AI-enhanced predictions of weather and climate extremes

Leone Cavicchia – Fondazione CMCC (Euro Mediterranean Center on Climate Change)

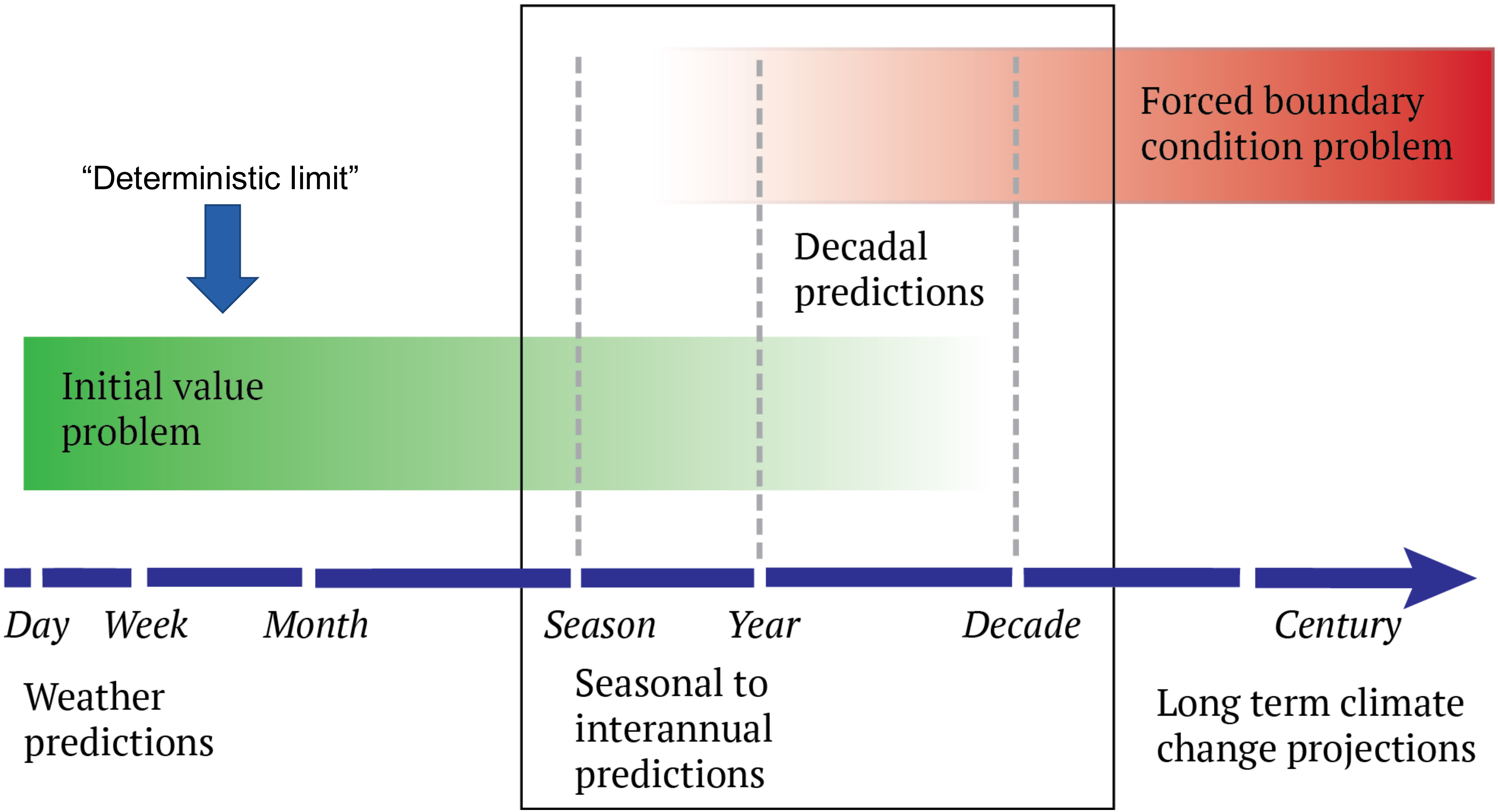
Colloqui di Fisica – Università Roma Tre

7-2-2023

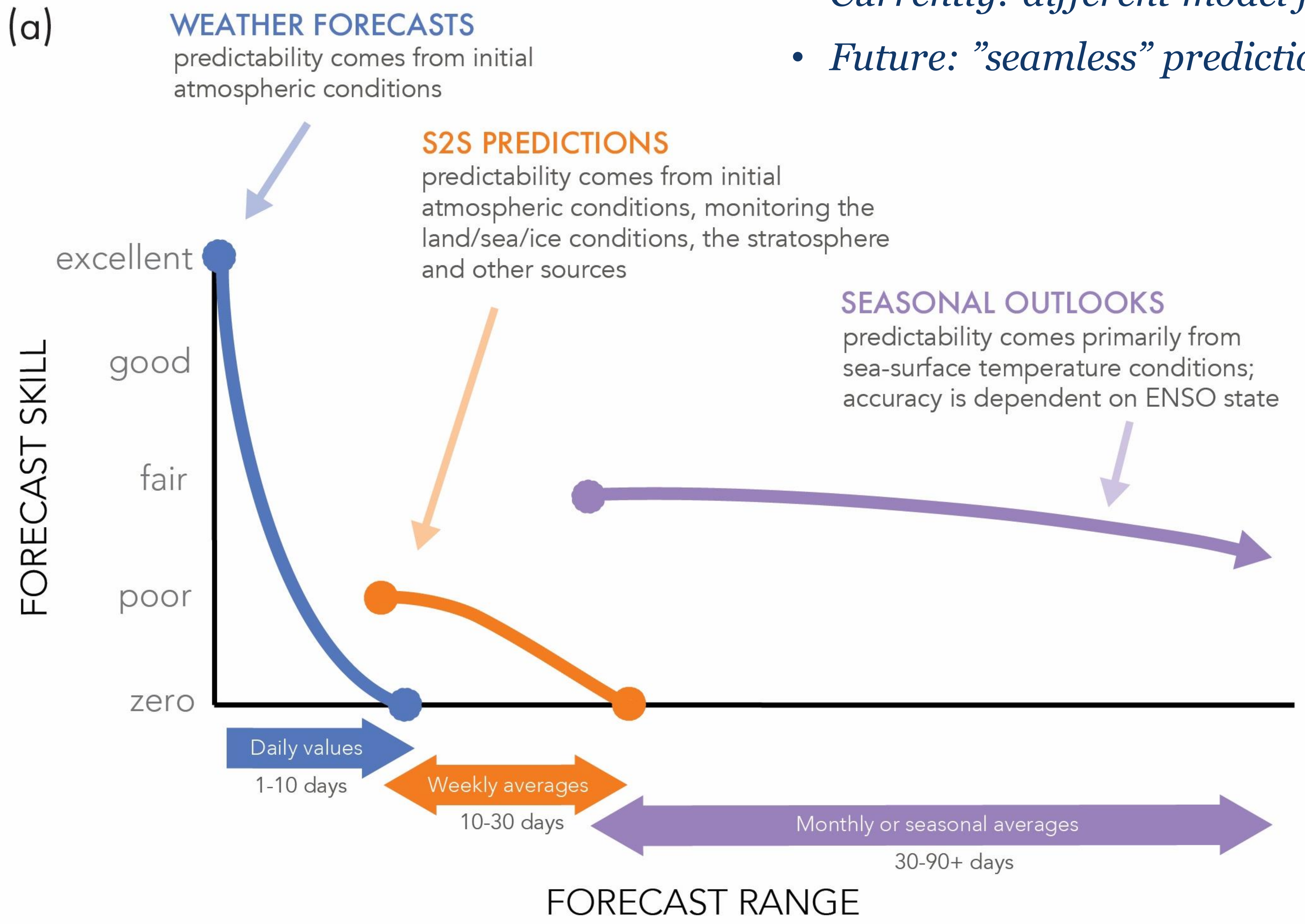
Outline

- *Climate predictions: achievements and challenges*
- *Artificial intelligence and climate modelling*
- *Climate prediction of tropical cyclones*

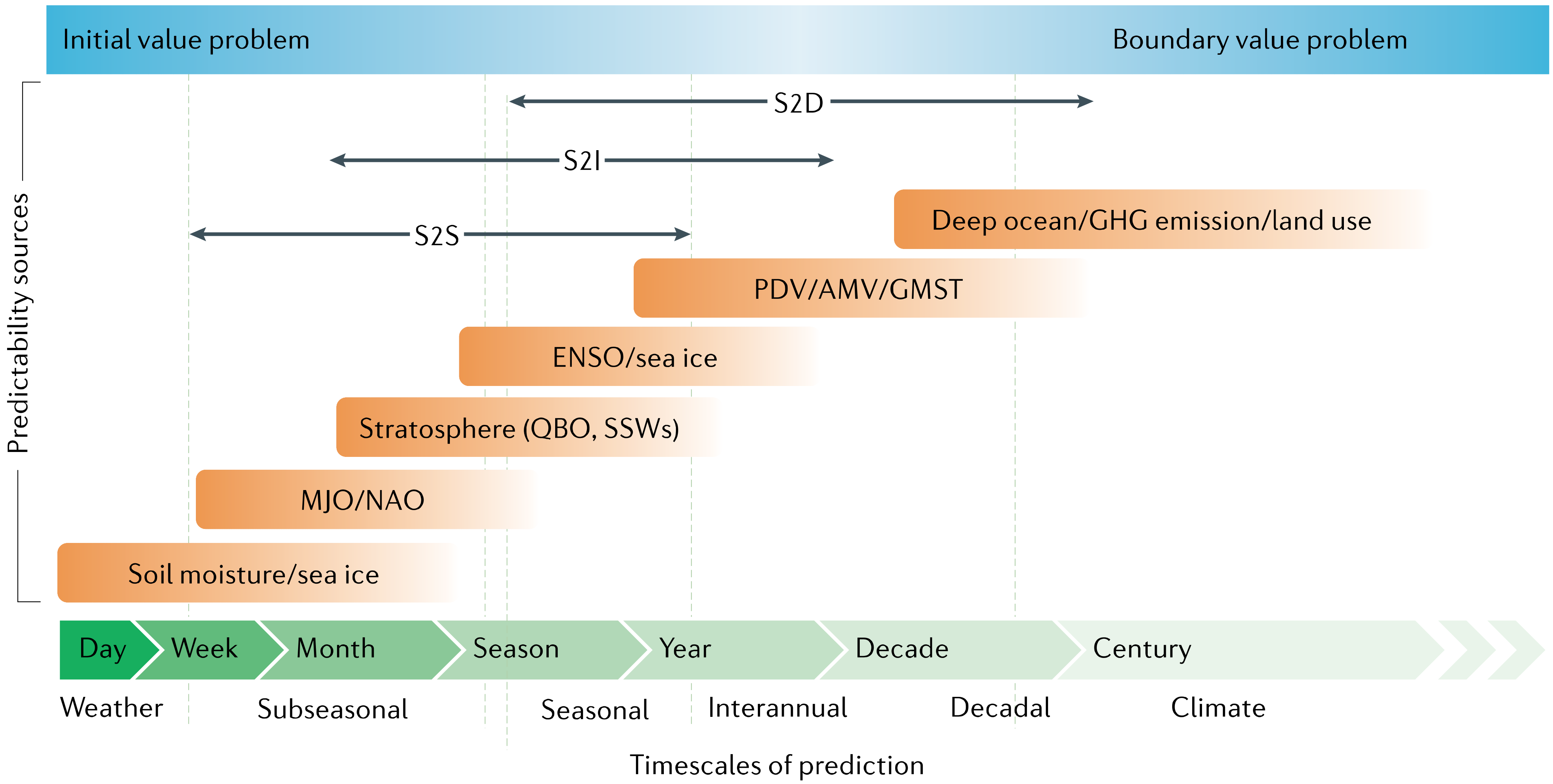
Climate predictions


Forced boundary condition problem
"Deterministic limit"
Decadal predictions
Initial value problem
Day
Week
Month
Season
Year
Decade
Century
Weather predictions
Seasonal to interannual predictions
Long term climate change projections

- *Currently: different model for each time scale*
- *Future: ”seamless” predictions*



a Predictability sources and timescales

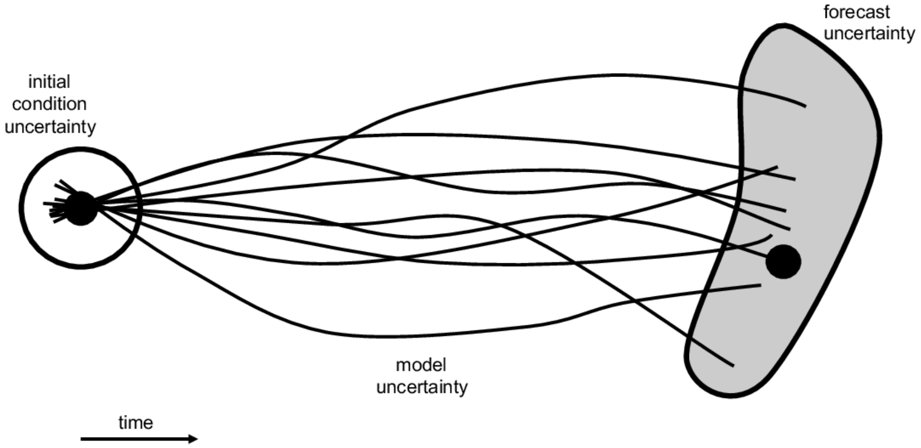


Source: WCRP

Sources of forecast uncertainty

The two main sources of uncertainty in dynamical climate prediction are:

- the lack of perfect knowledge of the initial conditions of the climate system



- the inability to perfectly model this system

⇨ parameter pertubation, multimodel approach

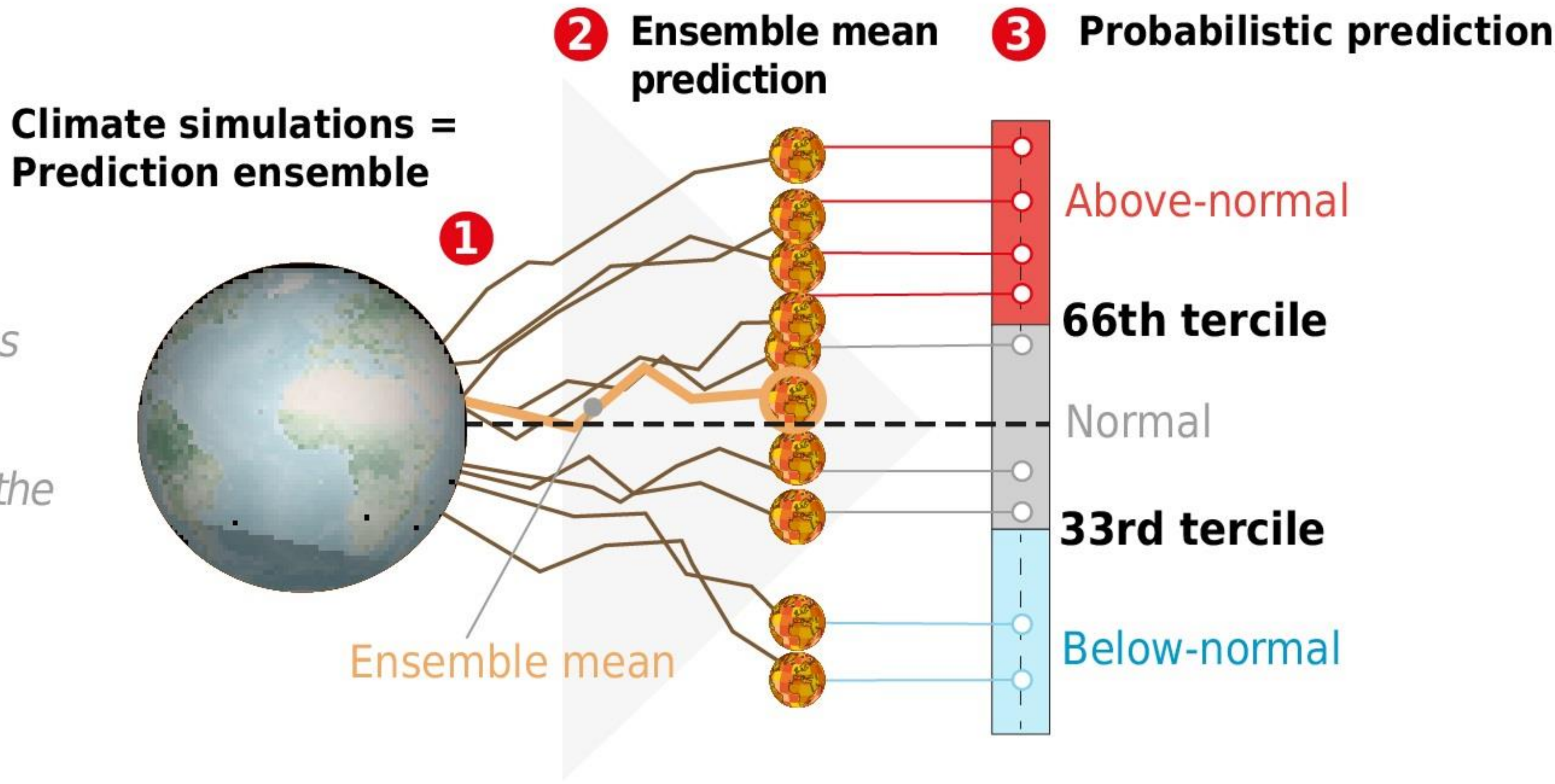
Climate predictions are ensemble predictions

