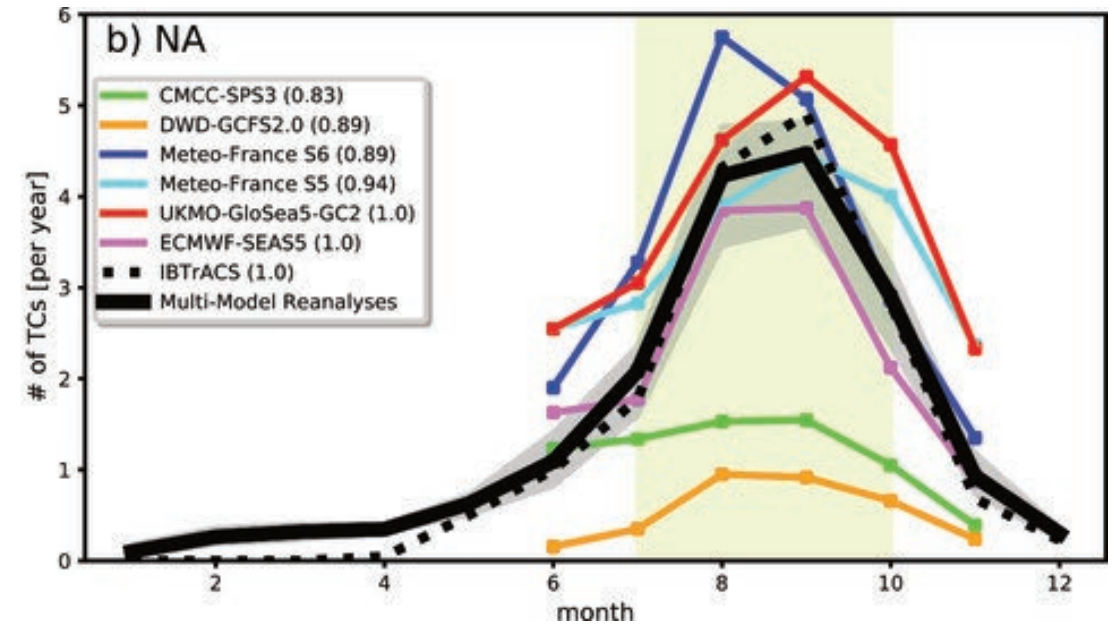
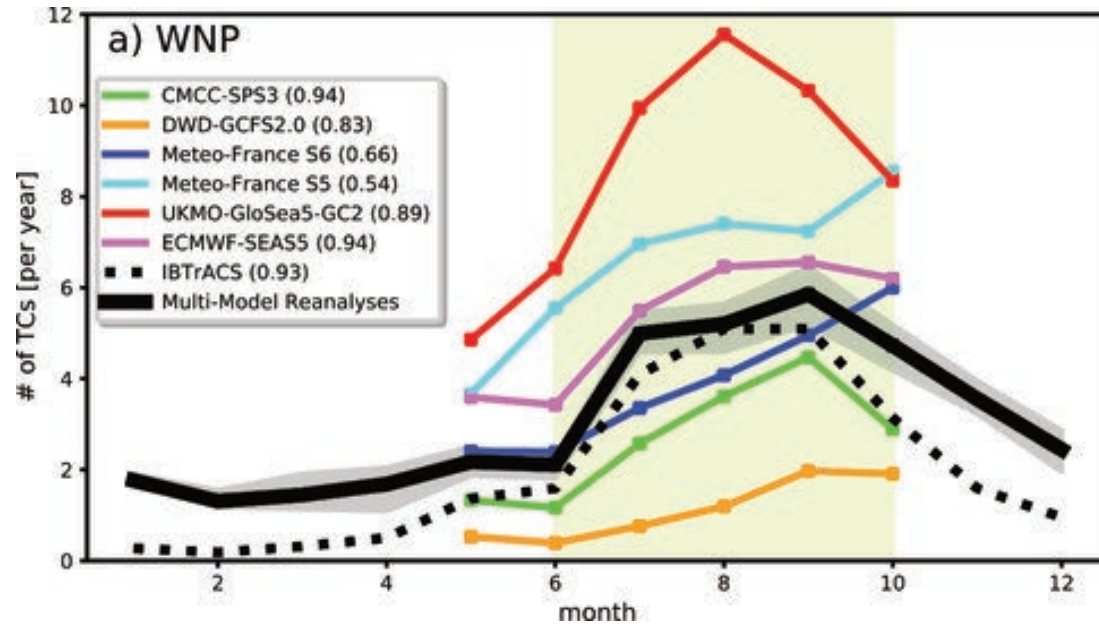






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# Cyclones in Seasonal forecast

