Assessing future hurricane risk in the Caribbean based on large-scale predictor fields

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Outline

- Introduction:
  - Research question
  - Motivation
- Methods:
  - Self organizing maps
  - Data & preprocessing
  - Construction of the self organizing map
- Preliminary results:
  - 25 types of tropical Atlantic weather
  - Observed tropical cyclone risk for the different weather types
  - tropical cyclone risk for the different weather types in 2 high-res CMIP6 models
- Summary
- Next Steps
- Questions for discussion

Research Question

What is the impact of global warming on the tropical cyclone risk for the Caribbean?

Challenges:

- Observational time series are too short to answer the question
- The representation of tropical cyclones (TCs) is weak in most global circulation models (GCMs)
- An analysis based on only very few GCMs that produce reasonable TCs wouldn’t capture the whole range of large scale responses to global warming (simulated by the ensemble of all GCMs)

Motivation

The motivation of this study is to bypass the difficulties of most GCMs to simulate reasonable TCs by only analyzing how changes in **large scale weather patterns** (under global warming) might affect TC risk in the Caribbean

Approach:

1. Classify weather types using Self Organizing Maps (SOM) in reanalysis
2. Map the potential for TC risk to the weather types using observations
3. Check whether the observed relationship between TC risk and weather types is also found in high resolution GCMs
4. Assess future TC risk by applying the relationship between weather types and TC risk to the full GCM ensemble

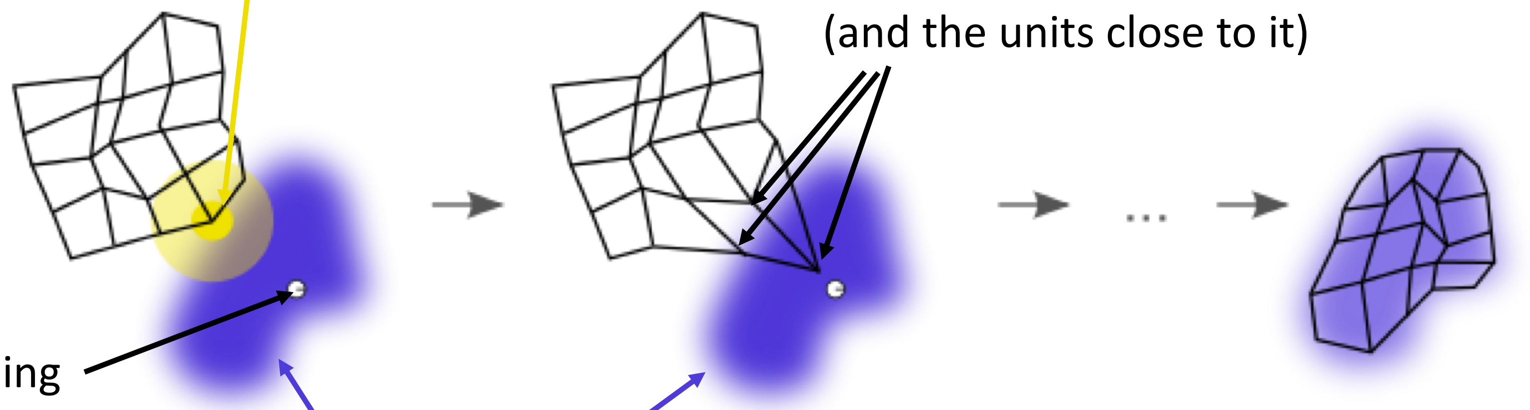
Method: Self Organizing Maps (SOM)

Dimensionality reduction:
map high-dimensional data (lat-lon grid of several climate variables) onto a 2-dimensional map

Advantages over (other) clustering algorithm:

- Similar number of members in each cluster
- Clusters are arranged in a meaningful manner (neighboring nodes are similar to each other)
- See Jaye et al. (2019) for a SOM application to cyclogenesis

One step in the training algorithm:



https://en.wikipedia.org/wiki/Self-organizing_map

Data & Preprocessing

- ERA5 on a 2.5x2.5 grid 10N-30N and 90W-10W
- "Remove" TC's from reanalysis:
  - At each time step where a TC was observed:
    replace the 9 grid-cells around the center of the TC with the mean of the surrounding grid-cells
- Weekly averages
- Standardized Anomalies to 1981-2010

  X = (X – X.mean(1981:2010)) / X.std(1981-2010)

=> assure that the self organizing maps aren't directly influenced by TCs and that a risk model based on these SOMs is applicable to GCMs that don't produce TCs

Training the Self Organizing Map (SOM)

Training period:

- ERA5 1981-2010

Input variables:

- Vertical Wind Shear (VWS): eastward wind 850mbar – 200mbar
- Mean Sea Level Pressure (MSLP)
- Relative Humidity at 600mbar (RH)

SOM algorithm: https://github.com/JustGlowing/minisom

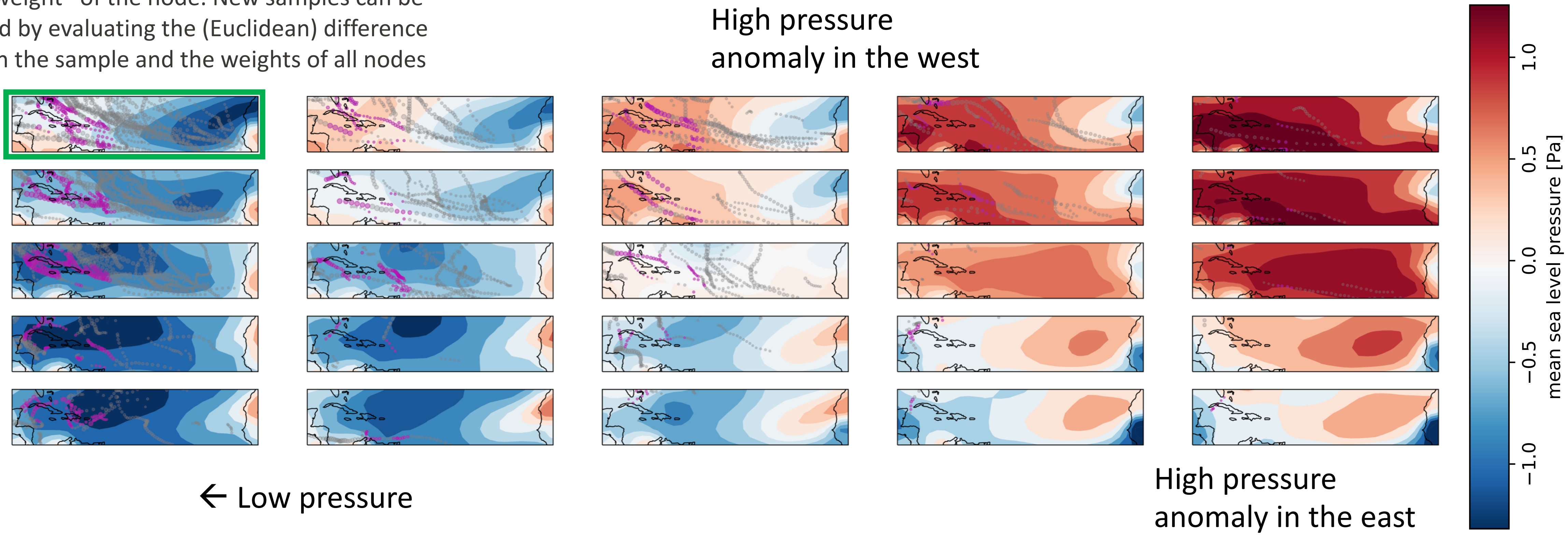
Input array

	$VWS_{lon1,lat1}$	$VWS_{lon1,lat2}$	$VWS_{lon1,lat3}$	…	$MSP_{lon1,lat1}$	$MSP_{lon1,lat2}$	…
T1							
T2							
T3							
…							

25 weather flavors: Mean Sea Level Pressure

This is one **node** of the SOM. The pattern shows the MSLP-“weight” of the node. New samples can be classified by evaluating the (Euclidean) difference between the sample and the weights of all nodes