▶ *Illustration of ensemble mean prediction and probabilistic prediction:*

1. *Multiple climate simulations (left side) form a prediction ensemble.*

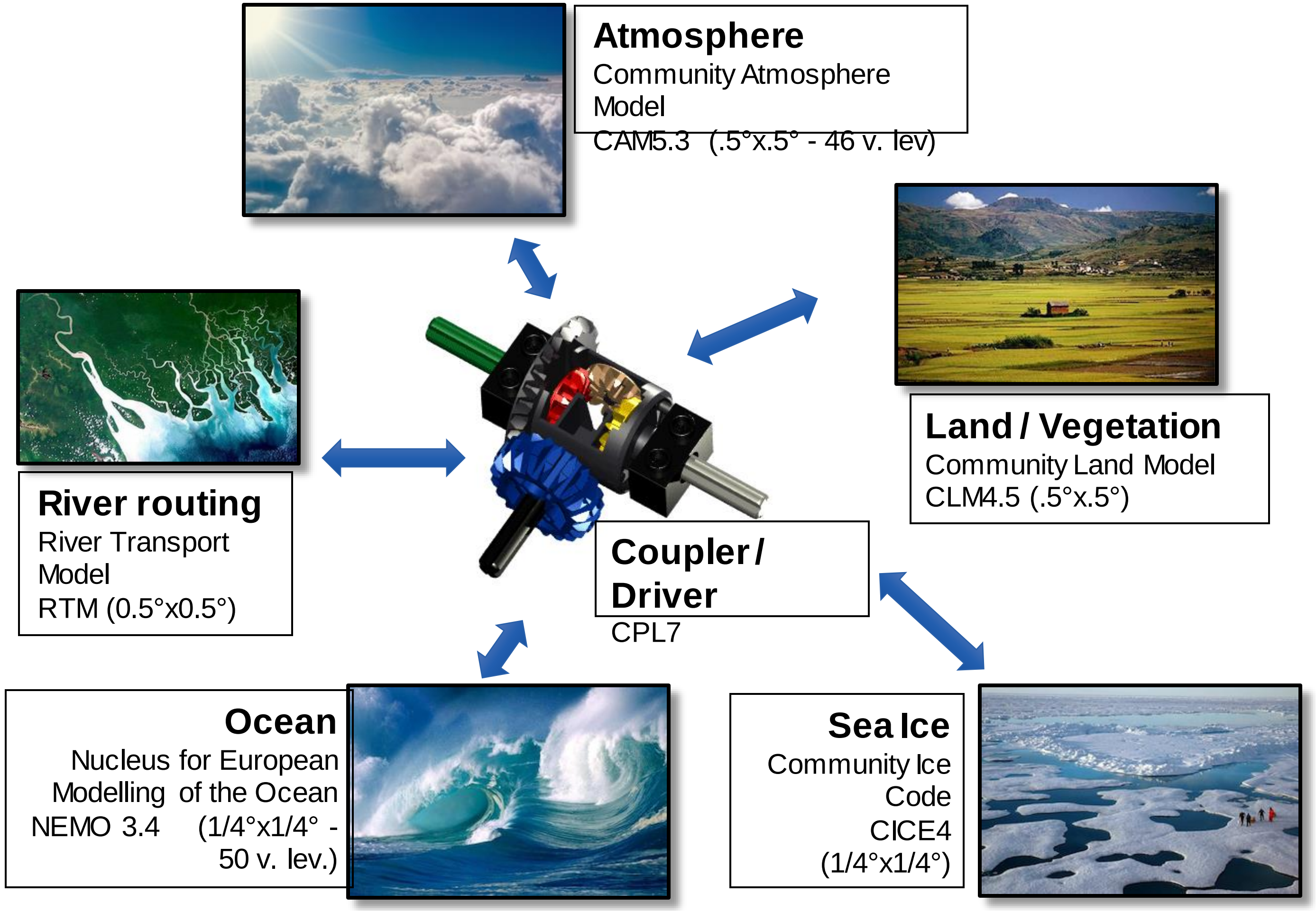
2. *The individual climate predictions are expressed as a deviation (anomaly) from a reference period in the past. The mean of all simulations of the prediction ensemble forms the ensemble mean prediction.*

3. *Dividing the individual climate predictions into the categories "above-normal", "normal", and "below-normal" (separated by the 33rd and 66th terciles of the reference period) leads to the probabilistic prediction (right side).*



https://www.dwd.de/EN/ourservices/kvhs_en/help/1_bkgrd_info/04_predictions/pics/ensemble.jpg

CMCC Seasonal Prediction System: SPS3.5



Operational since October 2020

The CMCC-SPSv3.5 initialization

Ten (10) atmospheric I.C.s are prepared starting from 1-day back in time atmospheric states provided by the 10 EDA analyses, interpolated to the CAM grid, then integrated in time in the SPS3.5 system up to the actual forecast start-date (1rst of the month, h: 00:00).

Three (3) land state I.C.s are obtained from the land analyses performed with CLM forced with atmospheric fields from different analyses (ECMWF, NCEP, linear interpolation of the 2)

Perturbed ocean I.C.s are created by generating nine (9) reanalyses through perturbation of the ocean observations (in the analysis step), perturbation of atmospheric forcing and introduction of stochastic physics, in the forecast step.

10 atmospheric ICs (1 day back lagged in time + SPS3.5 forecast)

3 CLM4.5 forced with **ECMWF** and **NCEP** atmospheric forcing to Land Surface

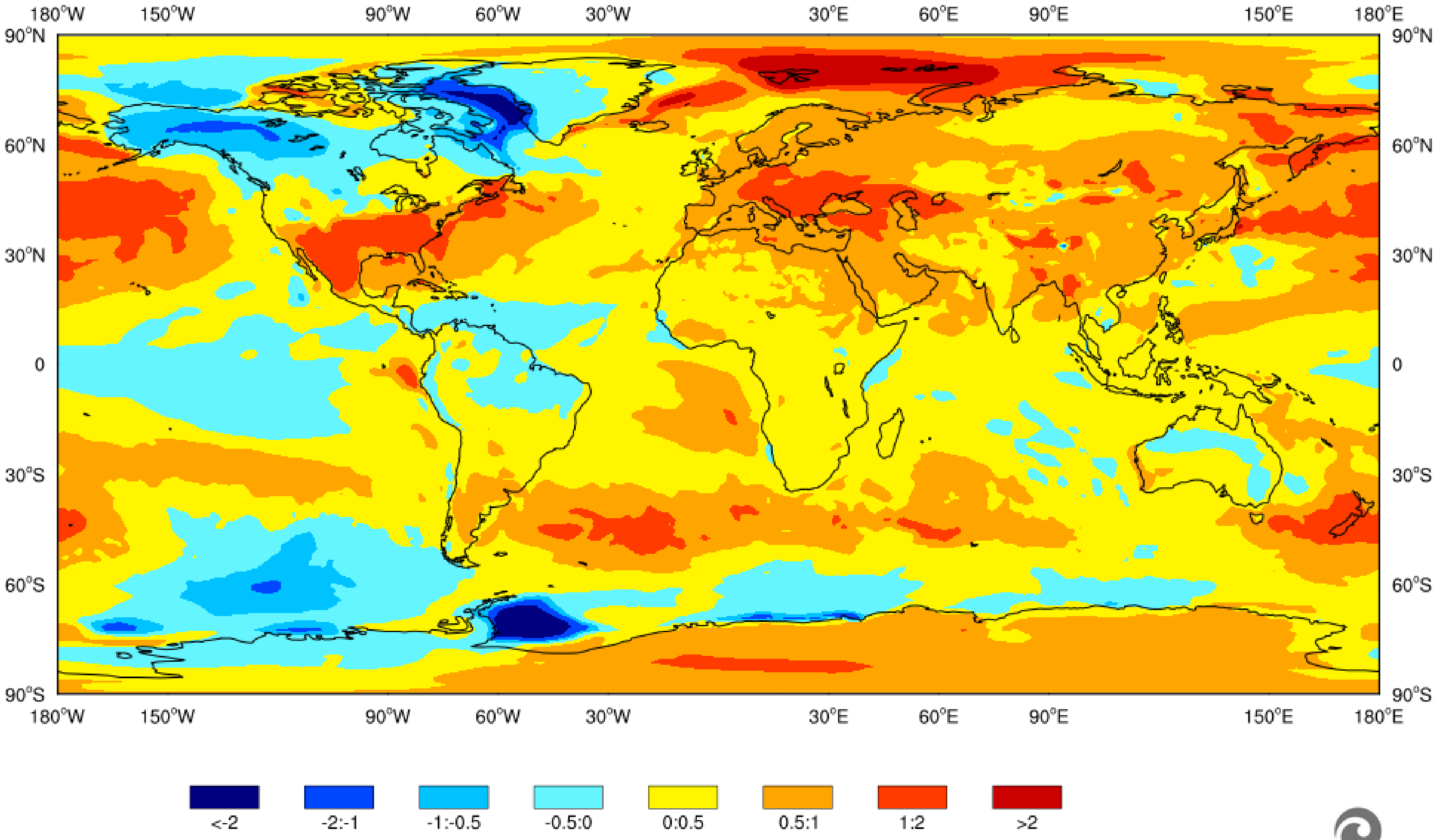
9 OCEAN ANALYSIS resulting from data assimilation

270 ICs → **50 forecast members**

Start-date 01-2023 Lead season 1 (FMA)

T2m anomalies [°C]

Deterministic forecast



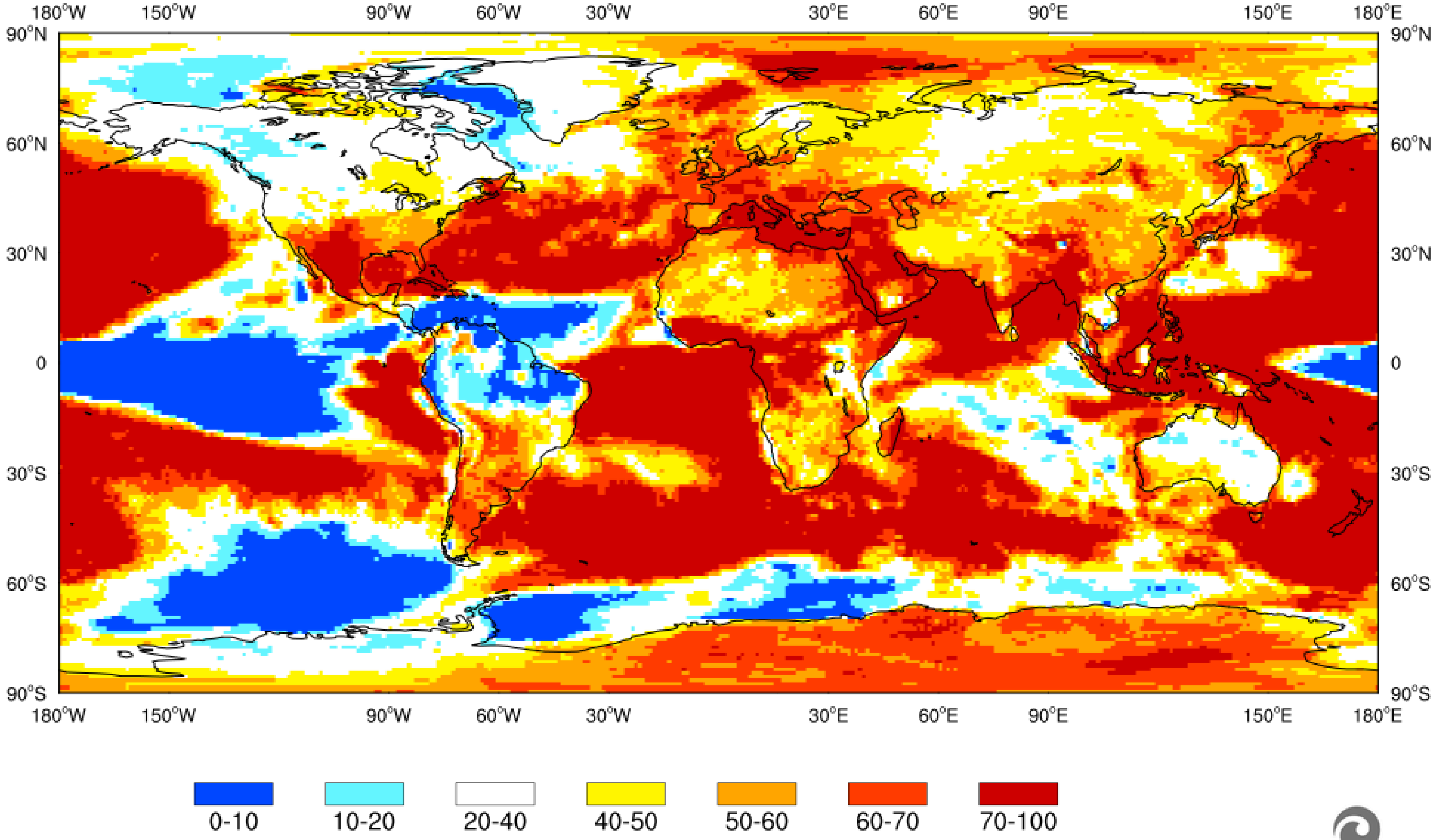
cmcc

sps.cmcc.it

Start-date 01-2023 Lead season 1 (FMA)

prob (t2m > upper tercile)