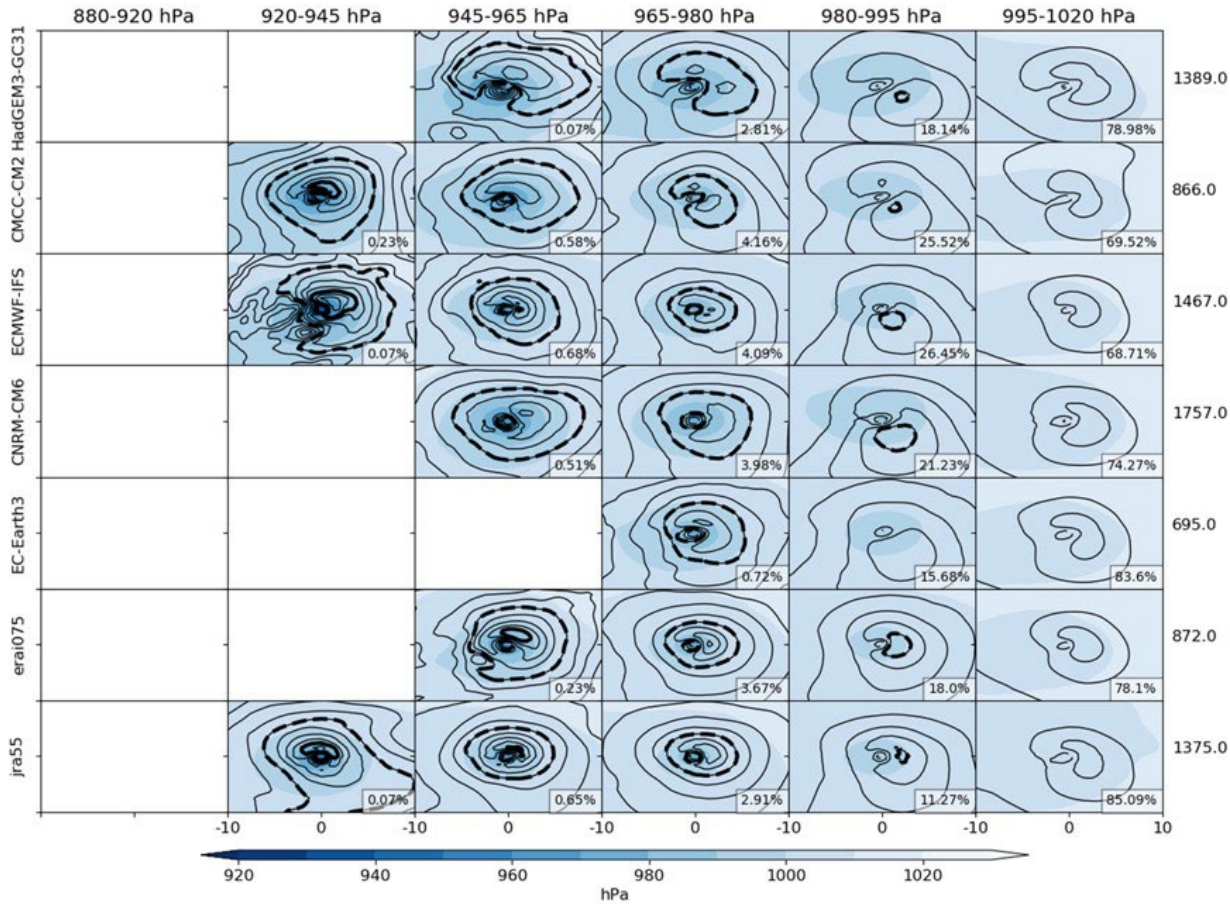


Befort et al 2022

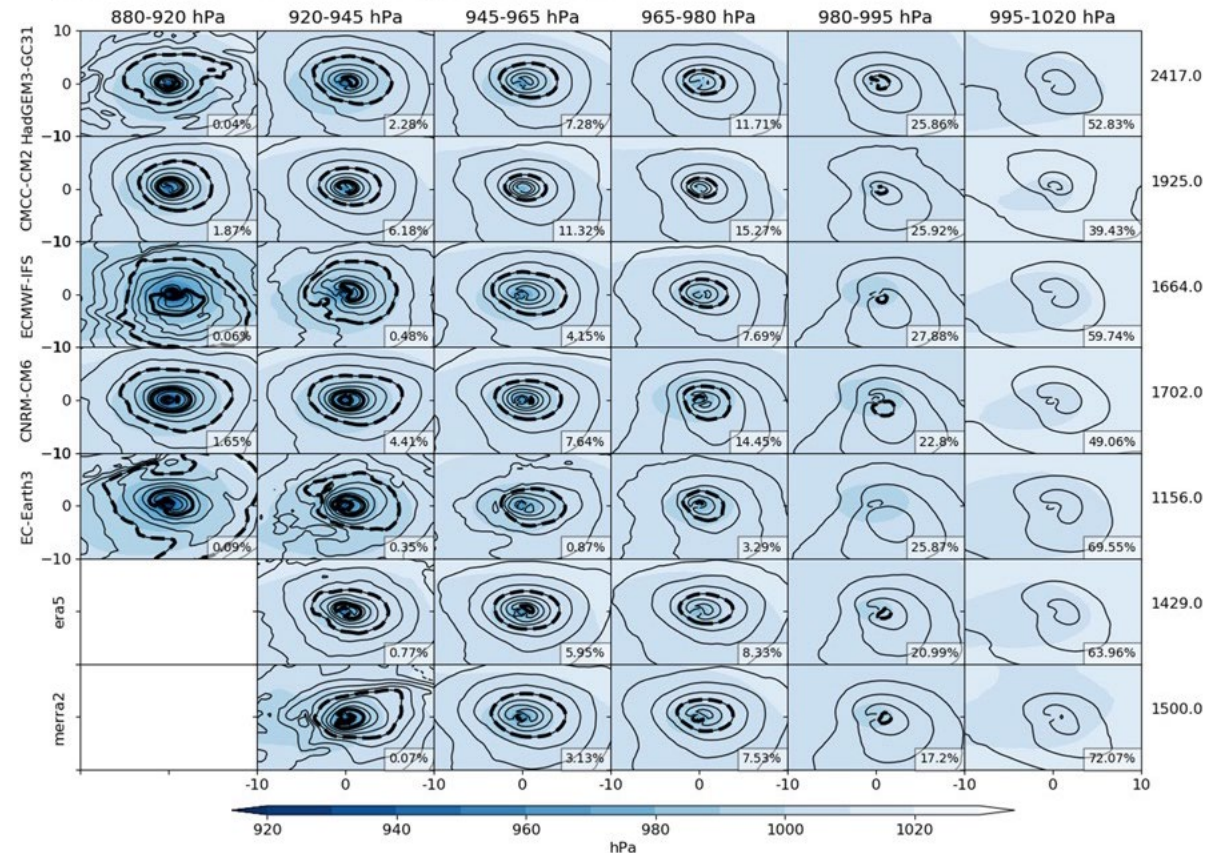


# Climate model resolution and TCs

(a) LR: Composite storms for 925 hPa tangential wind and psi



(b) HR: Composite storms for 925 hPa tangential wind and psi

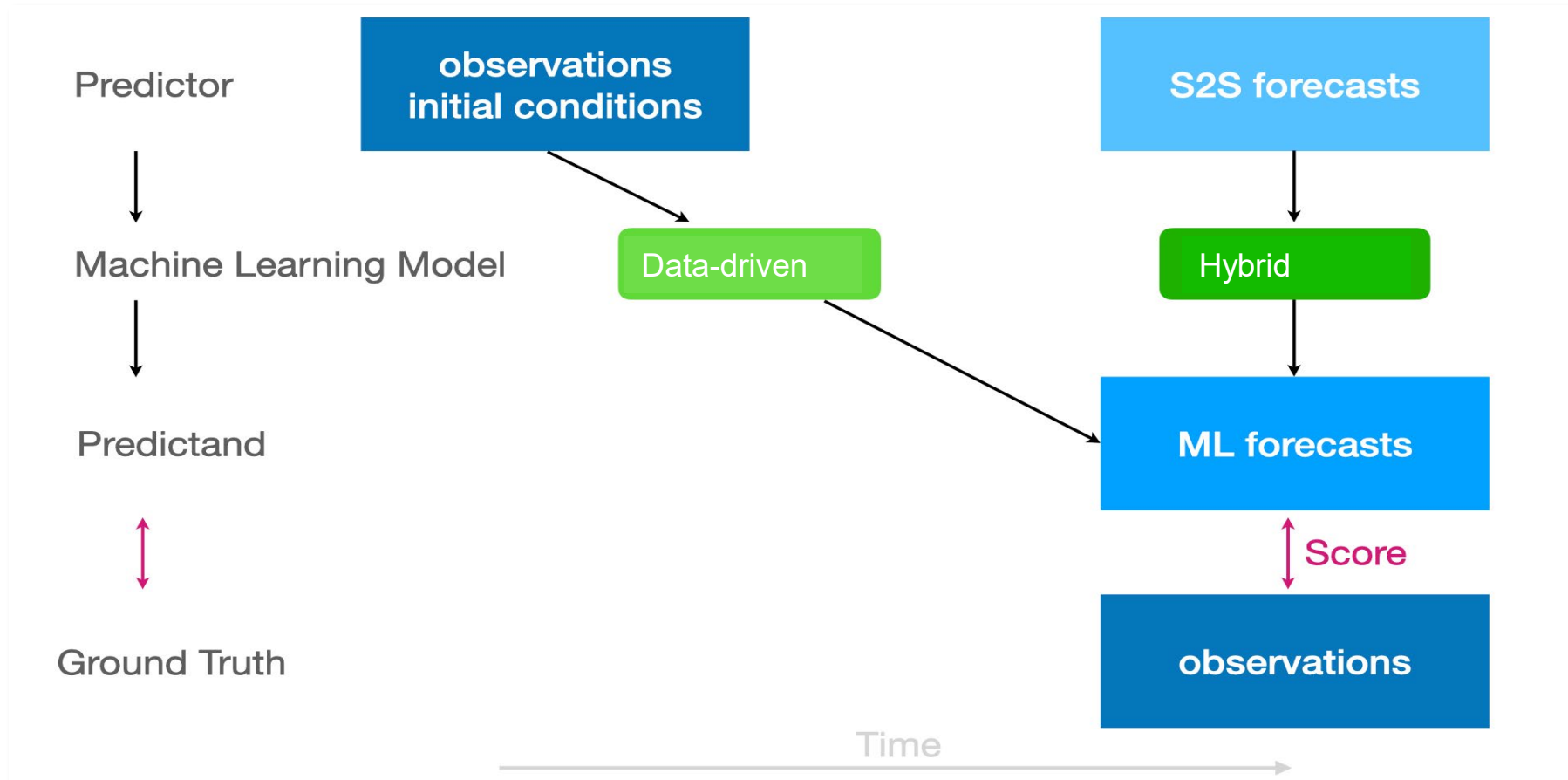