High pressure anomaly in the west



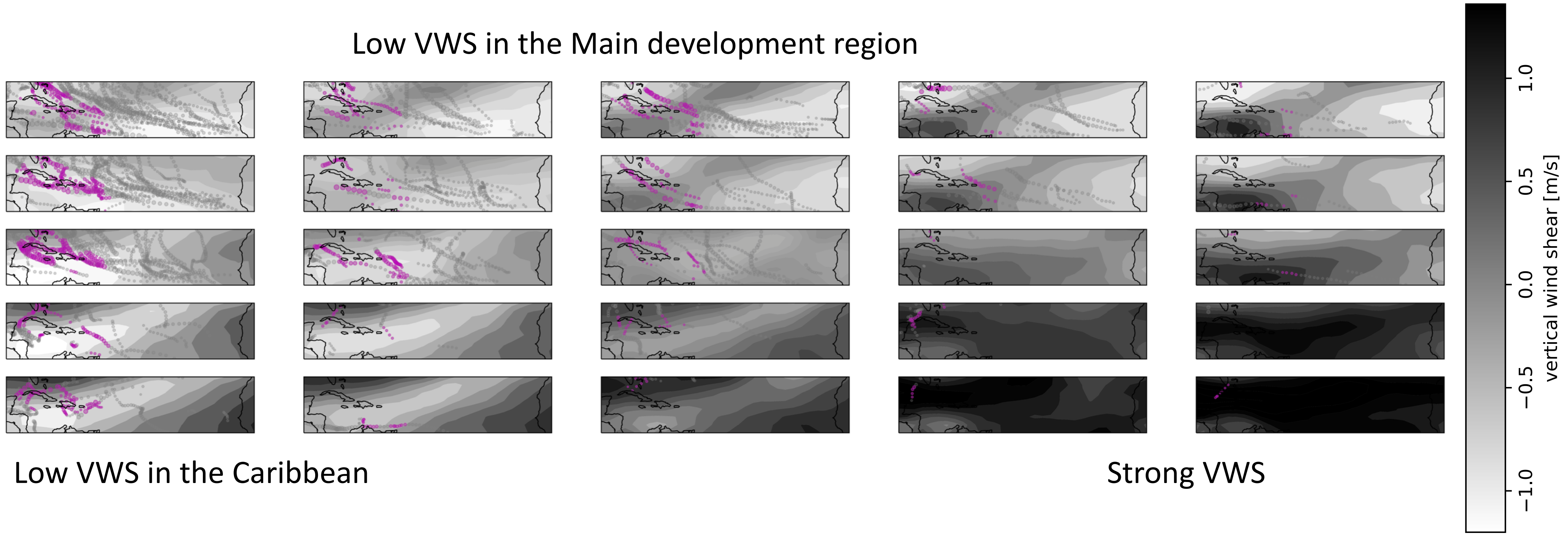
← Low pressure

High pressure anomaly in the east

Locations with a tropical storm the week after

Locations with a tropical storm the week after that are close (<2deg) to an island

25 weather flavors: Vertical Wind Shear (vws)

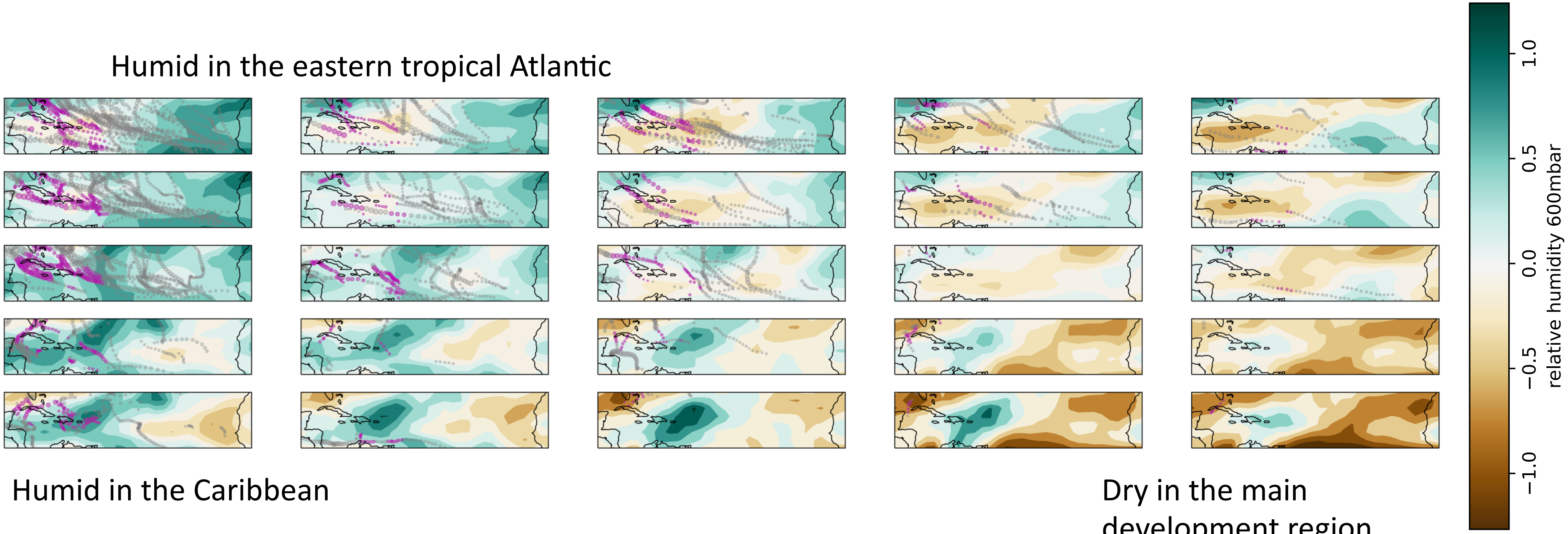


Locations with a tropical storm the week after

Locations with a tropical storm the week after that are close (<2deg) to an island