Probabilistic forecast

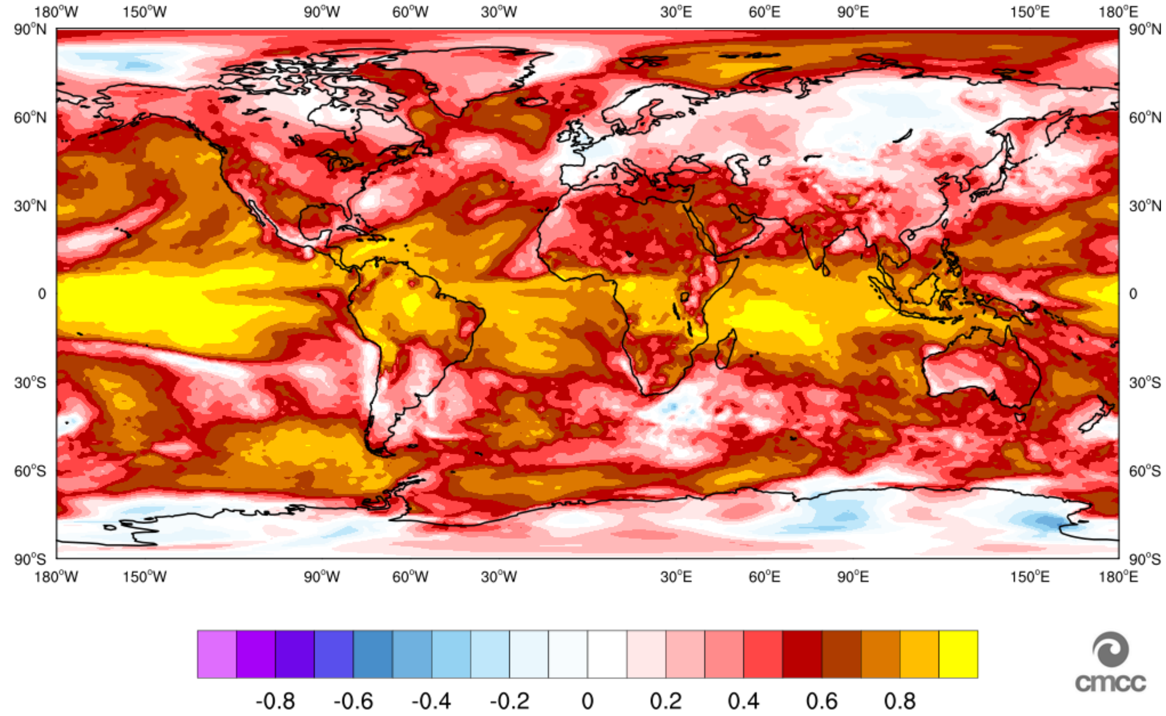


Seasonal prediction skill

SPS3.5: ACC global t2m (1993-2016) - members 40

January start-date - lead season 1

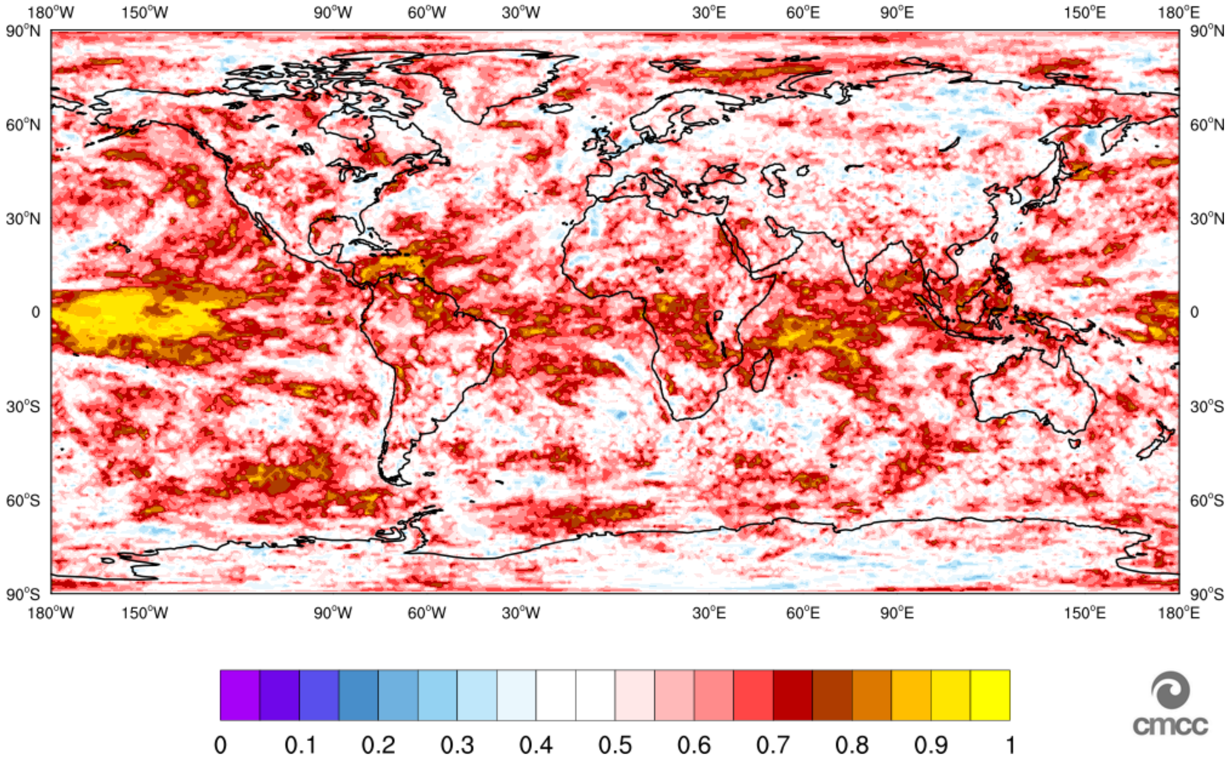
ACC= 0.50



SPS3.5 global: middle ROC (1993-2016) - members 40

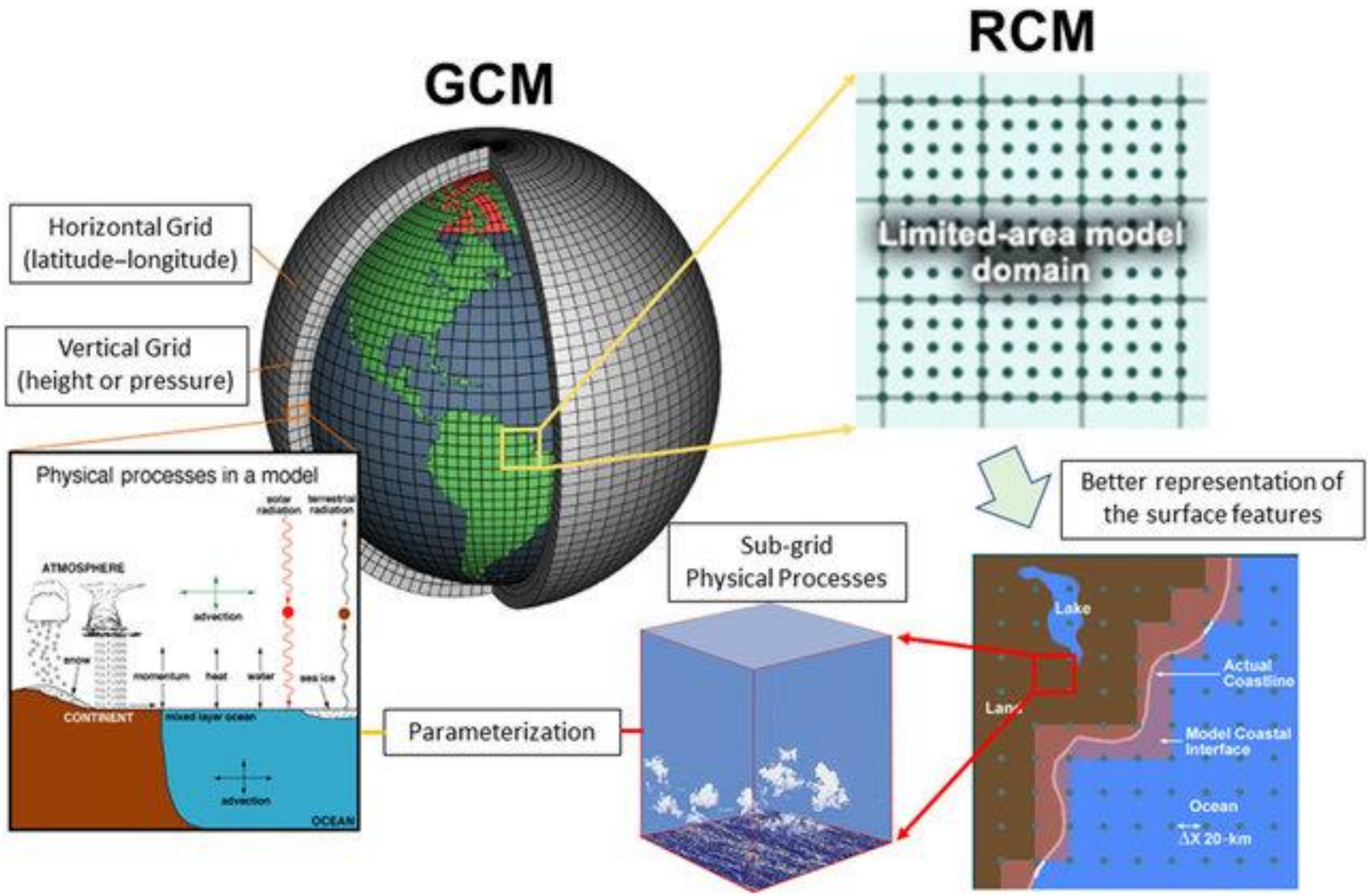
t2m - January start-date - lead 1

ROCSS= 0.59



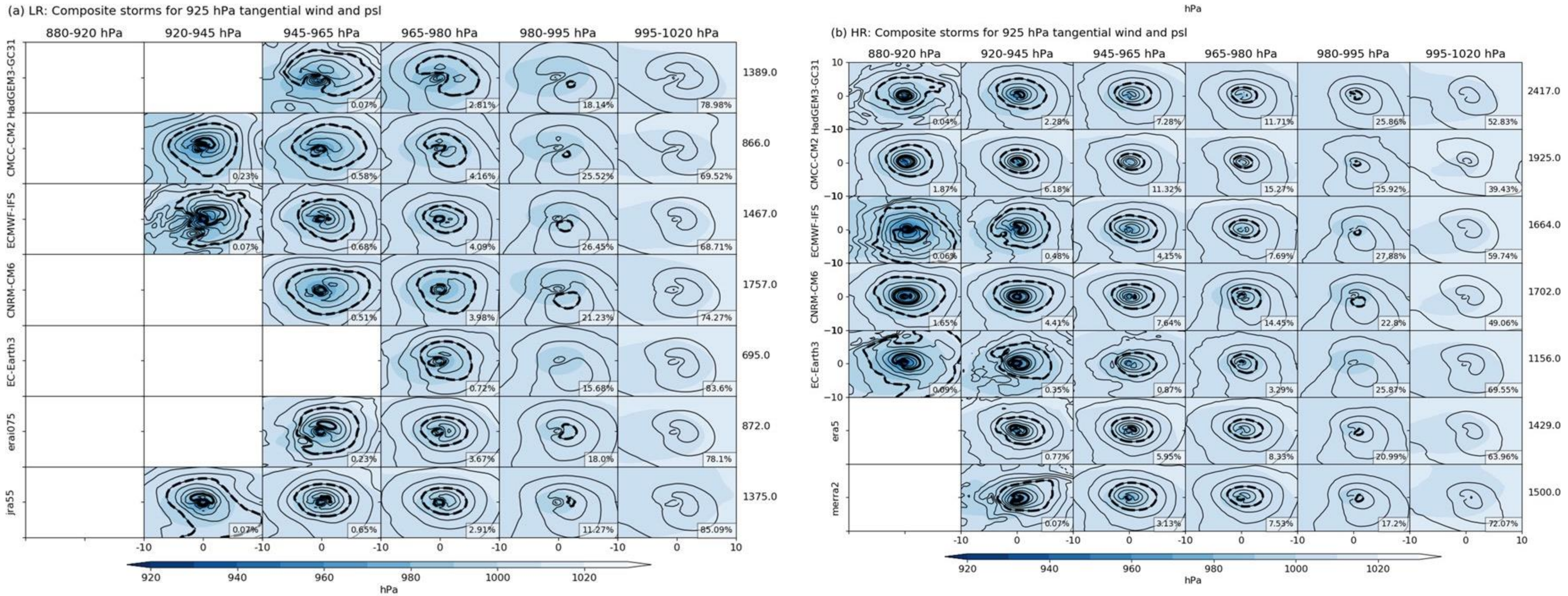
Climate models resolution

- *Climate models numerically approximate fluid dynamics equations on a discrete lat-lon grid.*
- *The resolution of the horizontal grid is determined by the available computer power.*
- *Sub-grid processes are represented by* ***physical parameterizations.***
- *Parameterizations are computationally expensive and depend on a large number of arbitrary parameters.*



- ➢ *The large number of ensemble members needer to produce skilful climate predictions limits the horizontal resolution to about 50 kms on today's supercomputers.*

Climate model resolution and extreme events



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

AI and climate modeling

Tropical cyclones

Tropical cyclones are severe weather systems that form over tropical and subtropical waters. They are also known as typhoons, hurricanes, or tropical storms depending on the region they form in. Tropical cyclones are characterized by strong winds, heavy rainfall, and high waves, which can cause widespread damage and pose a threat to coastal communities.

The formation of tropical cyclones is driven by the release of heat from the warm ocean waters. This heat energy creates an area of low pressure, which draws in air from surrounding areas. As the air rises and cools, moisture condenses and forms clouds, leading to the formation of a tropical cyclone. The cyclone develops a distinct eye, which is the center of the storm, and a surr

100% AI-generated slide!

Tropical cyclones can cause signi
communities. Strong winds and h
infrastructure, and heavy rainfall can lead to flash flooding and landslides. Tropical cyclones can also disrupt transportation and commerce, as ports and airports may close during the storm. In addition, the storm surge associated with tropical cyclones can cause significant coastal flooding, particularly in low-lying areas.

There are several ways to measure the intensity of tropical cyclones, including the Saffir-Simpson Hurricane Wind Scale, which classifies storms based on the maximum sustained winds. The scale ranges from Category 1, with winds of 74-95 mph, to Category 5, with winds in excess of 157 mph. In addition, the National Hurricane Center in the US uses a central pressure measurement to determine the intensity of a tropical cyclone.

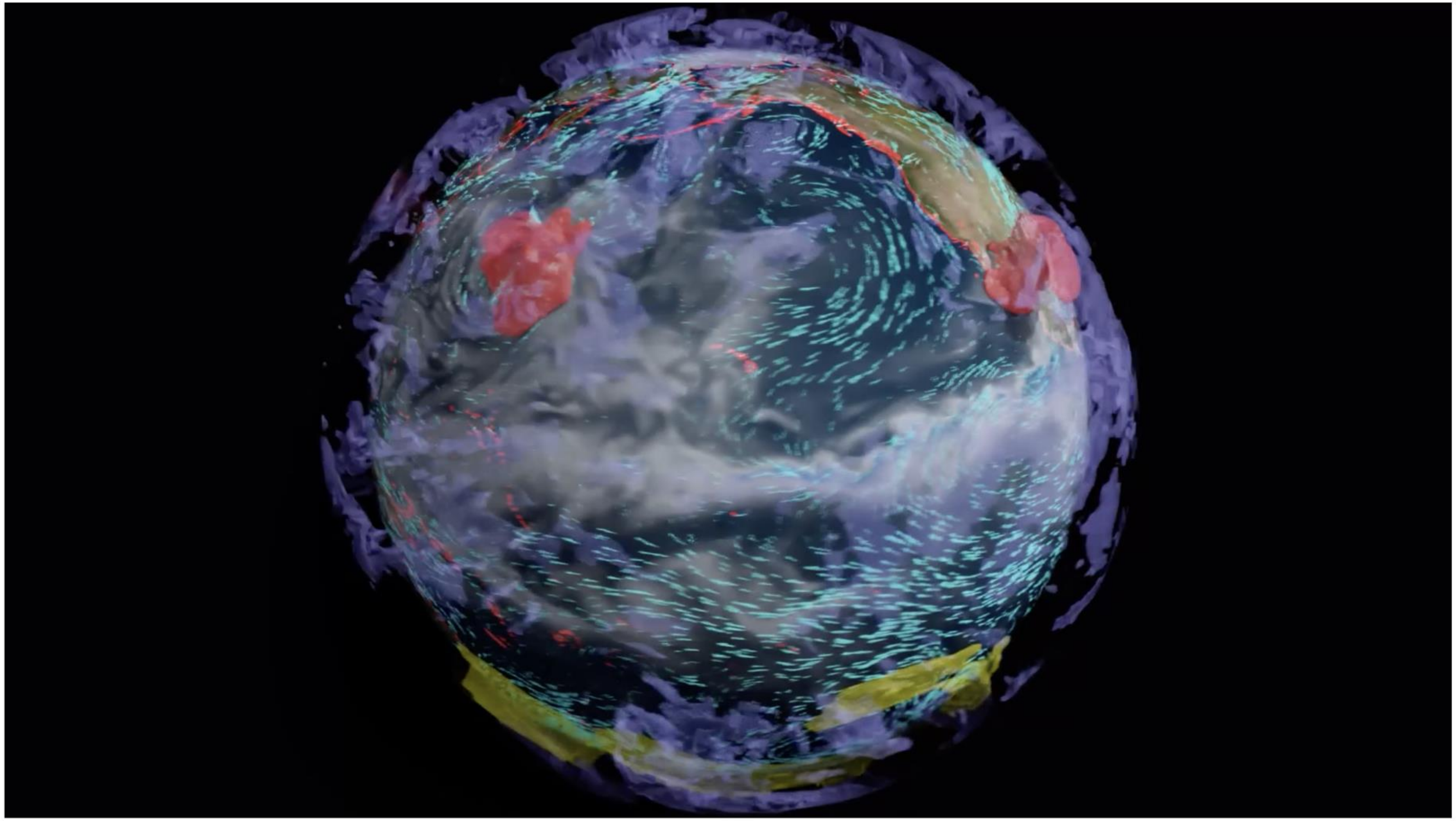
“Hurricane making landfall”, E. Delacroix

Climate and AI: Open Research Directions

- *AI to replace numerical models*
- *AI to improve climate modelling parameterizations*
- *AI to improve the detection of weather systems*
- *AI to improve numerical climate predictions and projections*

NVIDIA to Build Earth-2 Supercomputer to See Our Future

November 12, 2021 by JENSEN HUANG



ClimaX

Search

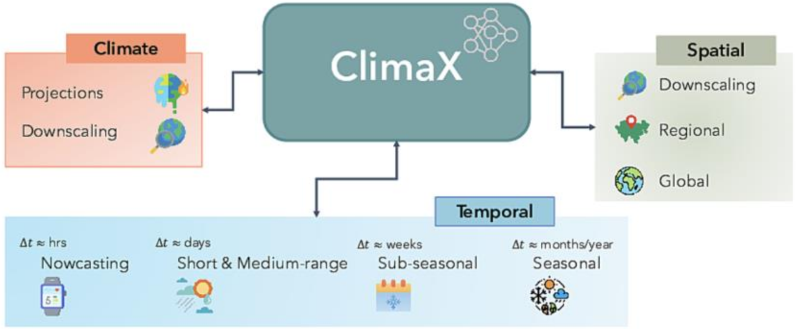
microsoft/ClimaX

ClimaX

A foundation model for weather and climate.

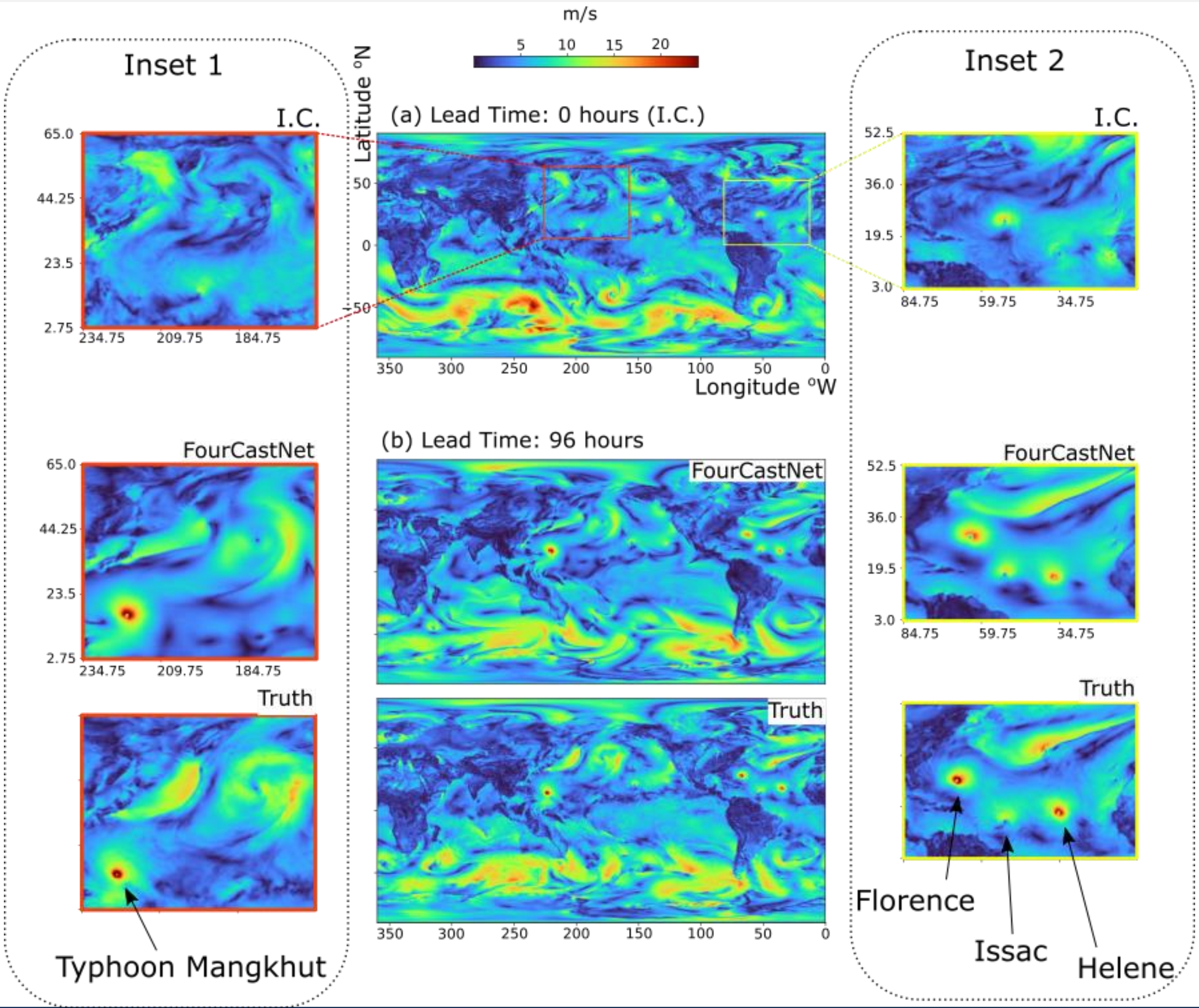
Paper

Code (coming soon)

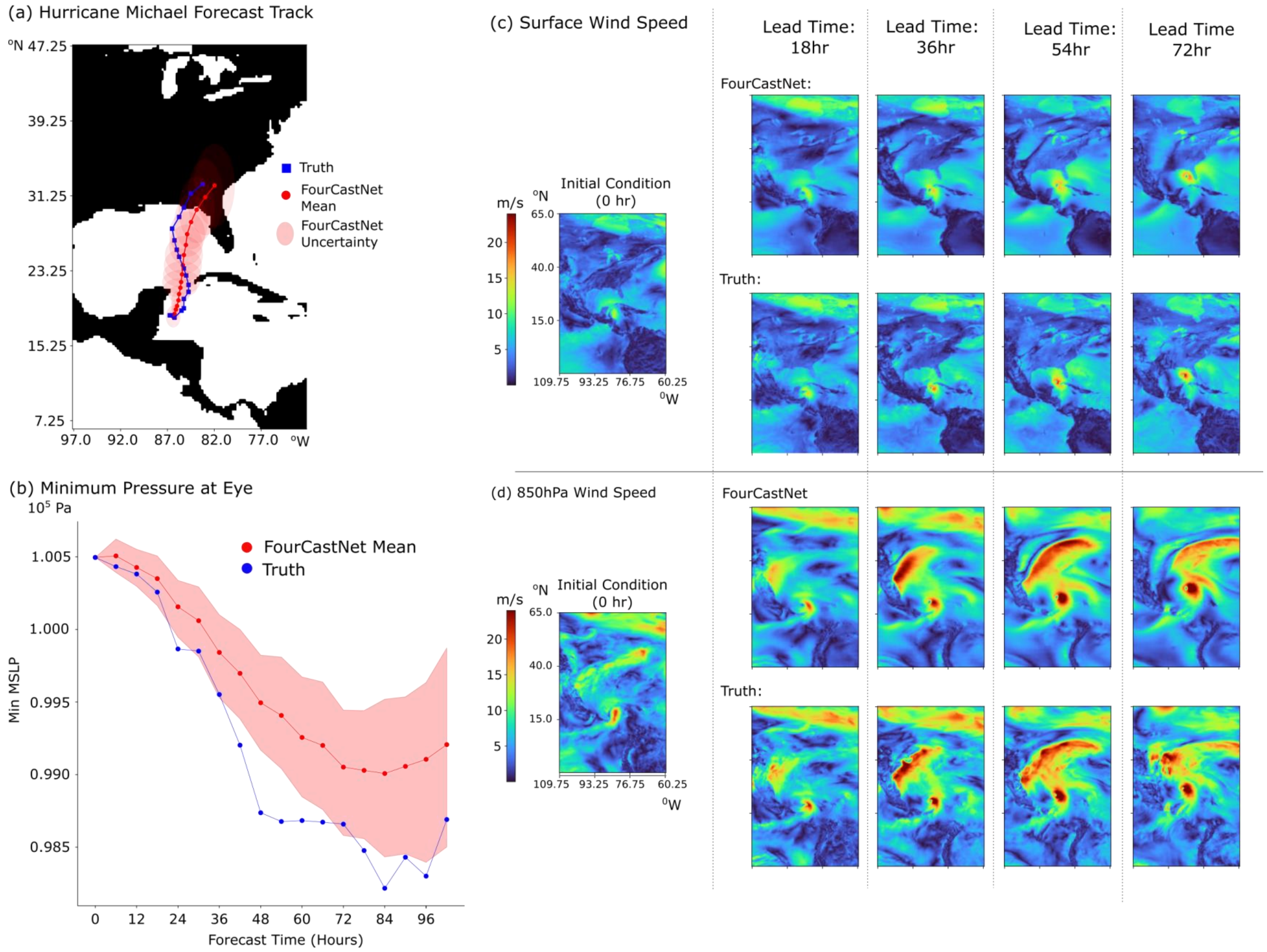


What is ClimaX?