Roberts et al (2020): Impact of Model Resolution on Tropical Cyclone Simulation Using the HighResMIP-PRIMAVERA Multimodel Ensemble

*Low-resolution models reproduce only a fraction of the observed cyclones, and are not able to reproduce intense cyclones*

# Two approaches to AI seasonal forecast

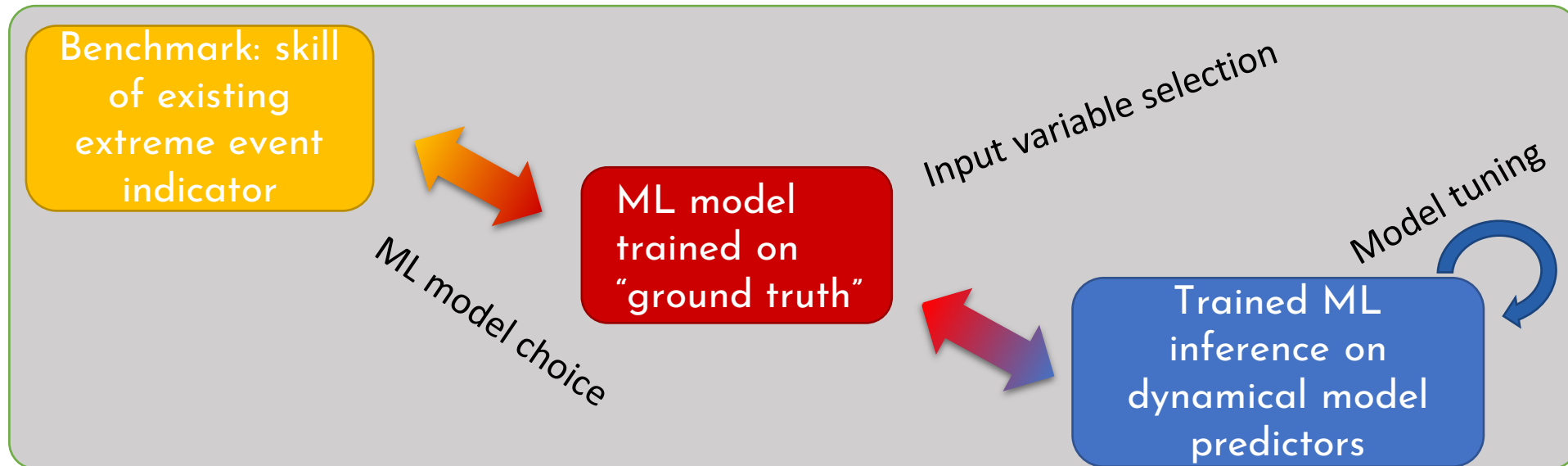
Adapted from : <https://s2s-ai-challenge.github.io/>