25 weather flavors: relative Humidity (600mbar)

Humid in the eastern tropical Atlantic



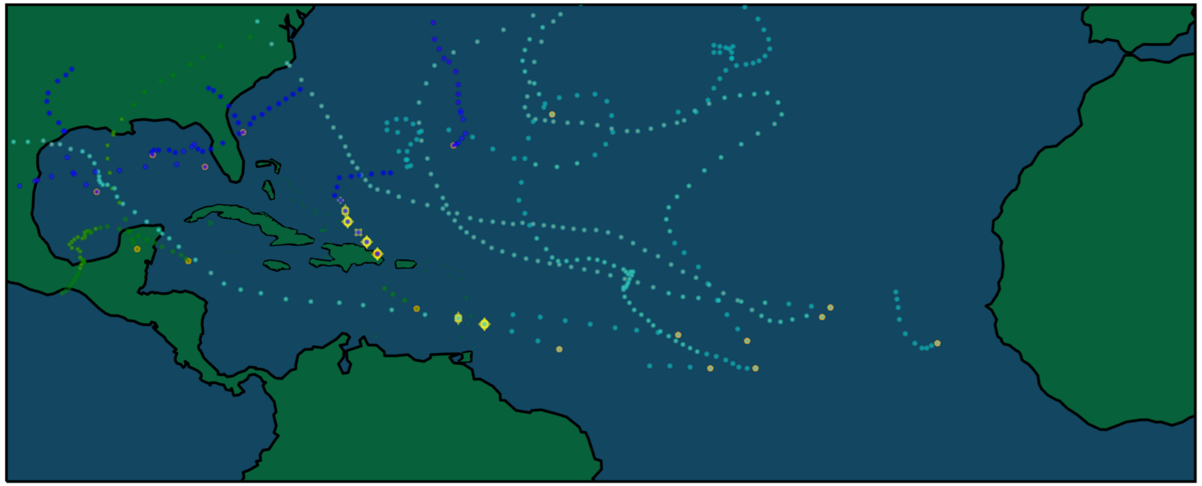
Humid in the Caribbean

Dry in the main development region

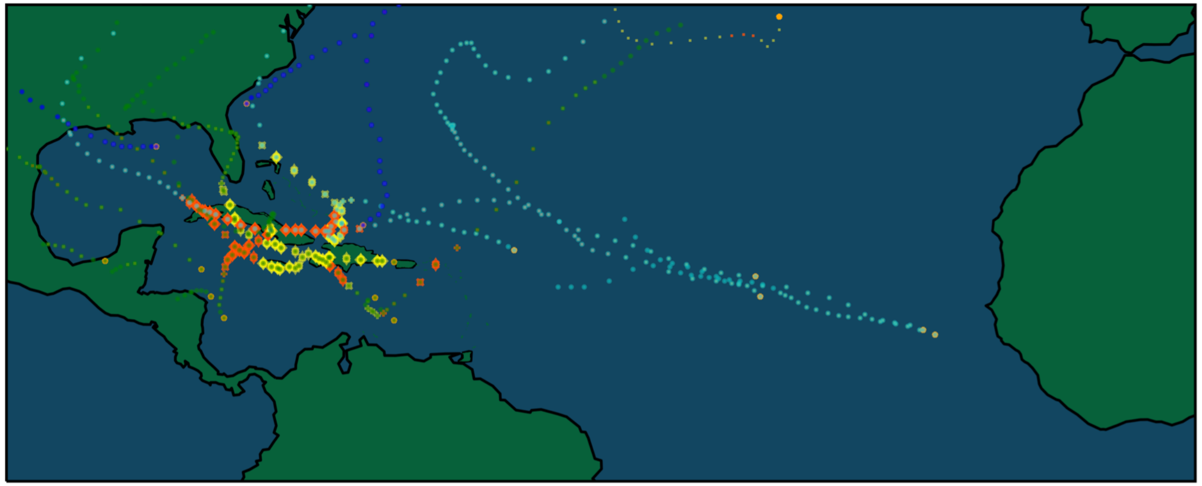
- Locations with a tropical storm the week after
- Locations with a tropical storm the week after that are close (<2deg) to an island