- ClimaX is the first foundation model for weather and climate science.
- Simple, flexible, and easy to use.
- Ample examples for the workflow to apply to various downstream tasks ranging from weather forecasting to climate downscaling.
- Supports efficient scalable distributed training, powered by PyTorch Lightning



FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators (arXiv:2202.11214)



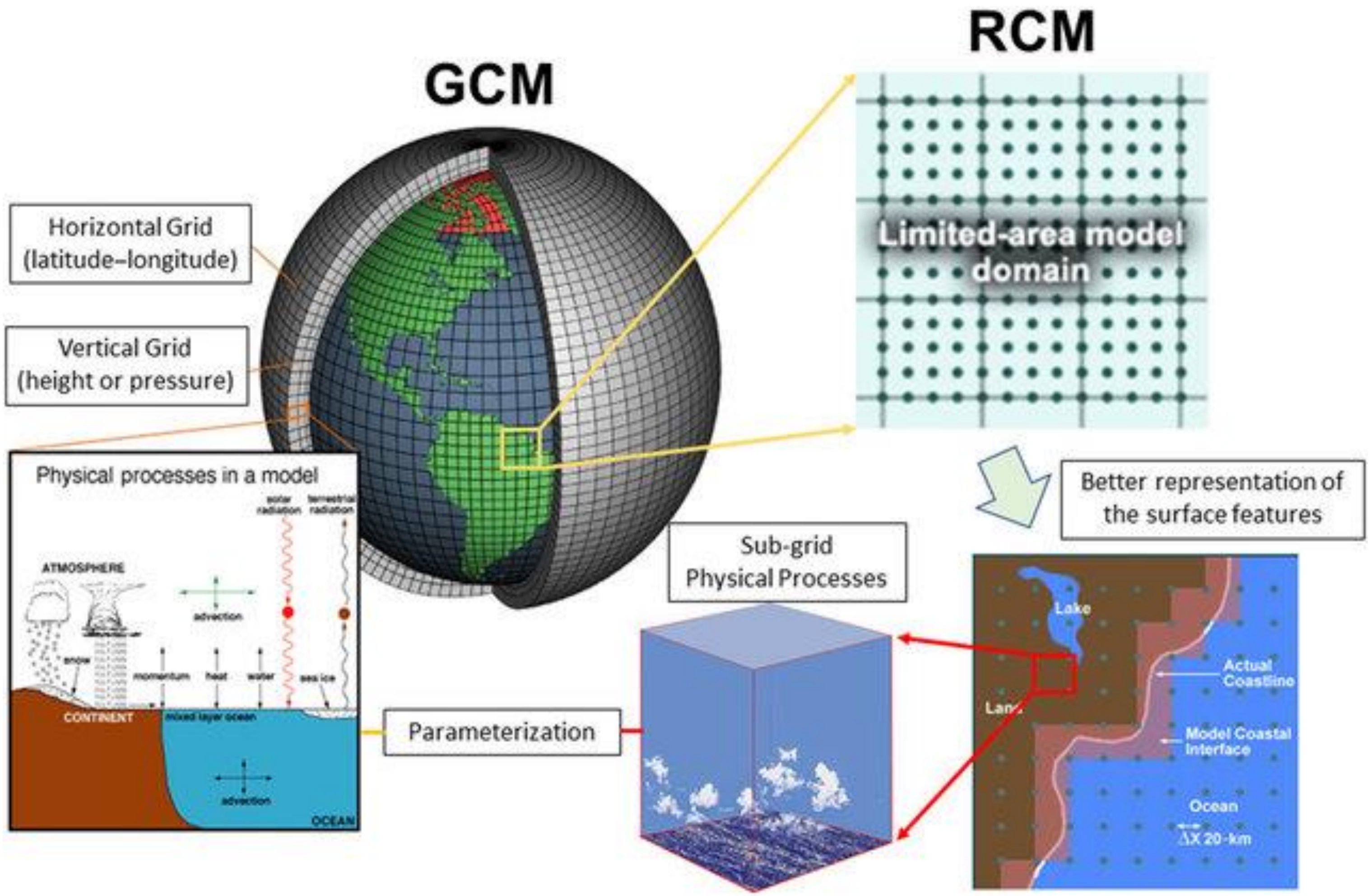
(a) Hurricane Michael Forecast Track
°N 47.25
39.25
31.25
23.25
15.25
7.25
97.0 92.0 87.0 82.0 77.0 °W
Truth
FourCastNet Mean
FourCastNet Uncertainty
(b) Minimum Pressure at Eye
10^5 Pa
Min MSLP
1.005
1.000
0.995
0.990
0.985
FourCastNet Mean
Truth
0 12 24 36 48 60 72 84 96
Forecast Time (Hours)
(c) Surface Wind Speed
Lead Time: 18hr
Lead Time: 36hr
Lead Time: 54hr
Lead Time 72hr
FourCastNet:
Truth:
Initial Condition (0 hr)
m/s
20
15
10
5
°N
65.0
40.0
15.0
109.75 93.25 76.75 60.25
°W
(d) 850hPa Wind Speed
FourCastNet
Truth:
Initial Condition (0 hr)
m/s
20
15
10
5
°N
65.0
40.0
15.0
109.75 93.25 76.75 60.25
°W

Limitations

- *Model skill have a comparable decay with respect to lead time with numerical models*
- *Not yet demonstrated whether a fully data driven forecast can reproduce unprecedented (i.e. not seen in the training set) events*
- *The data driven weather forecast model still needs reanalysis data (which are generated by a numerical model) for the training*
- *Data-driven climate prediction models still need numerical climate simulations in the training*

AI to improve Climate modelling

- *Climate models numerically approximate fluidodynamics equations on a discrete lat-lon grid.*
- *The resolution of the horizontal grid is determined by the available computer power.*
- *Sub-grid processes are represented by* ***phyiscal parameterizations.***
- *Parameterizations are computationally expensive and depend on a large number of arbirary parmaters.*
- *Parameterizations can be replaced by machine learning models trained on observations*
- *ML models are only trained once so running long climate simulations become less computationally expensive*



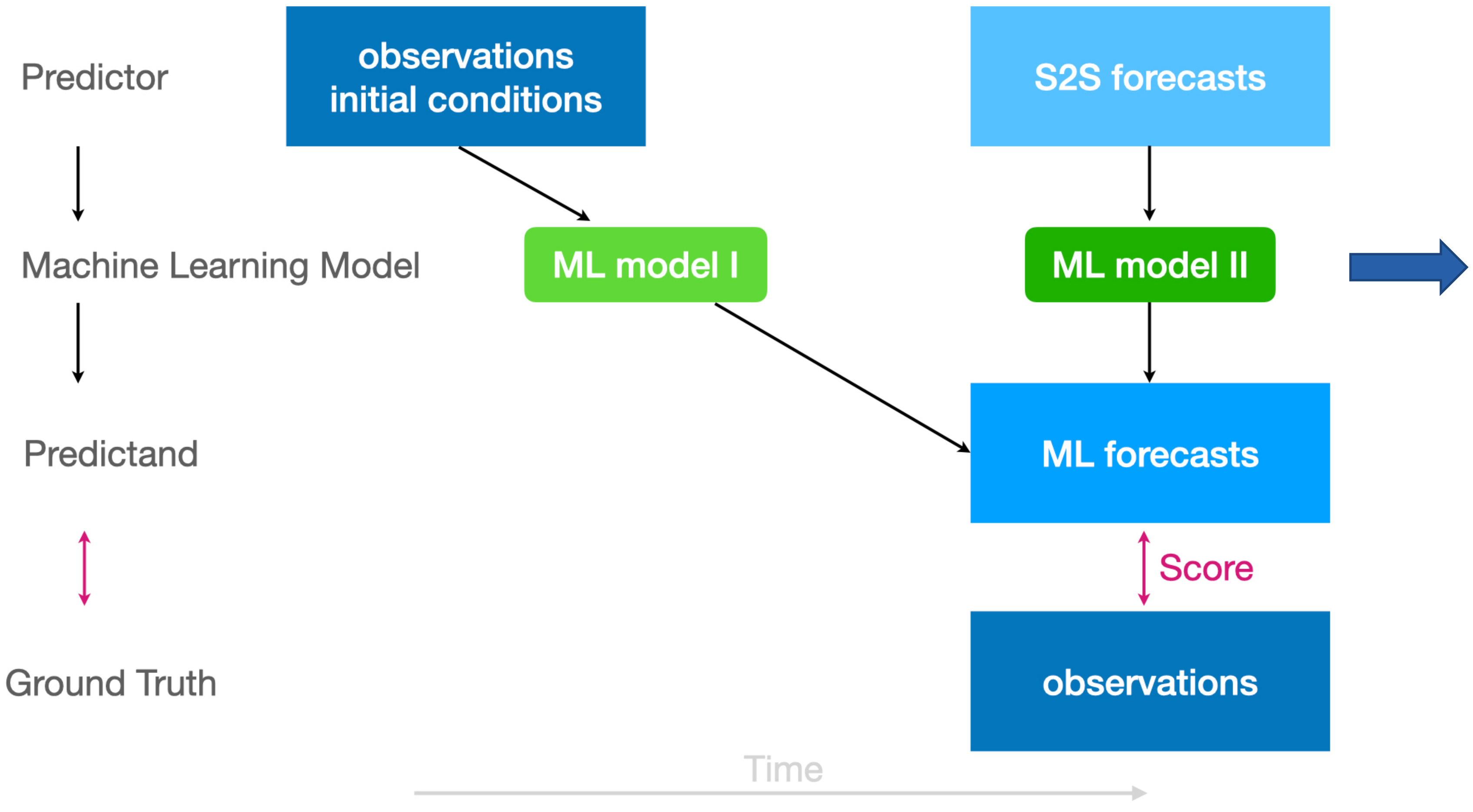
AI to improve weather events detection

- The detection of extreme events relies on algorithms developed for low resolution model data/ observations
  - ✓ Depend on a number of expert-determined thresholds for physical variables, that can be resolution or data source dependent
  - ✓ Are computationally inefficient
- Example: for the detection of a tropical cyclone look for all the minima in the mean sea level field, calculate the wind speed associated, then repeat for all time steps, then assign nearby points to the same cyclone track.

- Machine learning/deep learning can automate the detection process and make it more efficient

AI to improve climate prediction and projections

- In order to correctly reproduce extreme events climate models need to have a high spatial resolution
- This is not always computationally feasible because of the long integrations required (climate projections) and/or the large number of ensemble members needed to represent the uncertainty range (climate predictions)
- AI algorithms can improve the predictions e.g. exploiting the relationship between the extreme events and its large-scale drivers (which are better predicted by the model).



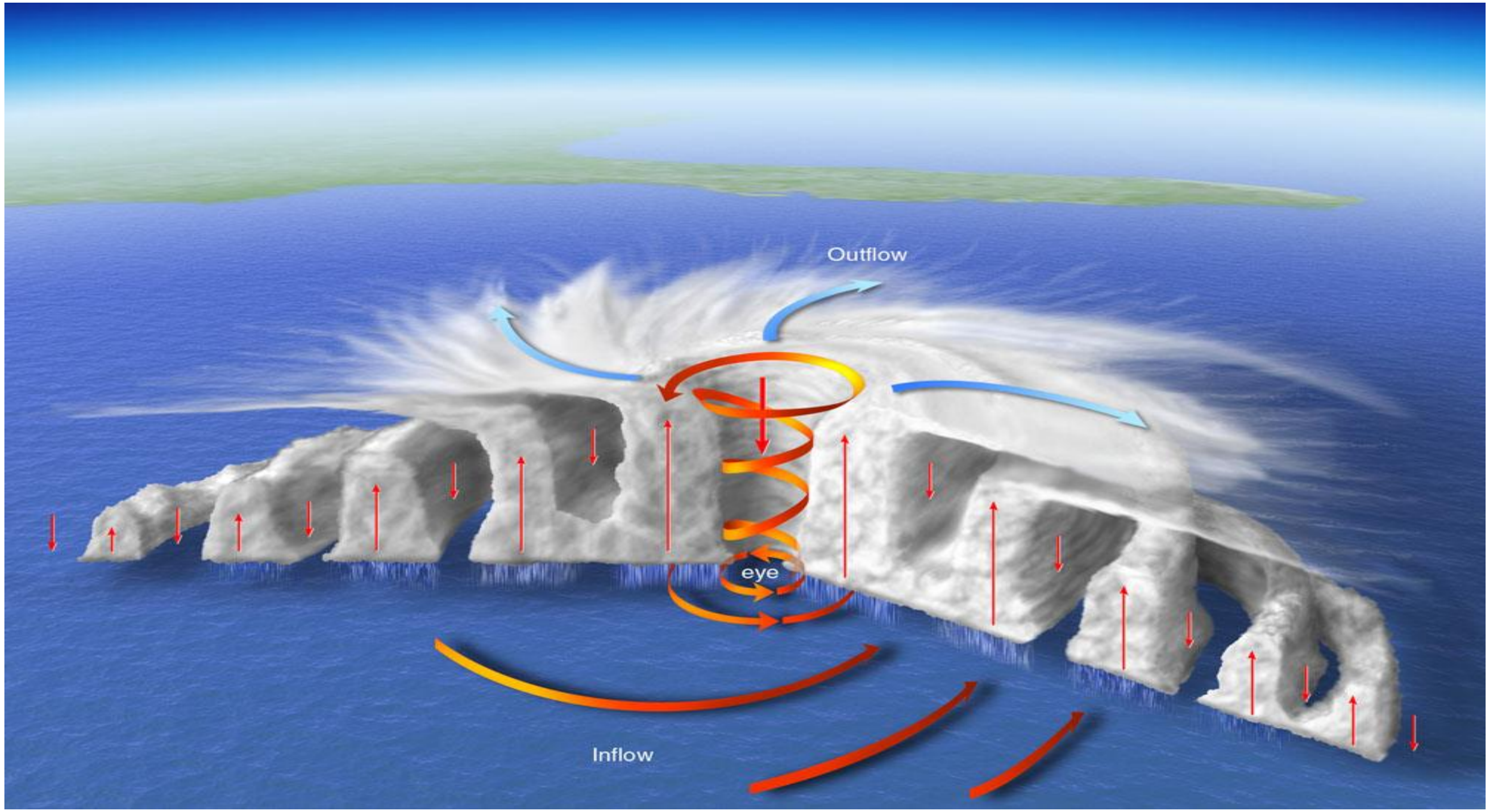
ML model trained on reanalysis to detect the cyclones large-scale drivers, then applied to SPS output

https://s2s-ai-challenge.github.io/

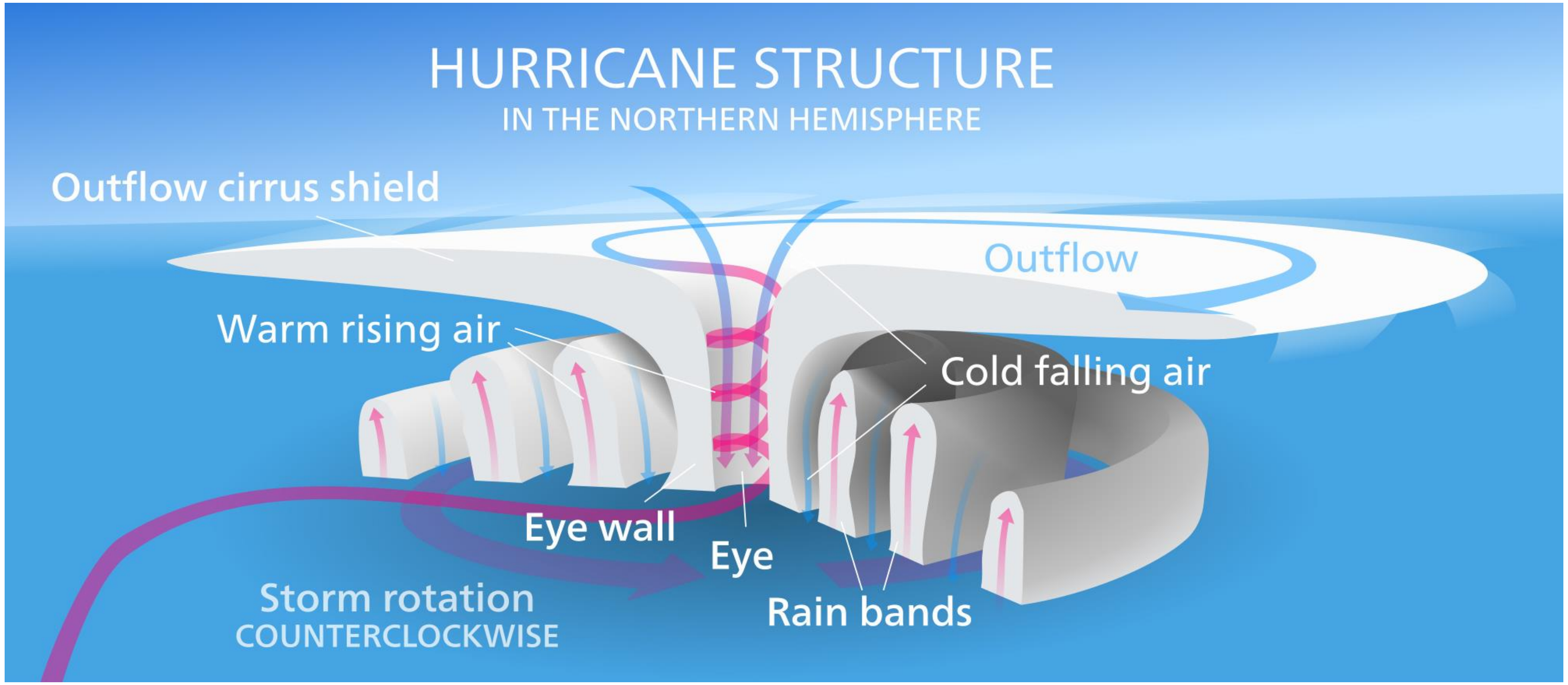
Tropical cyclones and climate prediction

Tropical Cyclones

- Tropical cyclones are **non-frontal low pressure systems** in the troposphere (at low latitudes)
- The **pressures** at the centers of TC are among the **lowest** ever observed at sea level (as low as 870 hPa)
- The **eye** (centre of a tropical cyclone) is an area of light winds and clear skies. Eye diameters are typically **40 km** (from 10 to 100 km)
- The eye is surrounded by a dense ring of clouds about 16 km high known as the **eye wall** which marks the belt of strongest winds and heaviest rainfall.