# CYCLOPS: AI-enhanced seasonal prediction of Mediterranean cyclones

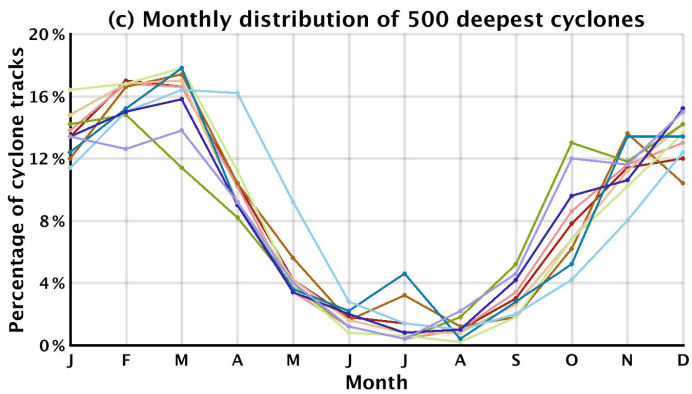
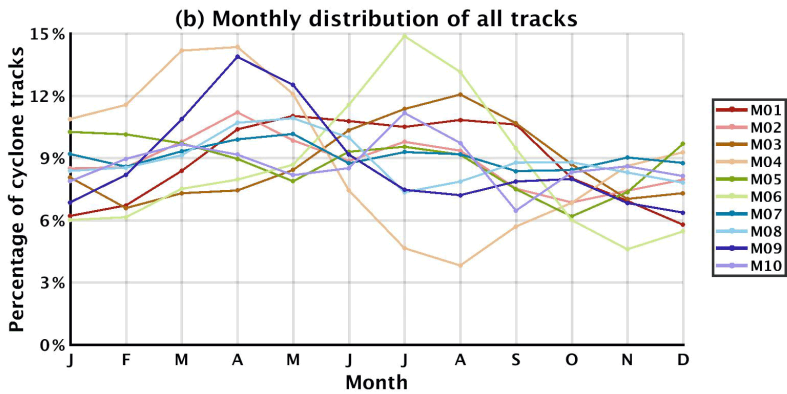
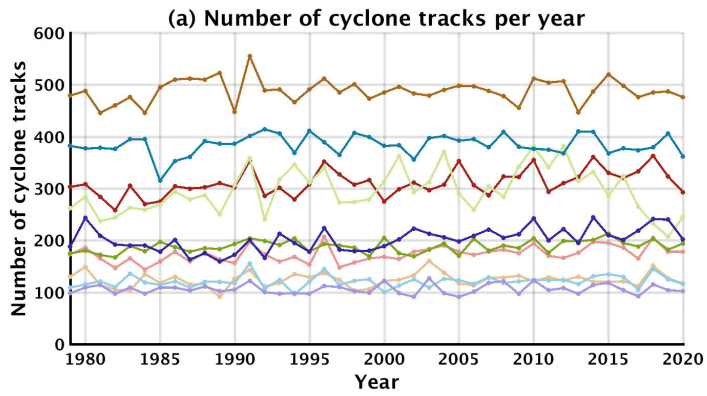
The aim of this project is to improve the prediction of cyclone activity, exploiting a **hybrid AI approach** where the occurrence of extremes is linked to large-scale meteorological fields produced by a dynamical model:

- First the (statistical) connection between the large-scale variables (predictors) and the extreme of interest (predictand) is established in the “ground truth” by training one or several ML models on observational/reanalysis dataset
- The trained ML model is then applied in inference mode on the same large-scale predictors from the dynamical seasonal forecast model hindcasts, and the prediction compared with observations.
- The ML model is tuned to compensate the effect of the dynamical model bias on the predictive skill.

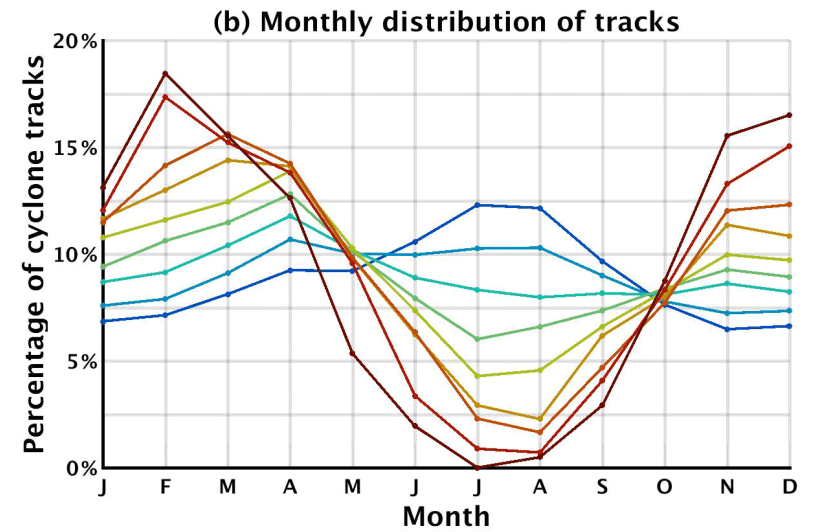
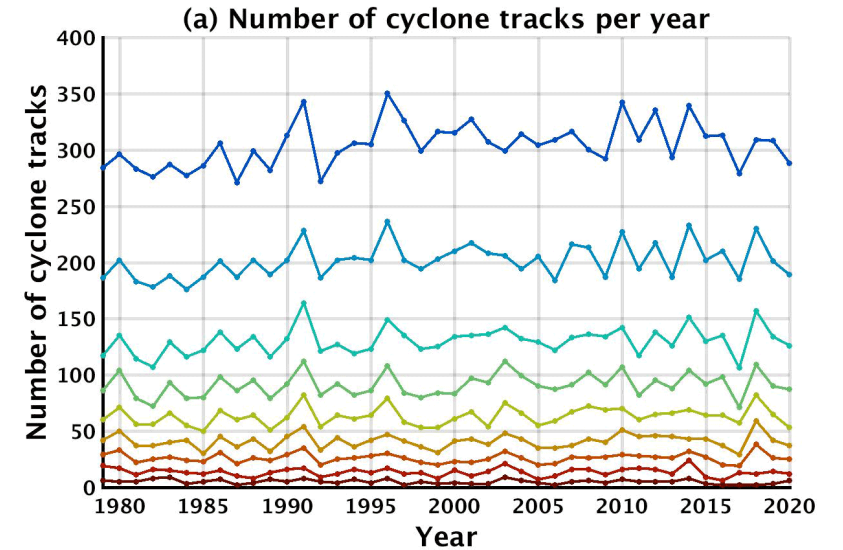