Step 2: Tropical cyclone risk for the Caribbean

2003

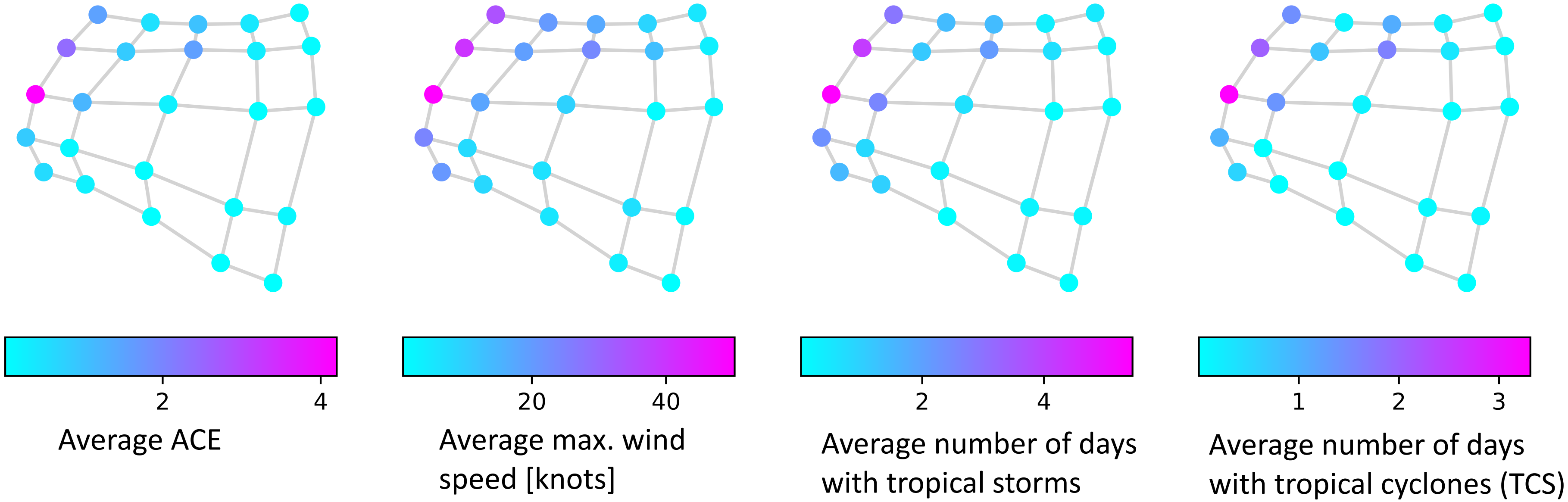


2008



- The number of TCs or the Accumulated Cyclone Energy (ACE) in the basin is only a first order indicator for TC risk in the Caribbean
- Additional information on the proximity of TC tracks to islands (indicated by orange and yellow markers) helps to better estimate risks

Potential for TC risk in the next week
-> only events closer than 2° from an island



The risk for TCs close to an island is higher for the nodes on the left side
As expected the weather of these nodes is characterized by low VWS, and high relative humidity

Summary of step 1&2:

- We classified weekly weather in 25 weather flavors using self organizing maps
- The risk of having TCs close to Caribbean islands in the following week is heterogeneously distributed amongst the weather types:
  - After weeks with strong VWS, the risk of TCs is reduced
  - After weeks with low relative humidity as well
  - The risk is also lower after weeks with high pressure anomalies over the tropical Atlantic

-> Are these relationships represented in global circulation models (GCMs) and do they hold outside of the training data?

The model world: TCs in CMIP6 - PRIMAVERA

To test whether the relationships between the identified weather types and TC risk hold under different climate states we analyze TC occurrences in high resolution GCMs from the HighresMIP ensemble

Here we use TC tracks published under the [PRIMAVERA project]

Roberts et al. (2020) find that most of the high resolution GCMs simulate TC frequencies that are close to the observations (bottom right)