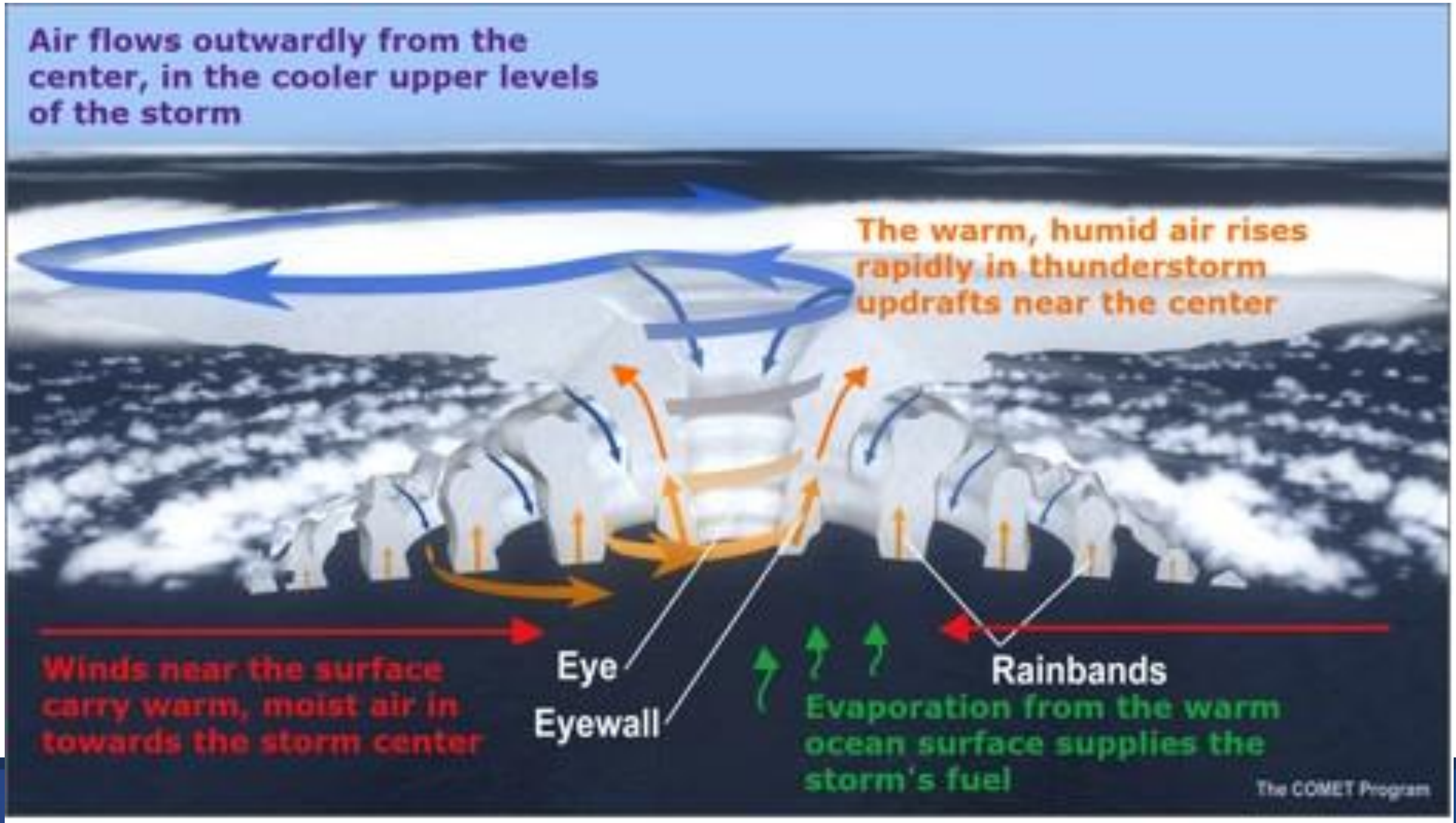


- Develop over warm water of the tropical and subtropical oceans
- Highly organized convection ('fuel' for TC)
- Intense rainfall
- Strong cyclonic wind near the surface
- Strong pressure gradient near eye directly associated with strong winds
- In order to be classified as a TC, surface winds greater than 33 m/s must be observed
- Last for many days and may experience extratropical transition

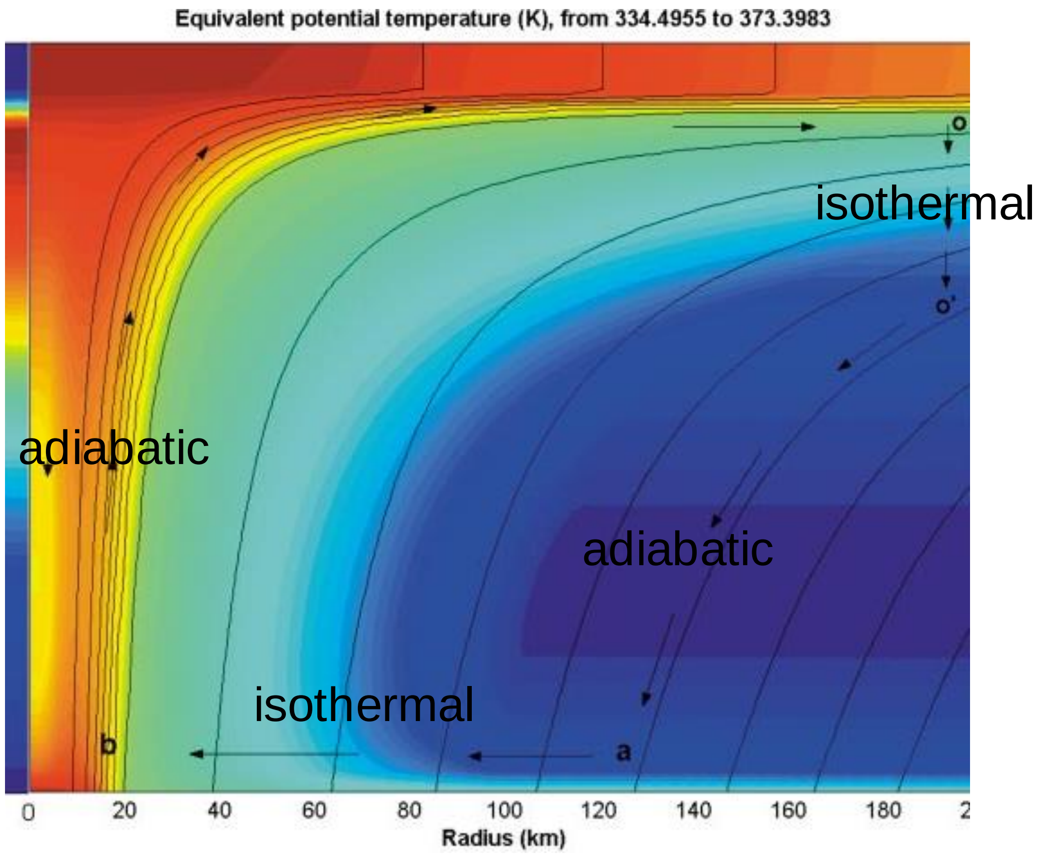


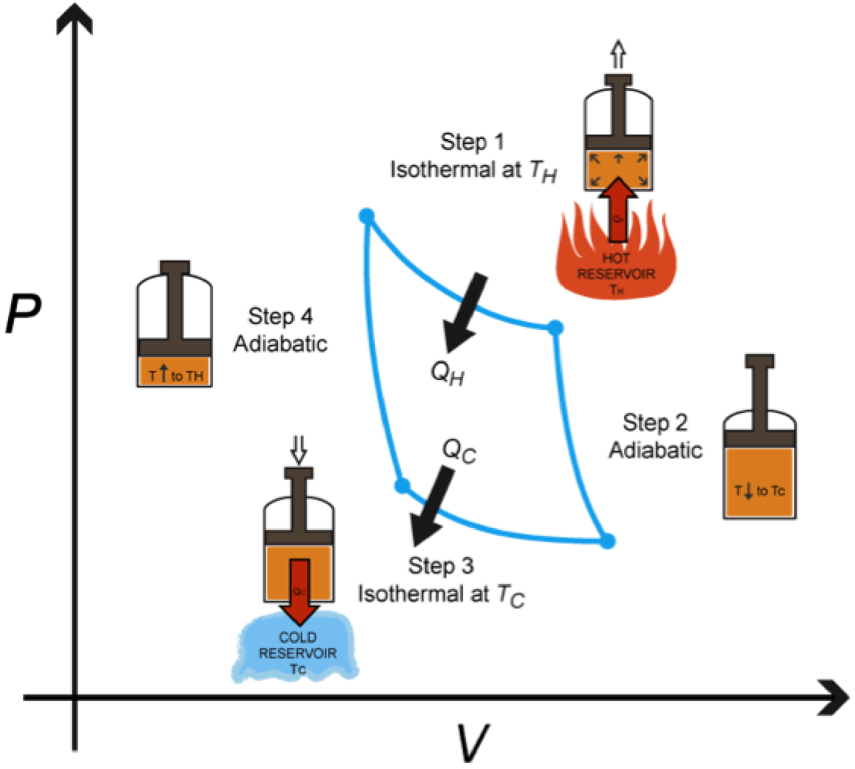
A tropical cyclone may be viewed as *a heat engine* that converts input *heat energy* from the surface into *mechanical energy* that can be used to do mechanical work against surface friction:

1. inflowing air near the surface acquires heat primarily via evaporation of water (i.e. latent heat) at the temperature of the warm ocean surface (during evaporation, the ocean cools and the air warms)
2. the warmed air rises and cools within the eyewall while conserving total heat content (latent heat is converted to sensible heat during condensation).
3. air outflows and loses heat via infrared radiation to space at the temperature of the cold tropopause
4. Finally, air subsides and warms at the outer edge of the storm while conserving total heat content.



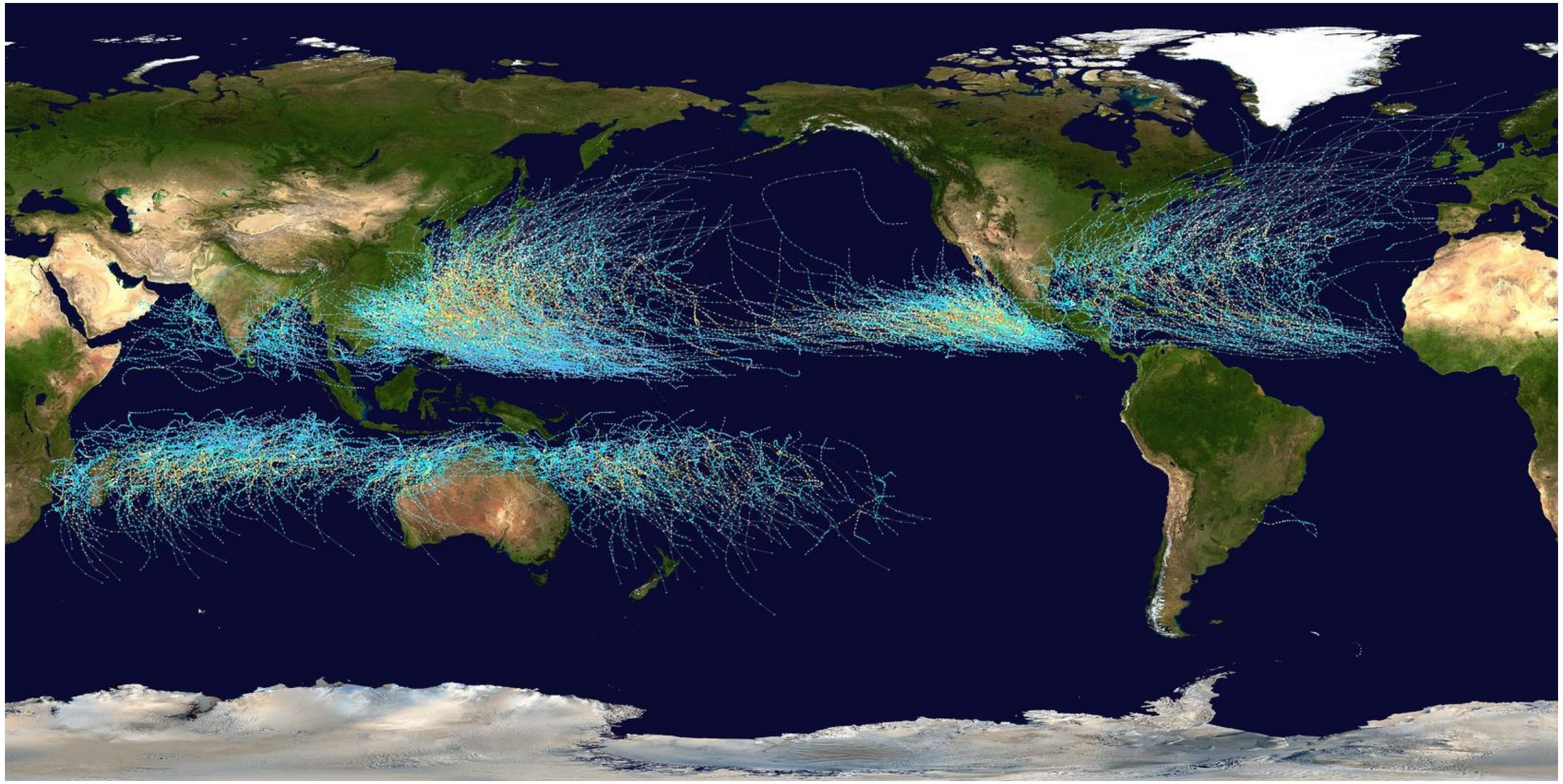
TCs as a Carnot engine





TC Climatology

- On average 80 TC per year (no theory to date to explain this number!)
- Between 100 and 2 000 km in diameter
- At least 500 km from the equator
- No TCs in the south Atlantic and east-western south Pacific



Develop in low latitudes from a pre-existing tropical low of some kind with sizeable spin and low-level inflow

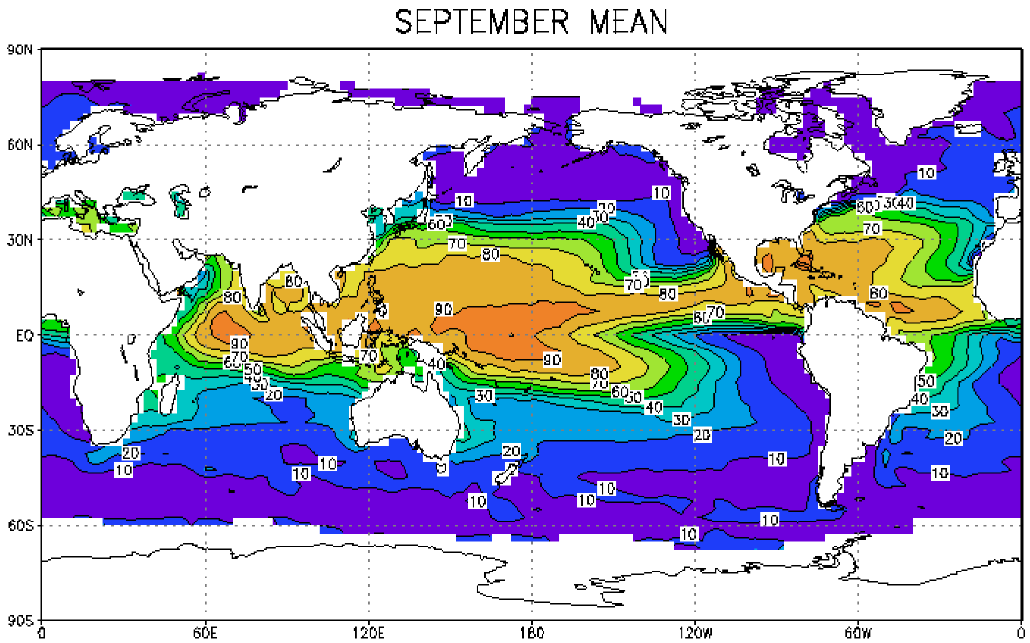
Transition to TC occurs if:

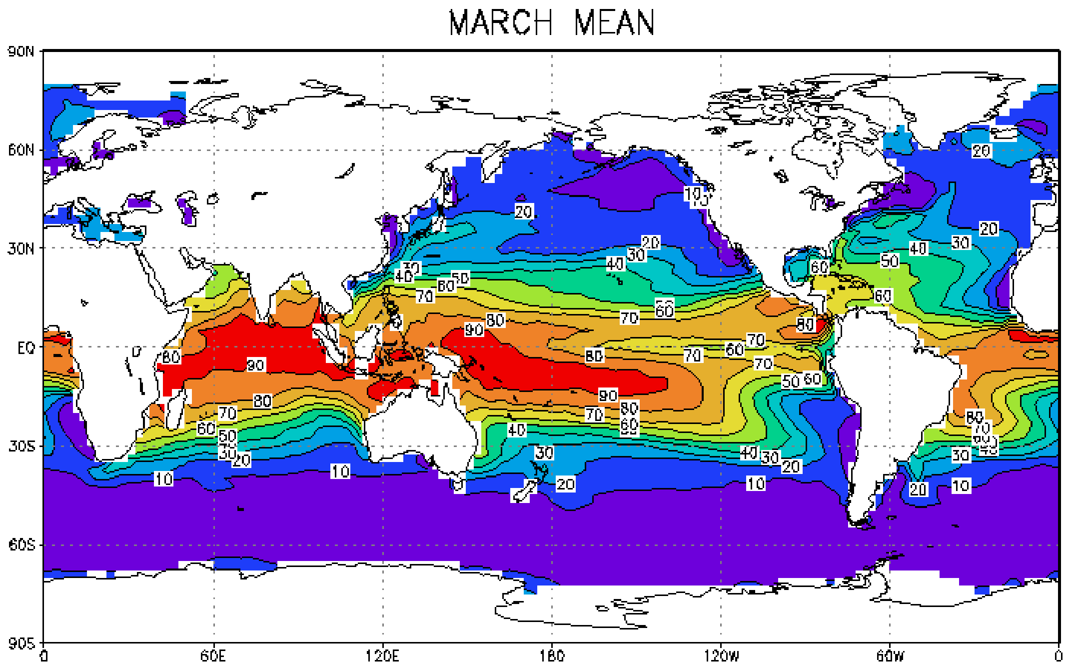
- Warm ocean (> 26.5^0 C)
- Unstable atmosphere (cools fast enough with height to encourage thunderstorm activity)
- Moist middle atmosphere (to support thunderstorm activity)
- Low vertical wind shear (little change of wind with height)

TC intensity

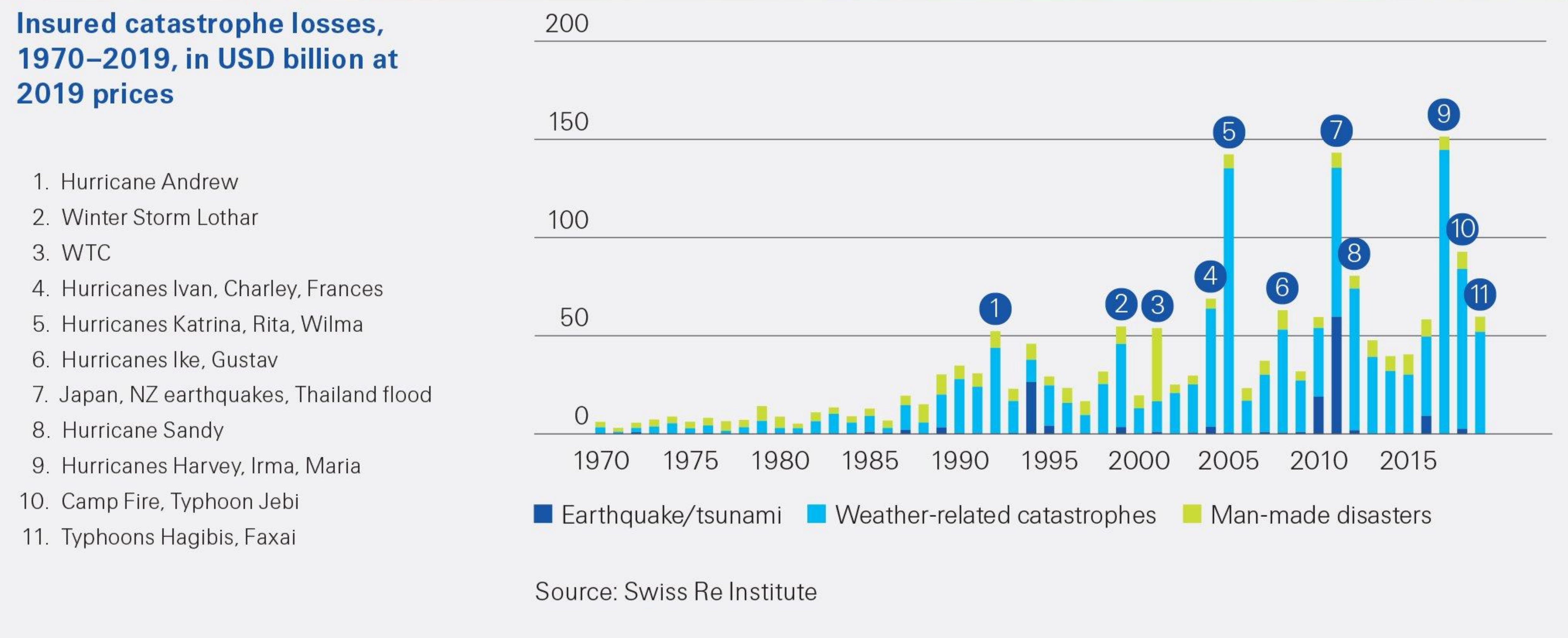
$$|V_{\max}|^2 \approx \frac{C_k}{C_D}\frac{T_s - T_0}{T_0}(k_0^* - k)$$

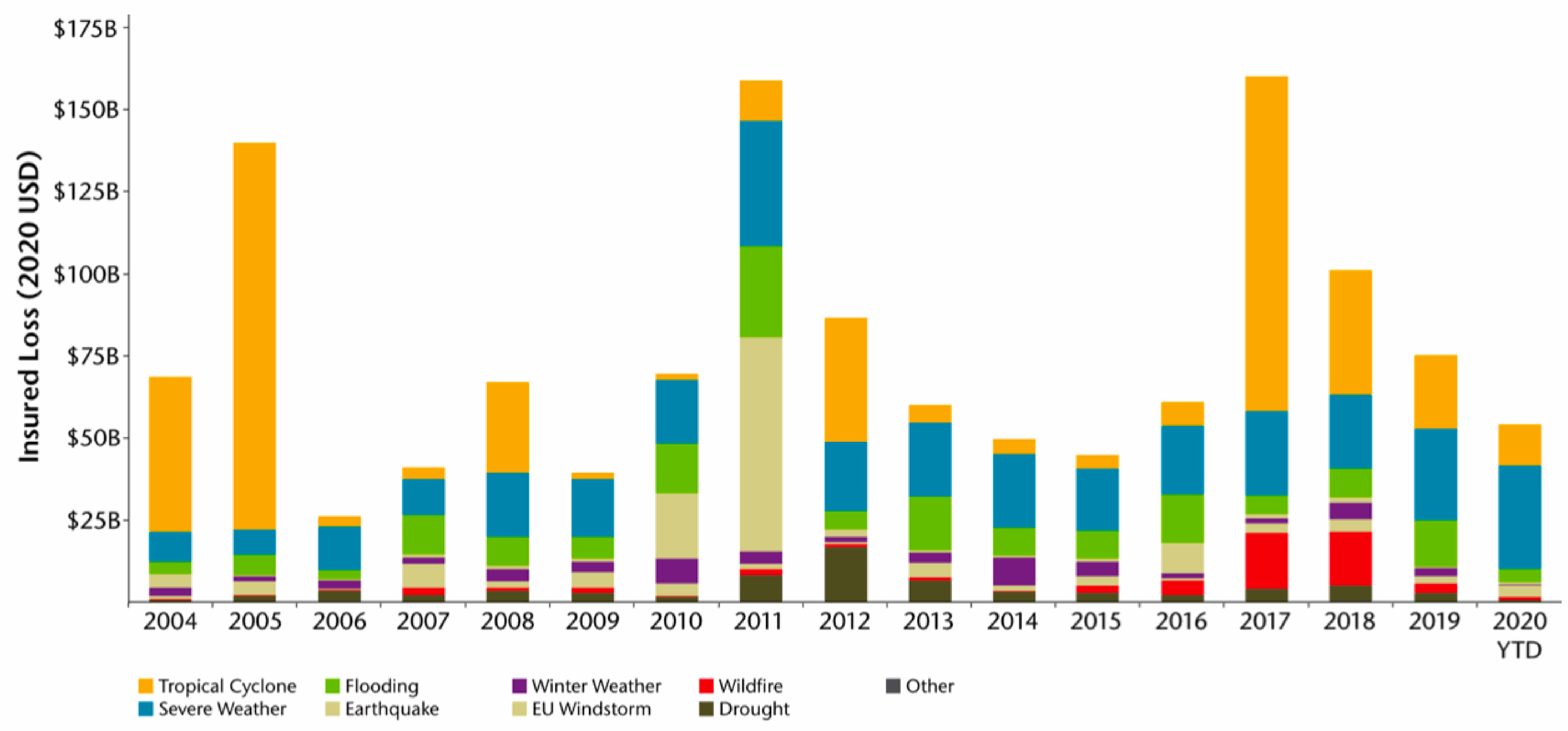
C_k: enthalpy exchange coefficient
C_D: drag coefficient
T_s: surface temperature
T_0: outflow temperature
k: enthalpy of air near the surface (boundary layer)
k_0*: enthalpy of air in contact with the ocean (water vapour saturation)





The importance of TC seasonal forecast

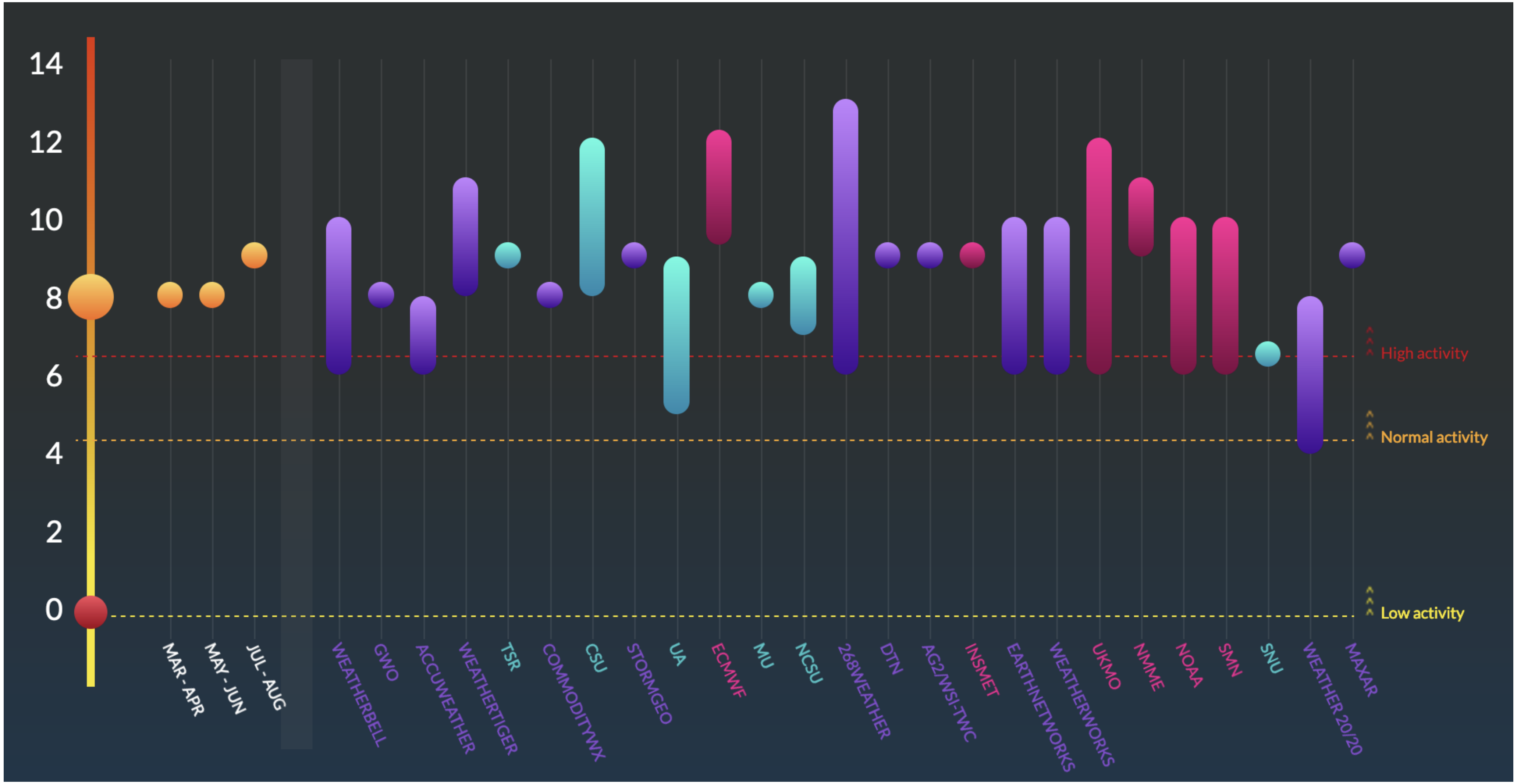




Source: Aon Catastrophe Insight

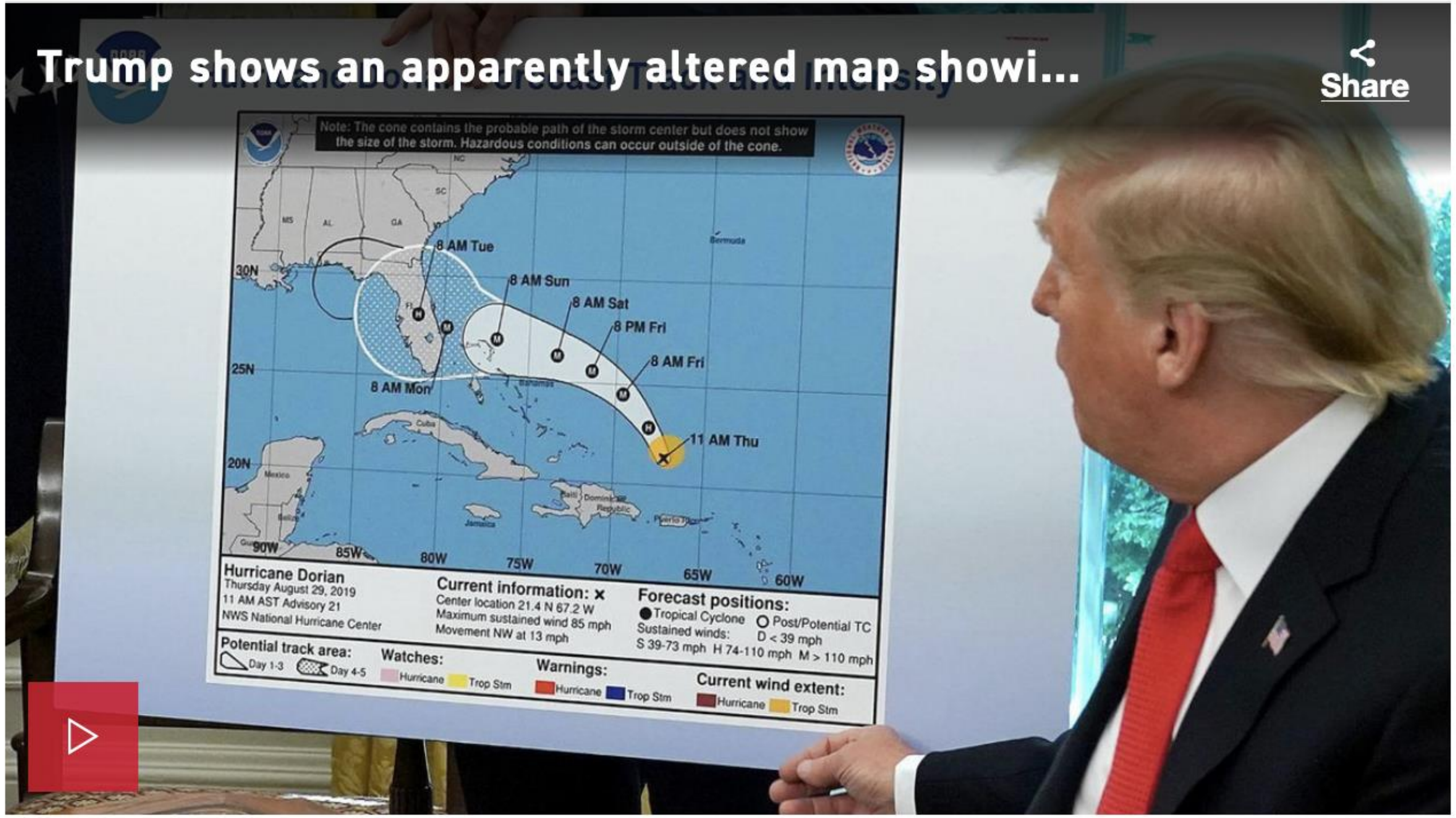
TC Seasonal Predictions

https://seasonalhurricanepredictions.bsc.es/predictions



TC predictability

- Good skill in NWP up to 5 days
- What about longer time scales?