# Data

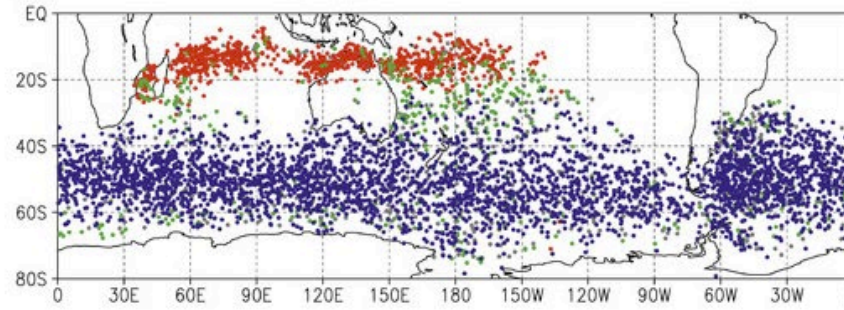


- No fully observation-based database (such as IBTrACS) available in the region
- Data from Flaounas et al. 2023 “best track” dataset, based on the consensus between ten different cyclone tracking algorithms applied to ERA5.
- In this work a confidence level of 7 has been used.

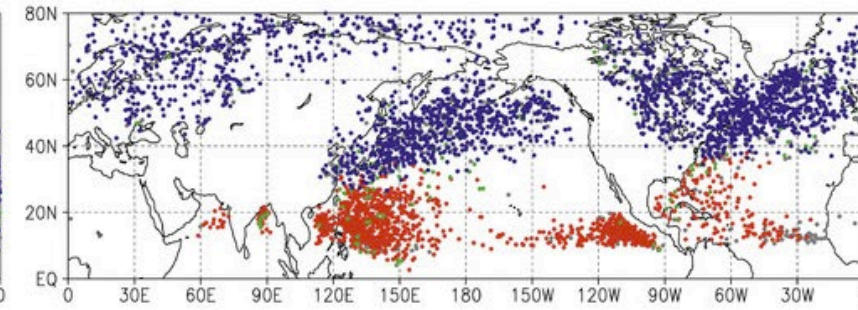


# Drivers

(a) SH summer (DJF)

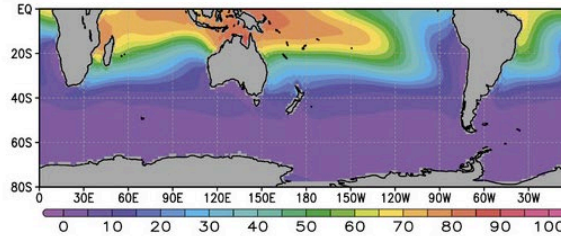


(b) NH summer (JJA)

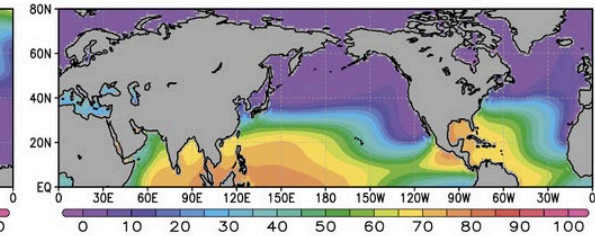


From Yanase et al. 2014

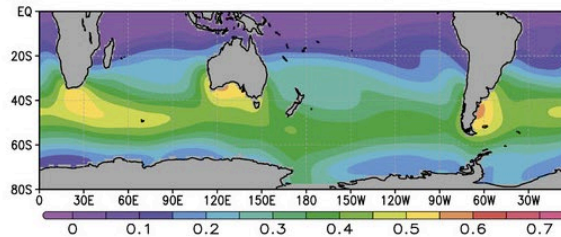
(a) Potential intensity in SH summer (DJF)



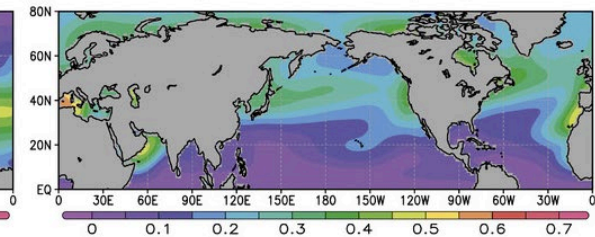
(b) Potential intensity in NH summer (JJA)



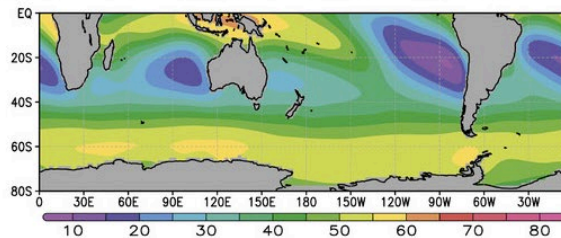
(c) Baroclinicity in SH summer (DJF)



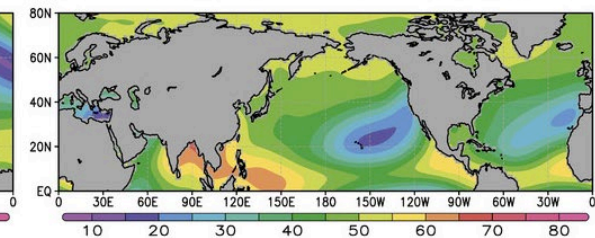
(d) Baroclinicity in NH summer (JJA)



(e) Relative humidity in SH summer (DJF)



(f) Relative humidity in NH summer (JJA)