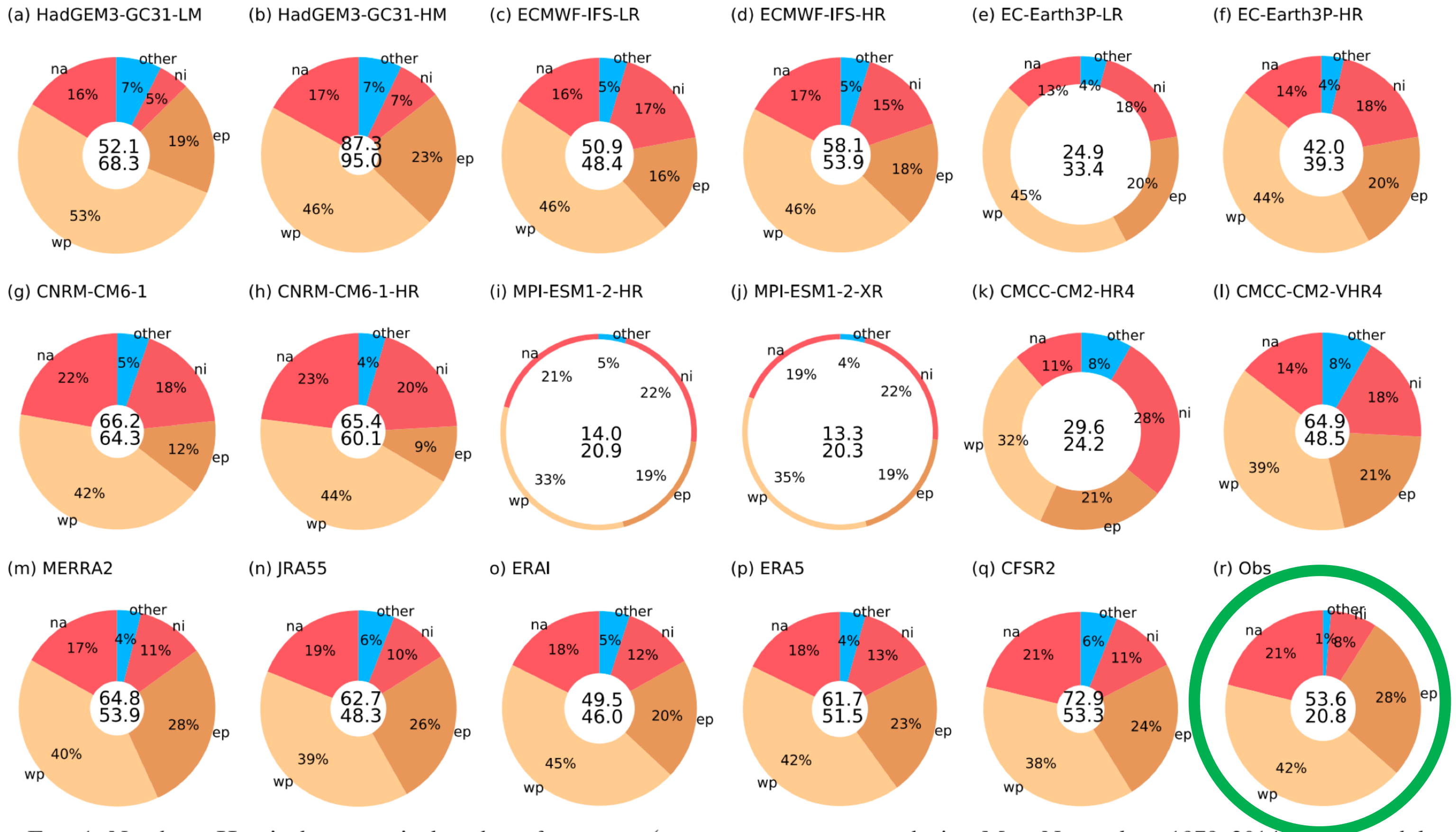


FIG. 1. Northern Hemisphere tropical cyclone frequency (mean storms per year during May–November, 1979–2014) from models, reanalyses, and observations, as diagnosed using the TRACK algorithm. The doughnut chart is divided into NH ocean basins; the totals in the center are (NH on top; SH underneath) mean storms per year (the Southern Hemisphere uses the October–May period). The thickness of the doughnut is scaled to the total NH TC observed frequency [i.e., doughnuts thicker than in (r) indicate more NH TCs, and thinner than in (r) indicate fewer NH TCs].