Trump shows an apparently altered map showing Hurricane Dorian impacting Alabama

TC Seasonal Predictions

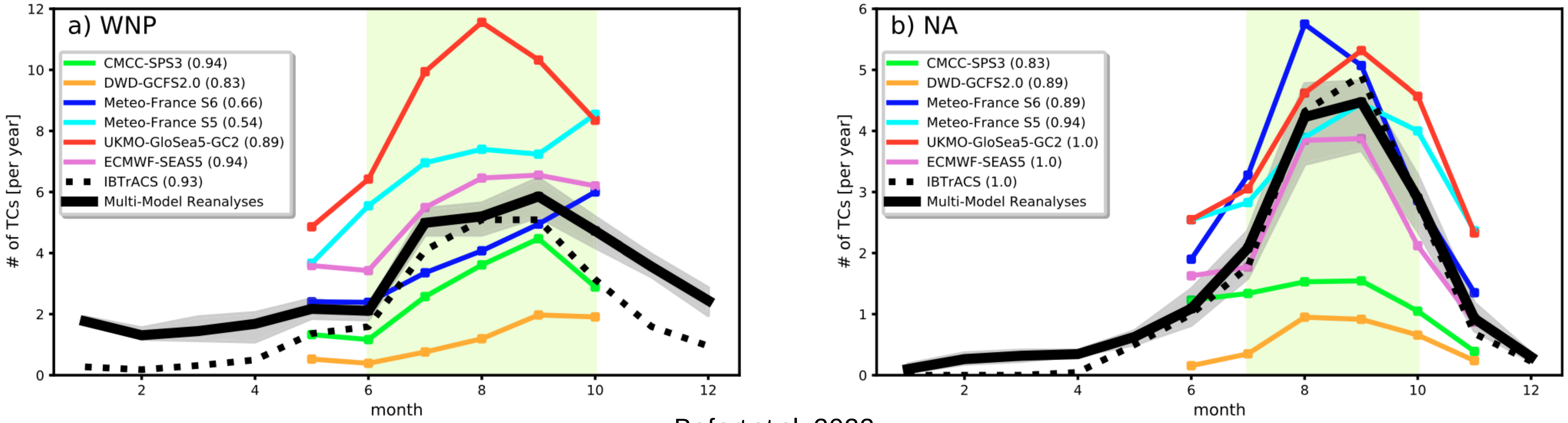
1. *Dynamical approach*
    - *Seasonal Prediction System: GCM initialized at 1-2 months lead time with slow-varying initial conditions (e.g. SST, soil moisture, sea ice)*
    - *Large ensemble (~ 50) of simulations obtained by perturbing initial conditions, allowing for probabilistic forecast*
    - *Apply TC detection scheme to all simulations*

2. *Statistical approach*
    - *Find a statistical relationship between the number of TCS and the state of the system at given lead time (e.g. analogues)*

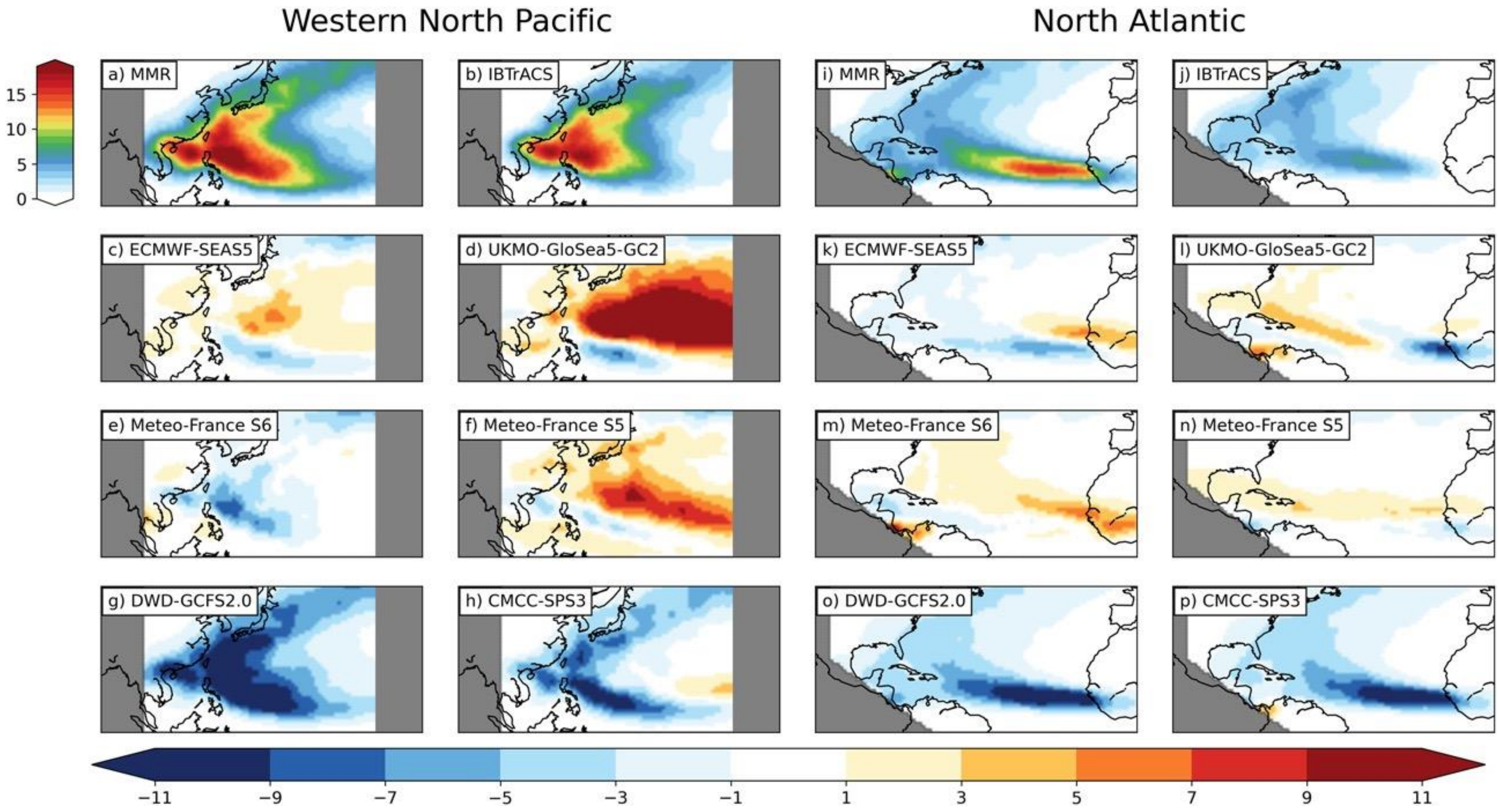
3. *Hybrid approach*
    - *Find a statistical relationship between large-scale drivers and observed TCs*
    - *Apply the relationship to the large-scale variables predicted by the dynamical system*

TC dynamical predictions

Model	Initial dates	Atmosphere resolution	Ocean resolution	Ensemble size
ECMWF SEAS5 (ECMWF-SEAS5)	May, June	TCO319/L91 ≈ 32 km	0.25°/L75	25
GloSea5-GC2 (UKMO-GloSea5-GC2)	May, June	N216/L85 ≈ 90 km	0.25°/L75	28
Météo-France S5 (Météo-France-S5)	May, June	TL255/L91 ≈ 80 km	1°/42 levels	15
Météo-France S6 (Météo-France-S6)	May, June	TL359/L91 ≈ 50 km	1°/75 levels	25
DWD (DWD-GCFS2.0)	May, June	T127/L91 ≈ 100 km	0.4°/L40	30
CMCC (CMCC-SPS3)	May, June	≈110 km/L46	0.25°/L50	40

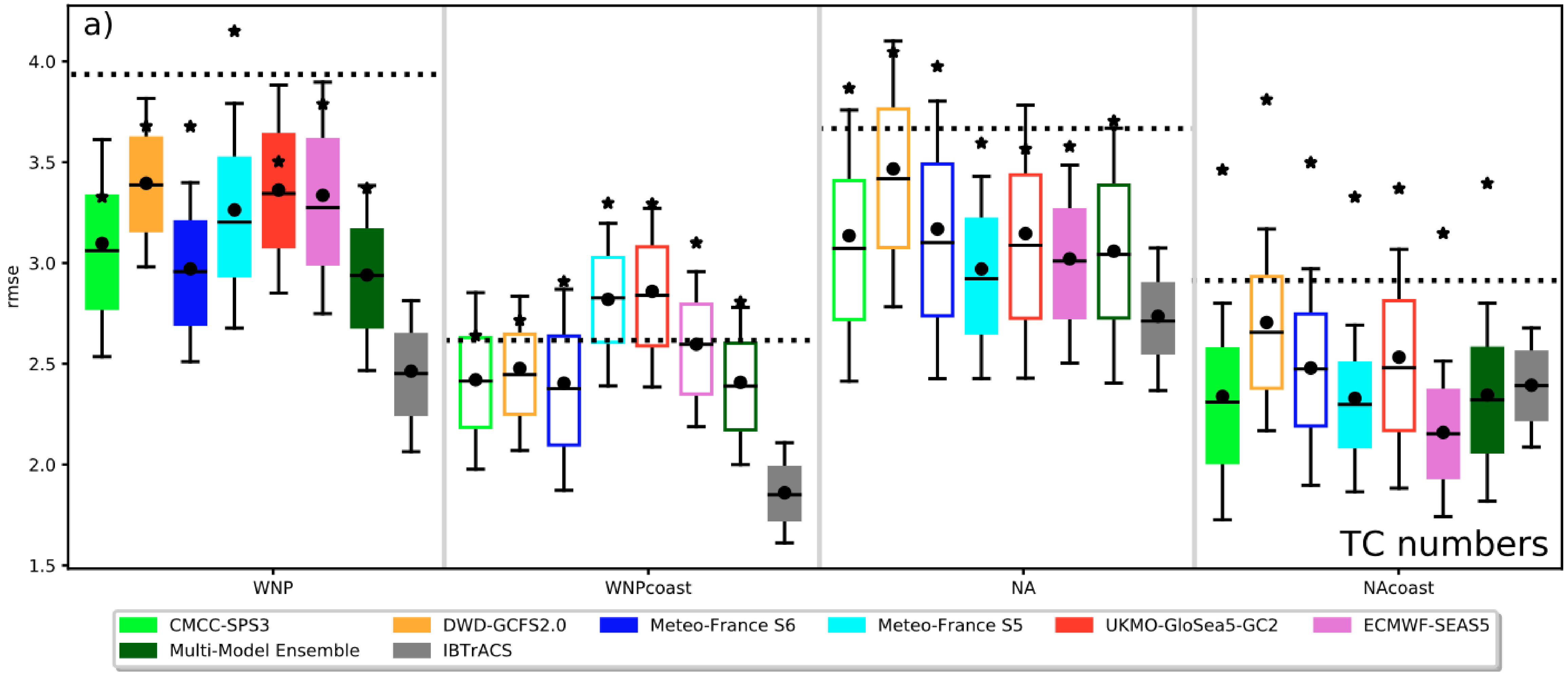


Befort et al. 2022



Befort et al. 2022

Cyclone track density



Befort et al. 2022

TC predictions

TROPICAL CYCLONE GENESIS POTENTIAL INDEX

- The tropical cyclone Genesis Potential Index (GPI) links the probability of TC formation to large-scale climate fields.
- The advantage of such formulation lies in the ability to predict TC activity without having to rely on the climate models skill in reliably reproducing individual TCs.
- Several formulations of GPI exist, e.g. as given by Emanuel & Nolan (2014).

$$GP = \left|10^5 \eta\right|^{3/2} \left(\frac{\mathcal{H}}{50}\right)^3 \left(\frac{V_{\text{pot}}}{70}\right)^3 \left(1 + 0.1 V_{shear}\right)^{-2}$$

Vorticity

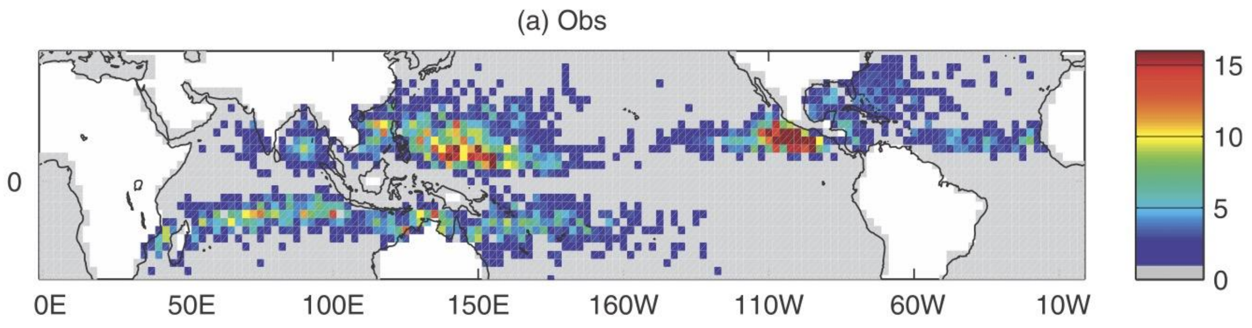
Humidity

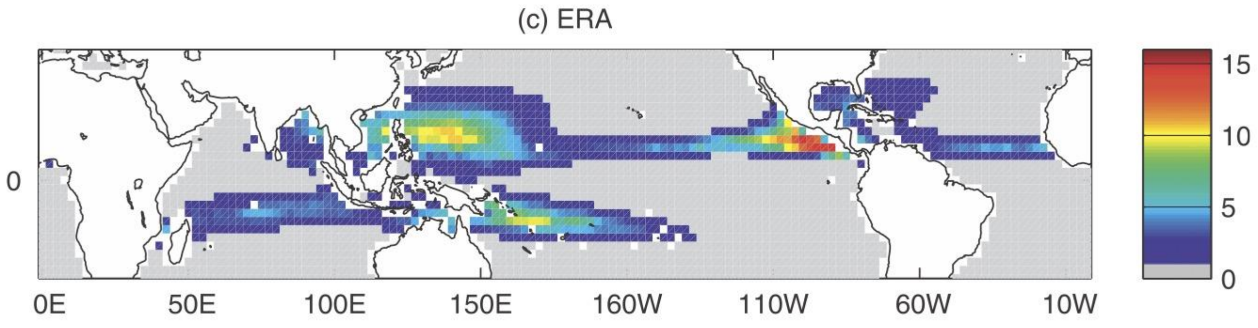
Potential intensity

Wind shear

GPI IS (FAIRLY) GOOD AT:

- Reproducing the spatial variability of TC genesis

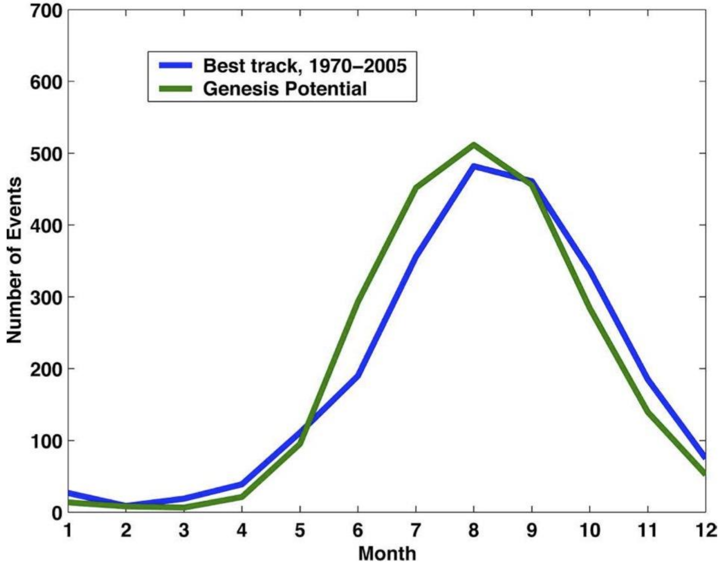


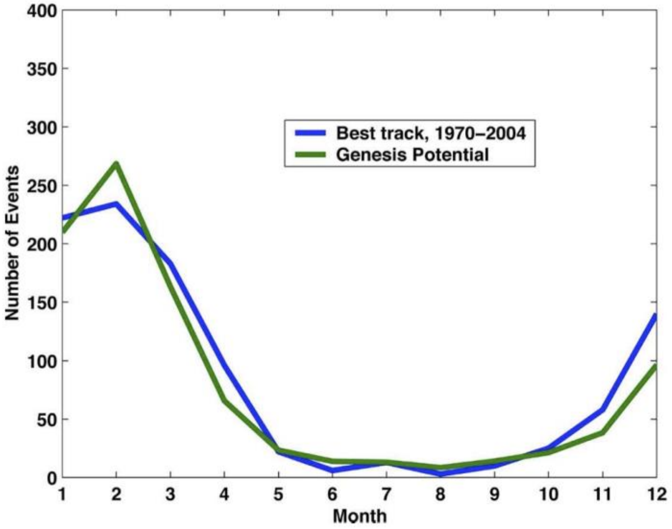


[Tippett et al 2011]

- Reproducing the seasonal cycle of TC genesis

NH



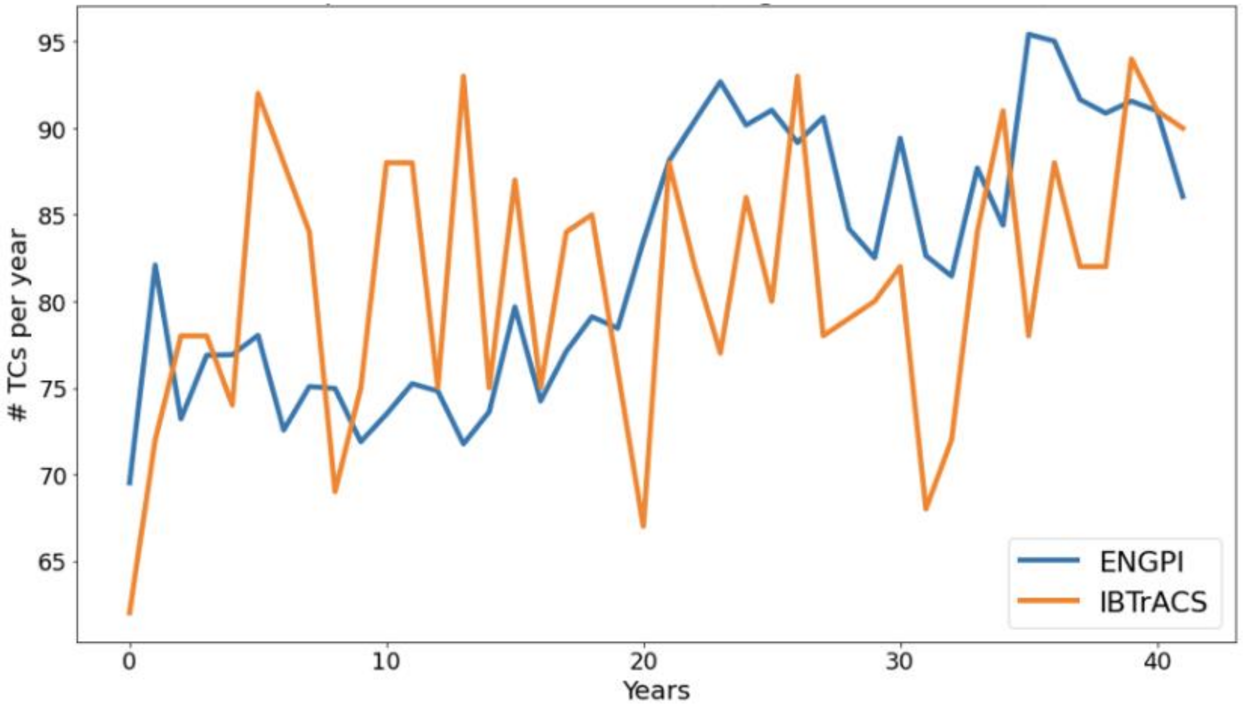


SH

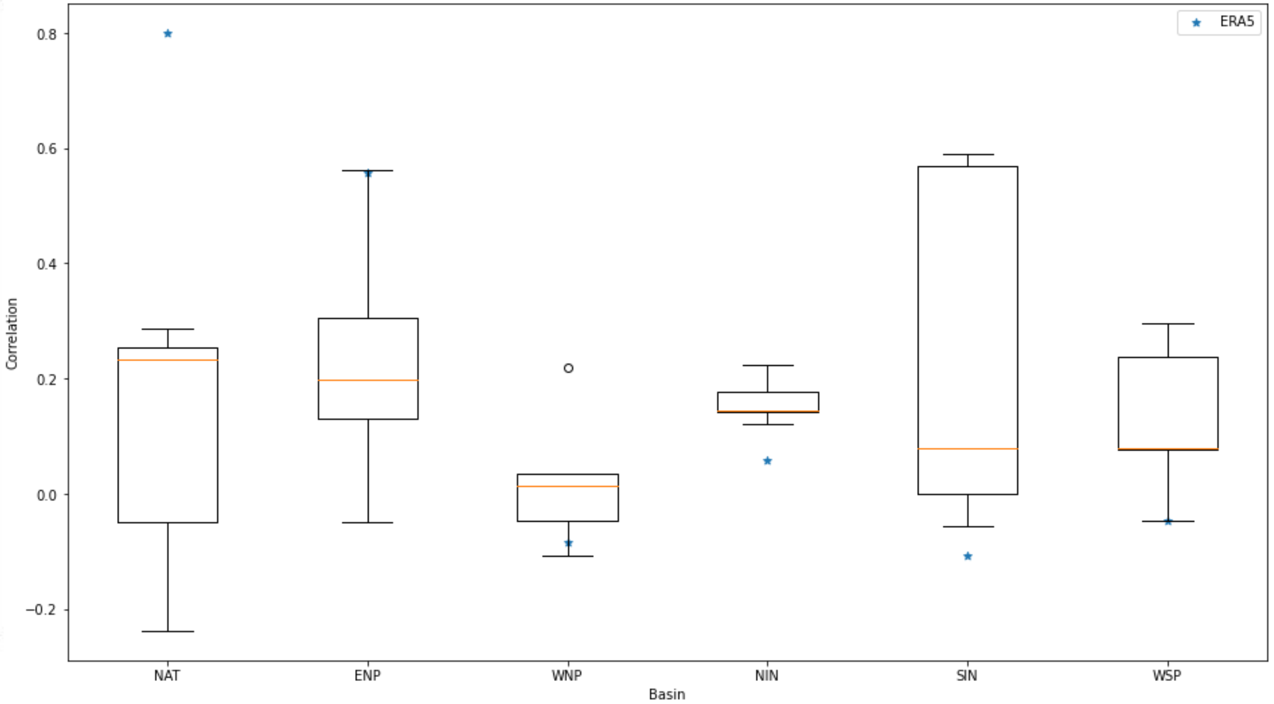
[Camargo et al 2007]

GPI Interannual variability

- GPI has a low skill in representing interannual variability
- decrease in performance when applied to GCM data. Overfitting?
- the GPI formula is hyper-parametrized with many arbitrary coefficients, are they optimally selected?