## Predictors

Tropical  
cyclogenesis

Vorticity  
Wind shear  
Humidity  
SST

Extratropical  
cyclogenesis

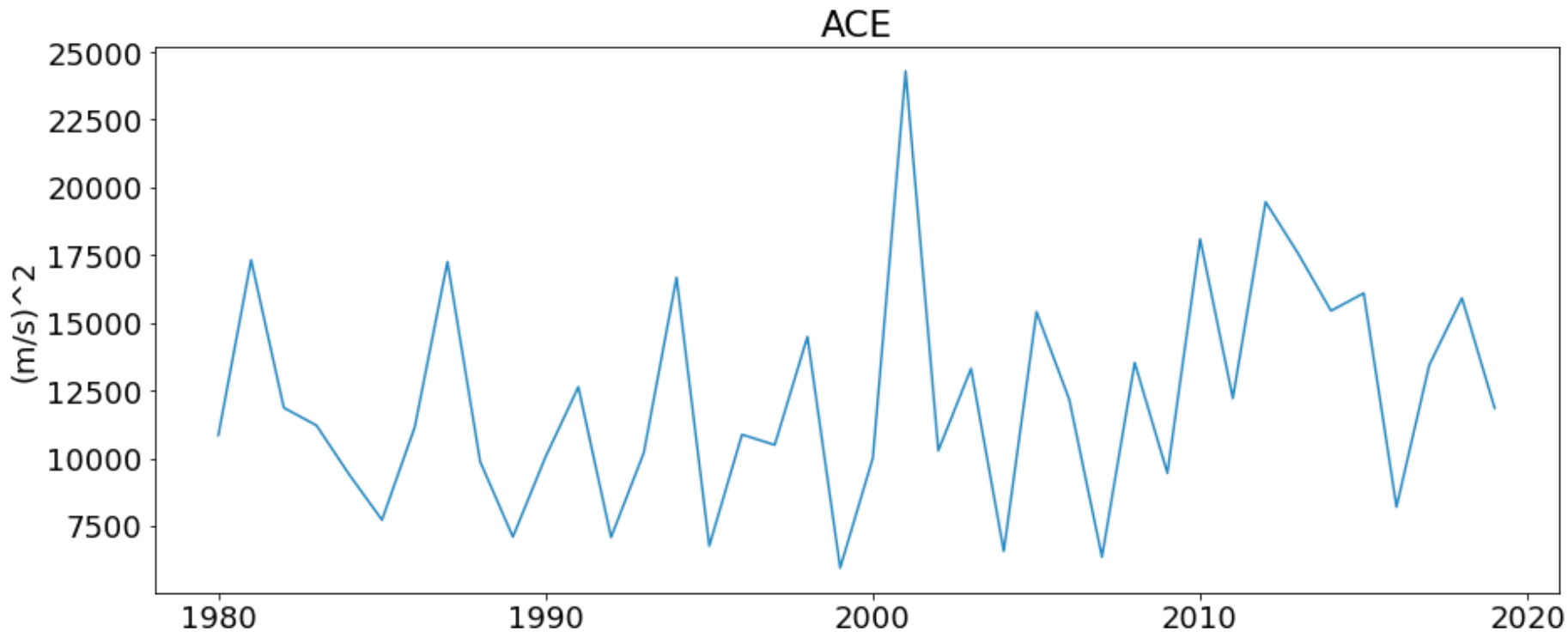
Eady growth  
rate

# Target

Common metrics used for cyclone activity include cyclone number, cyclone days and ACE (accumulated cyclone activity).

Here we focus on ACE, which has a number of advantages:

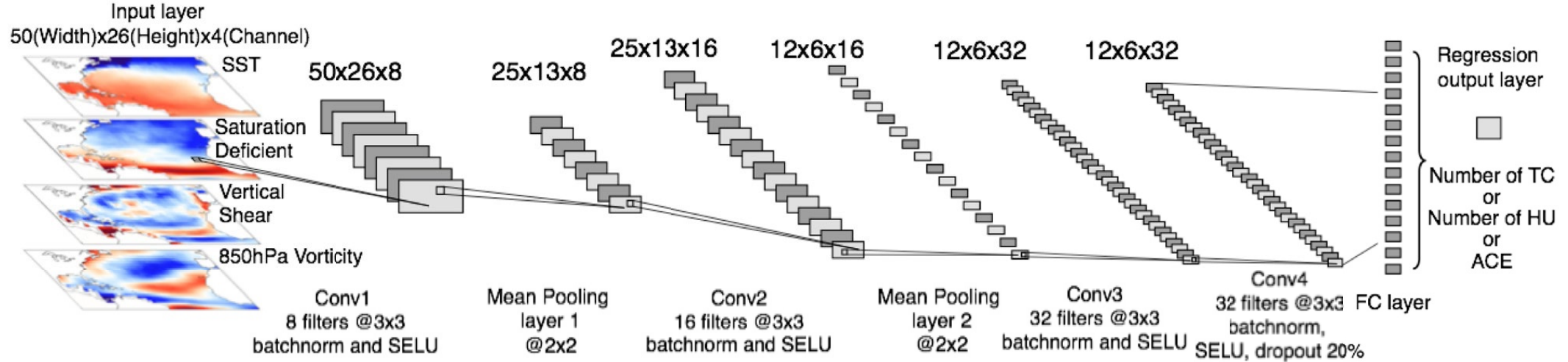
- Naturally gives more weight to more intense cyclones, with no need to impose ad hoc filters
- Less sensitivity on the details of the cyclone detection scheme used to produce the ground truth database