M. Roberts et al. 2020

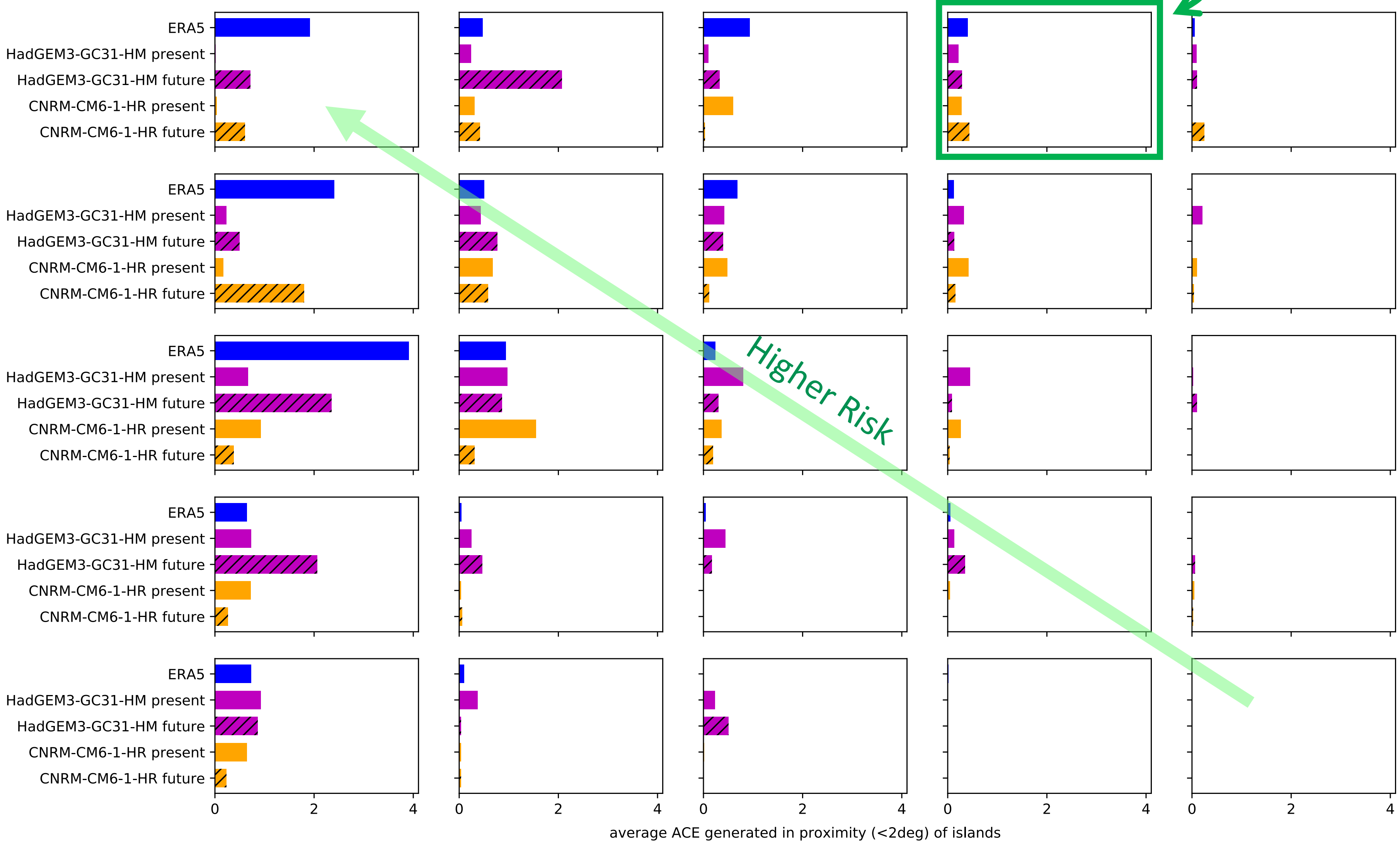
Application for CMIP6

- Data preprocessing as for ERA5
  - At each time step where a TC was tracked:
    replace the 9 grid-cells around the center of the TC with the mean of the surrounding grid-cells
  - Same grid as ERA5 (2.5x2.5 grid 10N-30N and 90W-10W)
  - Weekly standardized anomalies to 1981-2010

- Simulated weeks are classified using the self organizing map trained on ERA5 1981-2010

Preliminary results: ACE

These bars show the average ACE generated by TCs close to islands on weeks following samples that have been associated to this node