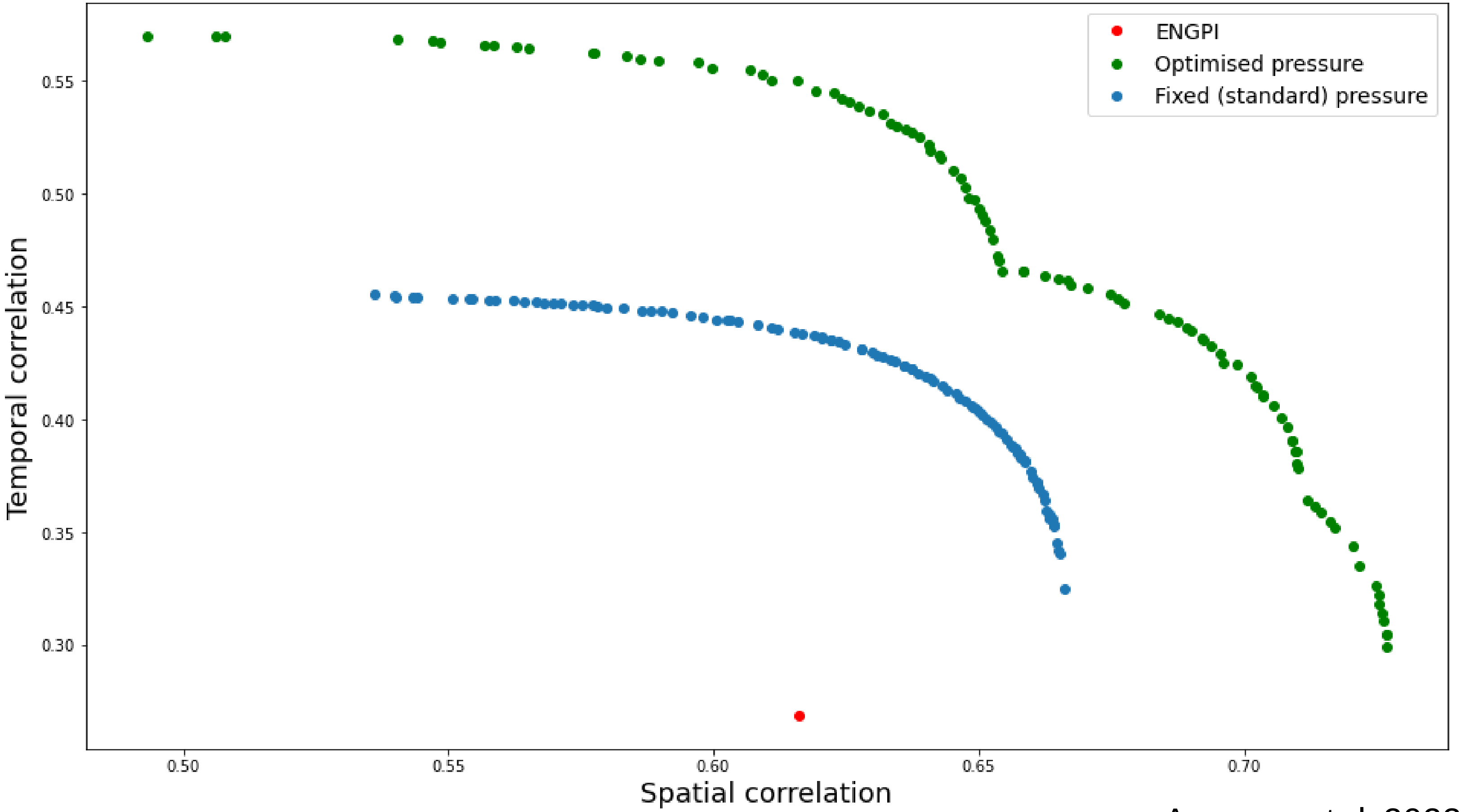


Ascenso et al. 2023

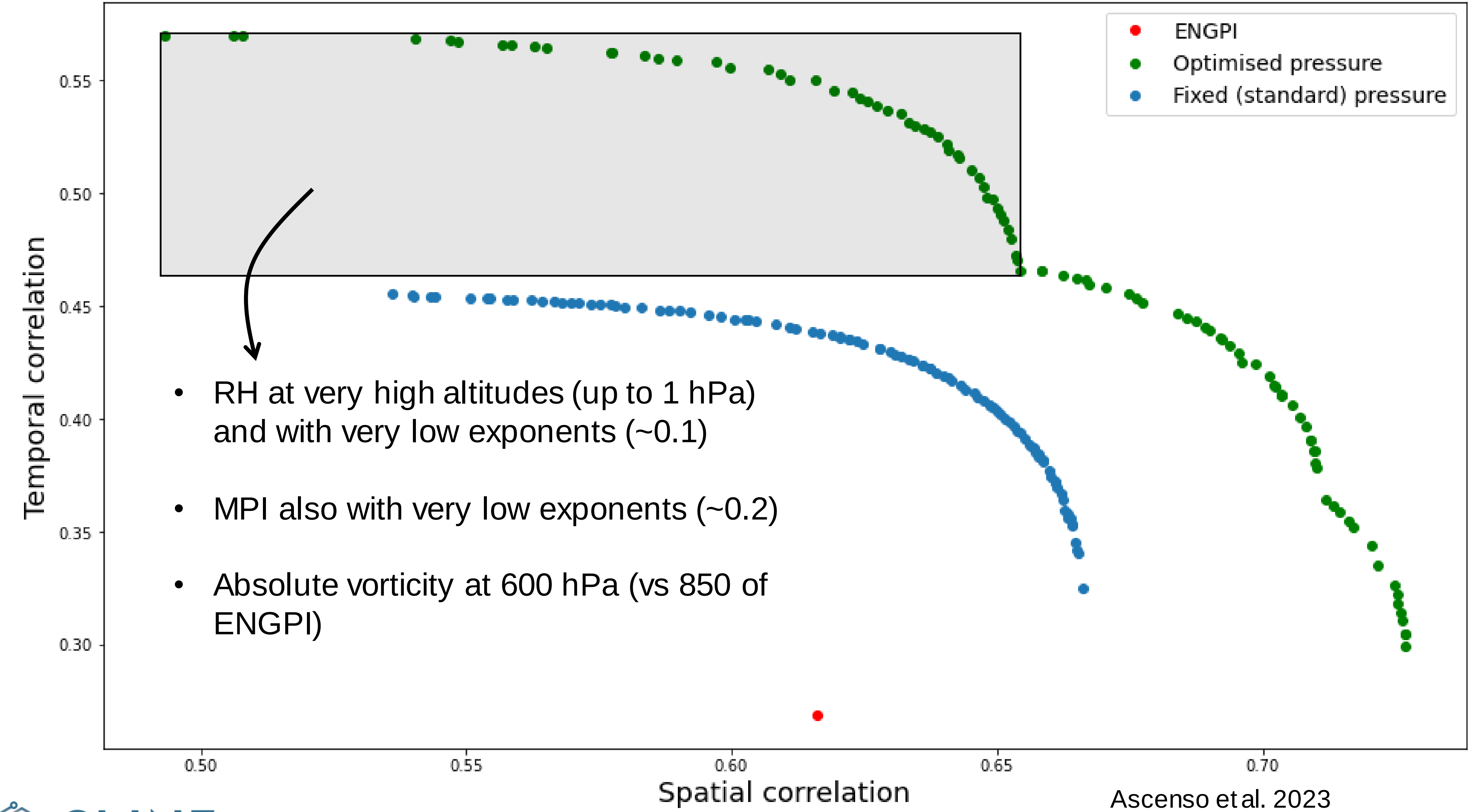


Cavicchia et al. under review

- *Multi-function optimization algorithm applied*
- *All the numerical coefficients of GPI allowed to vary*
- *Pressure level for the large-scale variables also allowed to vary*
- *Pareto front of solutions*

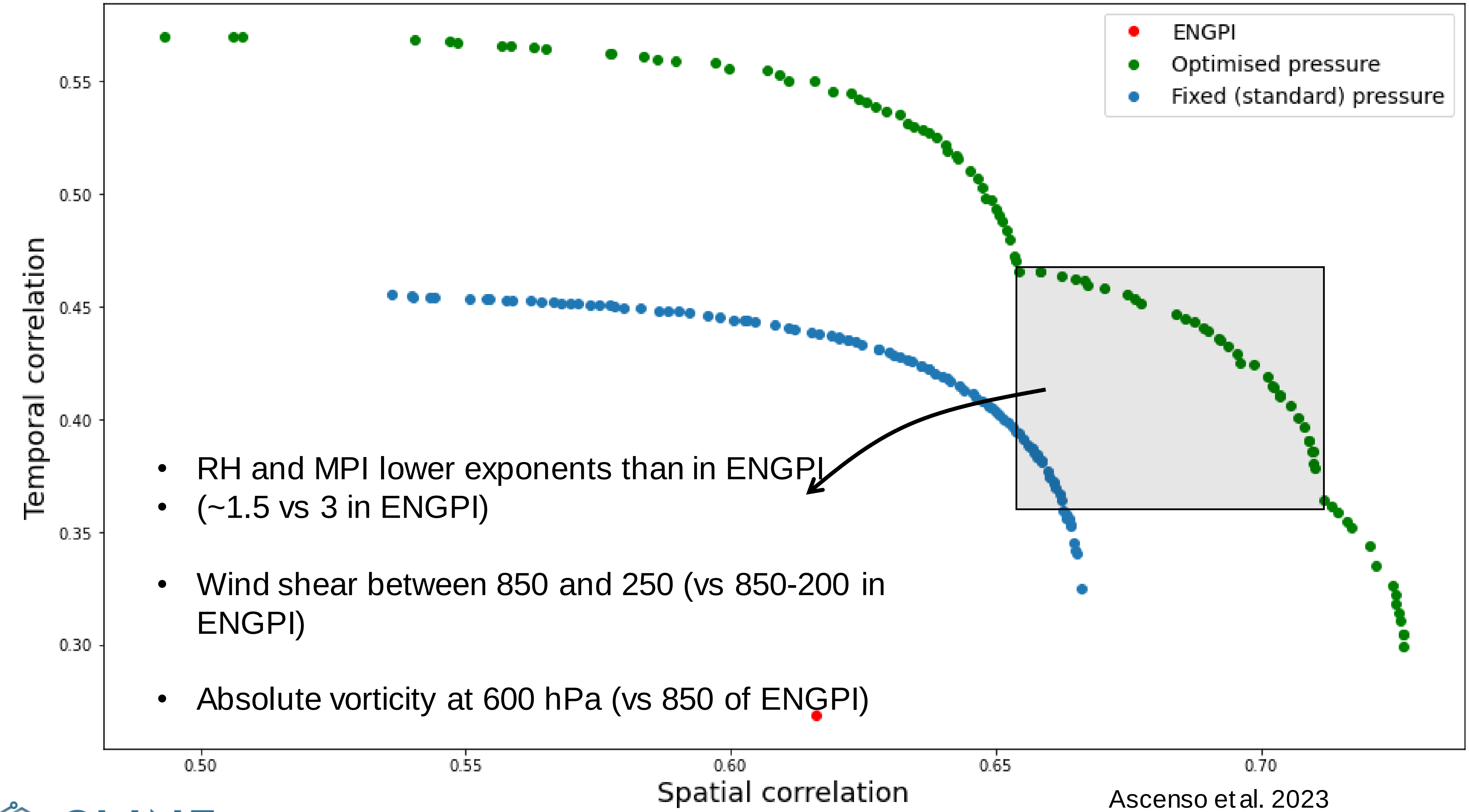


Ascenso et al. 2023



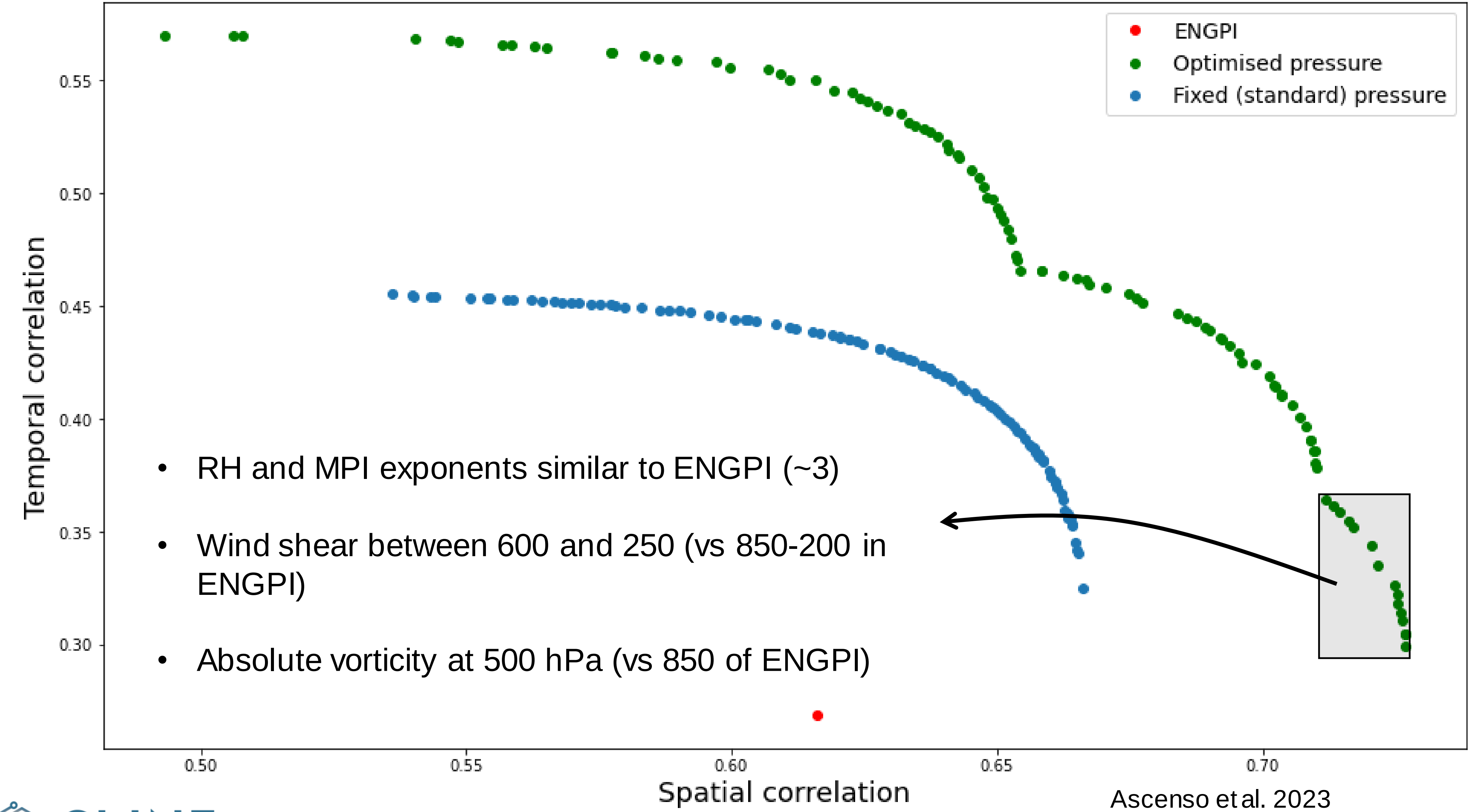
- RH at very high altitudes (up to 1 hPa) and with very low exponents (~0.1)
- MPI also with very low exponents (~0.2)
- Absolute vorticity at 600 hPa (vs 850 of ENGPI)

Ascenso et al. 2023



- RH and MPI lower exponents than in ENGPI
- (~1.5 vs 3 in ENGPI)
- Wind shear between 850 and 250 (vs 850-200 in ENGPI)
- Absolute vorticity at 600 hPa (vs 850 of ENGPI)

Ascenso et al. 2023



- RH and MPI exponents similar to ENGPI (~3)
- Wind shear between 600 and 250 (vs 850-200 in ENGPI)
- Absolute vorticity at 500 hPa (vs 850 of ENGPI)

Ascenso et al. 2023

Take-home messages

1. ***Climate predictions: achievements and challenges***
   - *Predictions on time scales longer than two weeks are based on large ensemble of climate model simulations*
   - *At the horizontal resolution allowed by current supercomputers prediction of extreme events remain challenging*

2. ***Artificial intelligence and climate modelling***
   - *Artificial intelligence has recently entered the arena of weather and climate forecast in a number of different ways*
   - *A promising direction of research is hybrid AI-numerical forecast, with the two complementing each other*

3. ***Climate prediction of tropical cyclones***
   - *Tropical cyclones are one of the worst category of natural disaster, and they are a good test for new methods for AI-enhanced prediction*

cmcc
Centro Euro-Mediterraneo
sui Cambiamenti Climatici

www.cmcc.it