$$ACE = 10^{-4} \sum v_{\max}^2$$



# Model 1 (CNN)



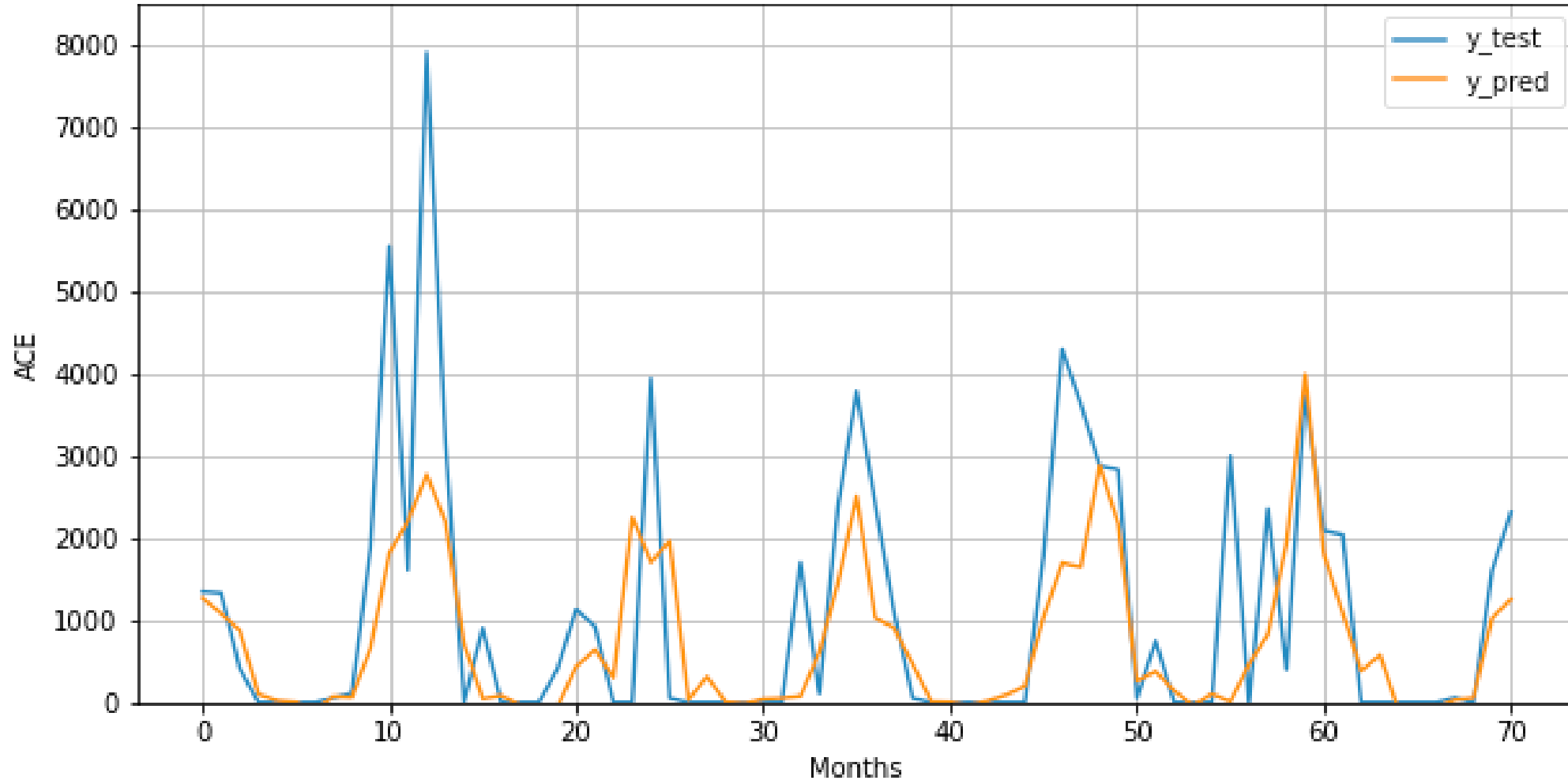
CNN architecture from Fu et al. 2022

Some changes made with respect to original architecture to optimize for the current problem:

- Reduction of the dimension of conv layers
- Added dropout and L2 regularization
- Implementation of early stopping
- Changed loss function to LogCosh
- Change Mean Pooling with Max Pooling

# Model 1 (CNN)

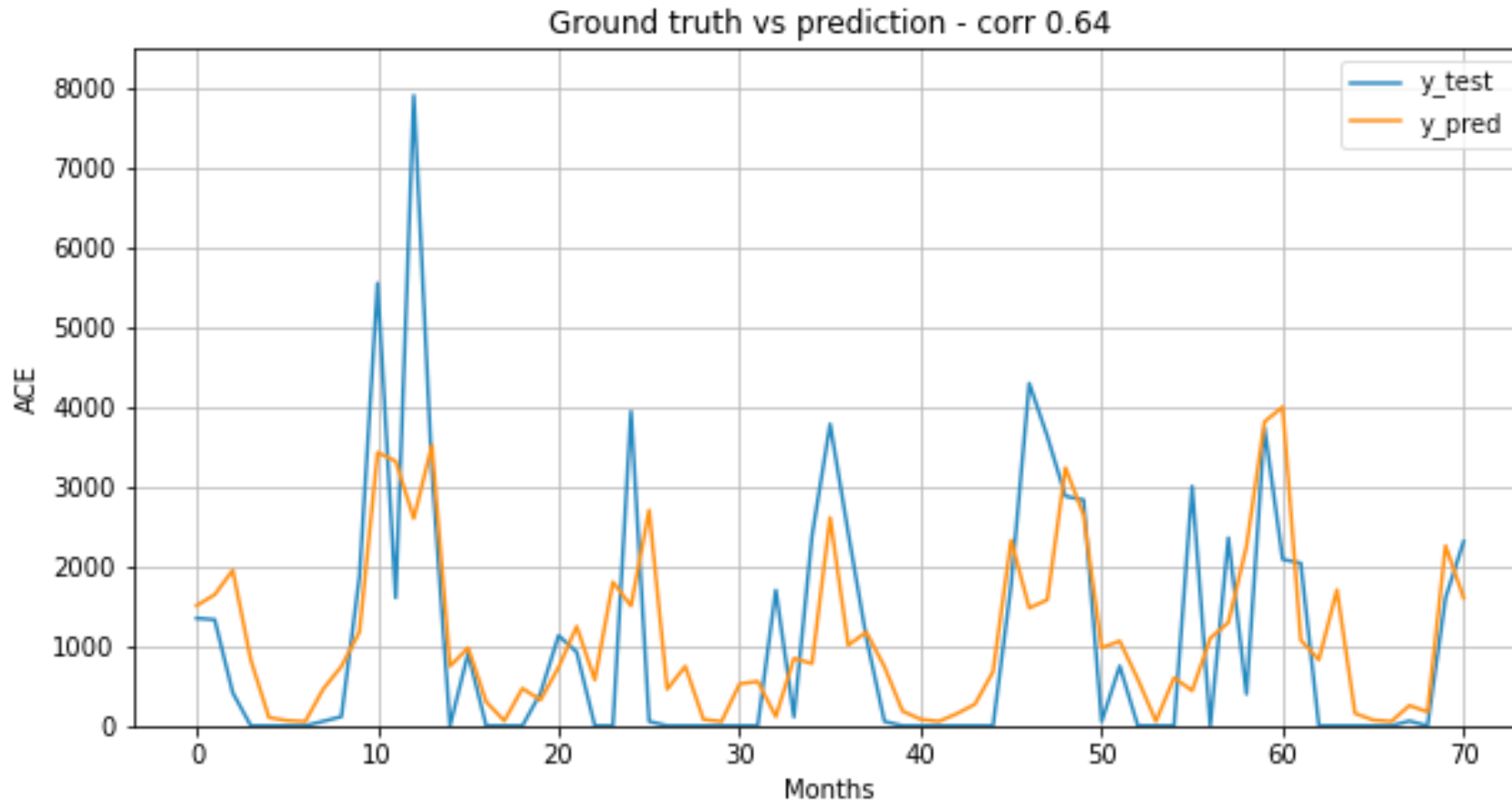
Ground truth vs prediction - corr 0.73



# Model 2 (RF)

Simpler model based on random forest regressor:

- 15 features: spatial averages of the five drivers across western, central and eastern Mediterranean



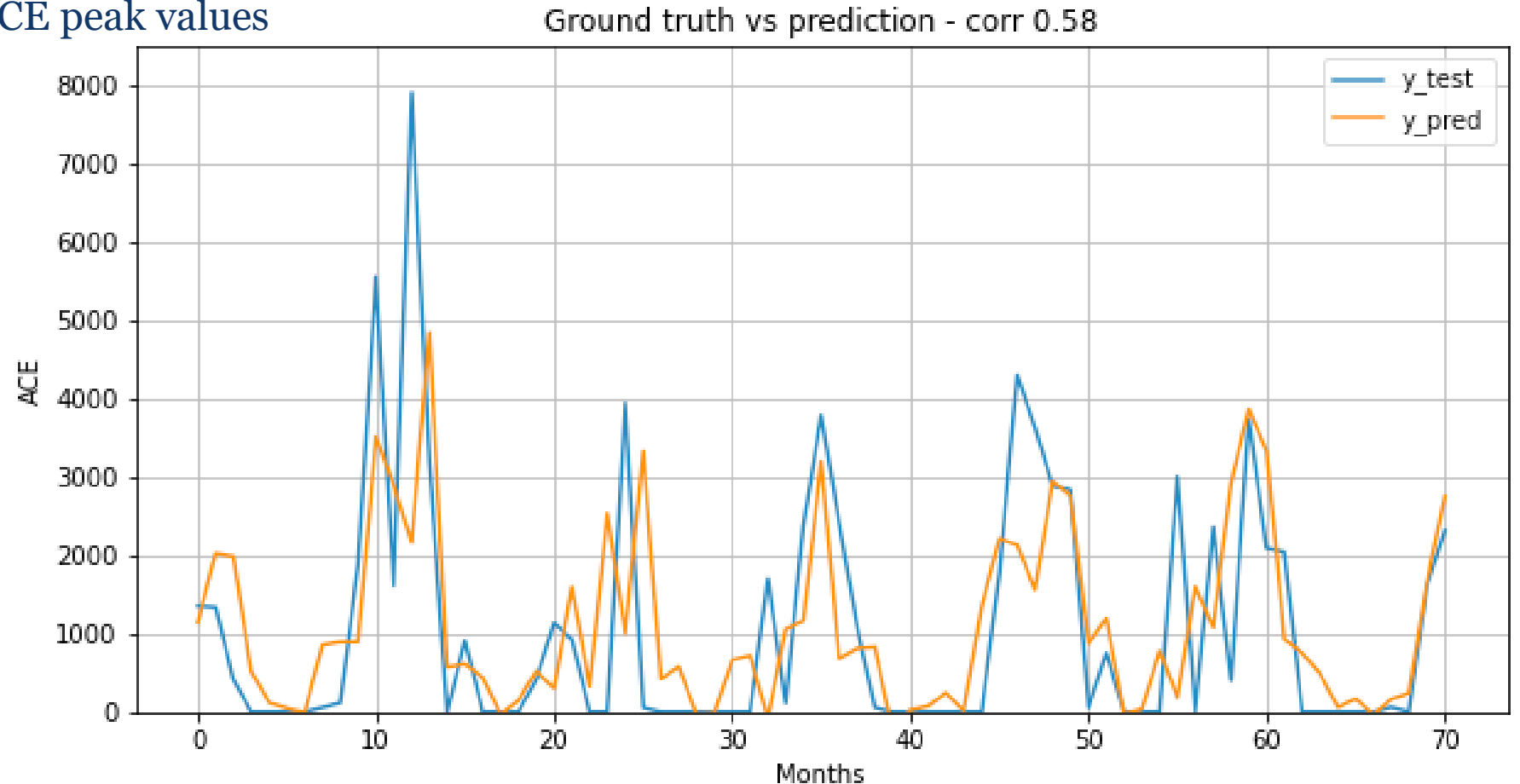
	feat_imp
<b>avo_C</b>	0.441095
<b>rh_E</b>	0.102472
<b>avo_E</b>	0.063274
<b>sst_E</b>	0.051824
<b>avo_W</b>	0.046821
<b>ws_W</b>	0.040147
<b>egr_C</b>	0.040074
<b>ws_E</b>	0.035922
<b>sst_W</b>	0.035149
<b>egr_E</b>	0.033059
<b>egr_W</b>	0.032087
<b>rh_W</b>	0.028478
<b>sst_C</b>	0.026530
<b>ws_C</b>	0.012721
<b>rh_C</b>	0.010347



# Model 3 (XGB)

Simpler model based on boosting (XGB algorithm):

- 15 features: spatial averages of the five drivers across western, central and eastern Mediterranean
- Better representation of ACE peak values



# Model summary and next steps

CNN	<ul style="list-style-type: none"><li>• Good result for correlation</li><li>• Takes into account spatial patterns</li></ul>	<ul style="list-style-type: none"><li>• Not so good skill for the amplitude of ACE peaks</li></ul>
Random Forest	<ul style="list-style-type: none"><li>• Easier to interpret</li></ul>	<ul style="list-style-type: none"><li>• Needs assumptions on spatial patterns</li></ul>
XGB	<ul style="list-style-type: none"><li>• Better representation of peak values</li></ul>	<ul style="list-style-type: none"><li>• Lower correlation</li></ul>

- Apply trained models to forecast data
- Best strategy to switch from reanalysis to forecast world? Fine-tuning? Full retraining on hindcast period?



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