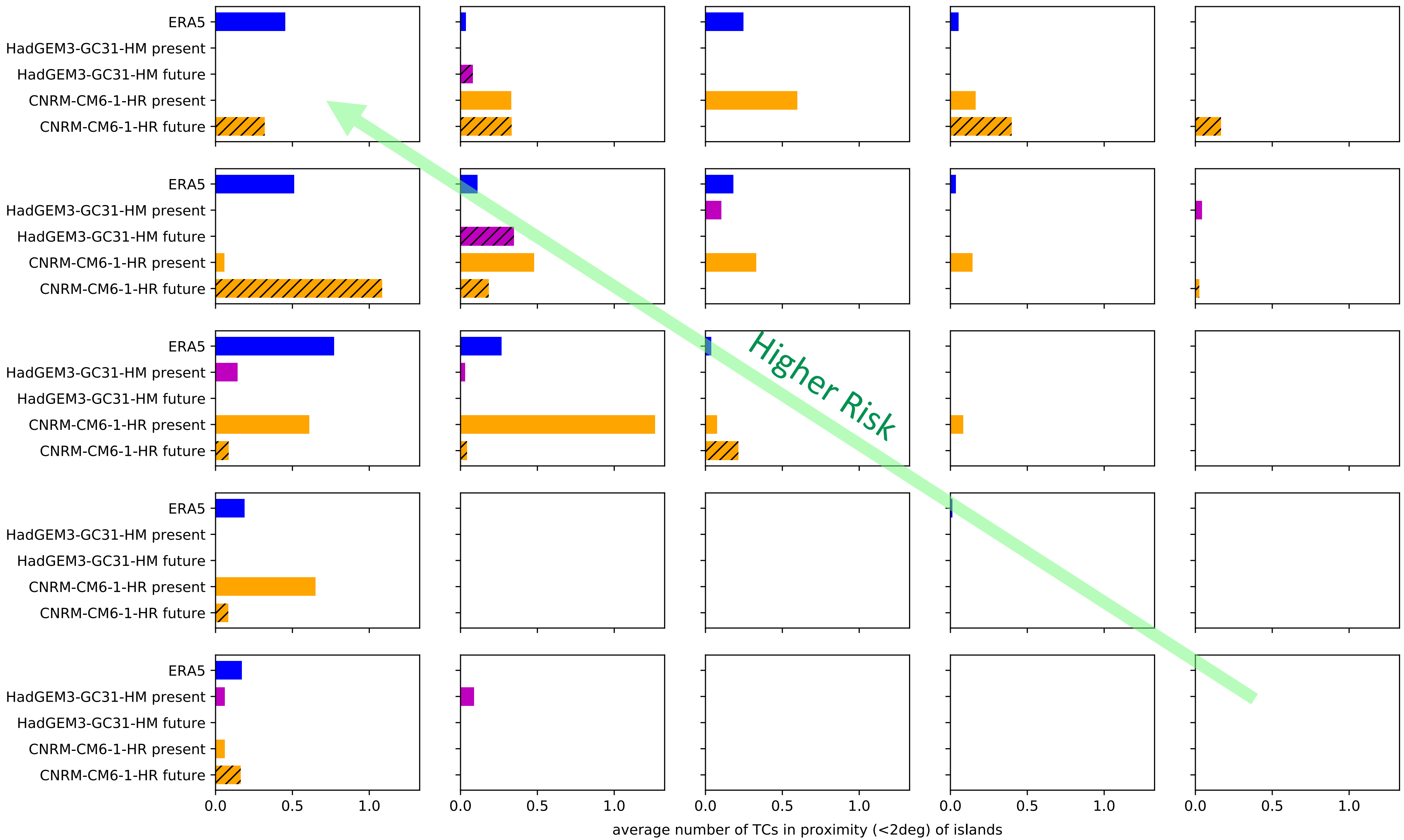


The overall tendency of higher ACE (one week after) weather types associated to nodes on the left and on the top is reproduced by the two tested GCMs

These weather types are characterized by low VWS, low pressure anomalies (especially in the MDR) and rather humid conditions

Within the nodes with higher ACE potential (top left corner), differences between ERA5 and the models are considerable

Preliminary results: number of TCs



For the number of TCs, the same remarks are valid as for ACE (previous slide)

Here the differences between different data products for the high risk nodes (top right) are even larger

Summary

- We classified tropical Atlantic weekly weather patterns into 25 weather types
- For each weather type we assessed the observed risk of TCs close to Caribbean islands one week later
- As expected this risk is higher when vertical wind shear is low and the air is humid
- Preliminary results suggest, that the observed relationship between weather types and TC risk are generally represented by (the 2 tested) high resolution global circulation models

Next steps

- Evaluate whether the identified relationship between weather patterns and TC risks is robust under global warming
  - Perform the same analysis for more high resolution GCMs
- Build a risk model based on the classified weather types
- Assess the impact of global warming on hurricane risk in the Caribbean by applying this risk model to climate projections of the entire CMIP6 (and CMIP5) ensemble

Questions for discussion

- Do you think it is reasonable to apply self organizing maps on a combination of vertical wind shear, mean sea level pressure and relative humidity?
- Do you think “weekly” is the right time scale for such an analysis?
- Do you think it would be interesting to construct SOMs with training data from ERA5 and high resolution CMIP6 present runs to have more training data?

Thank you for your interest!

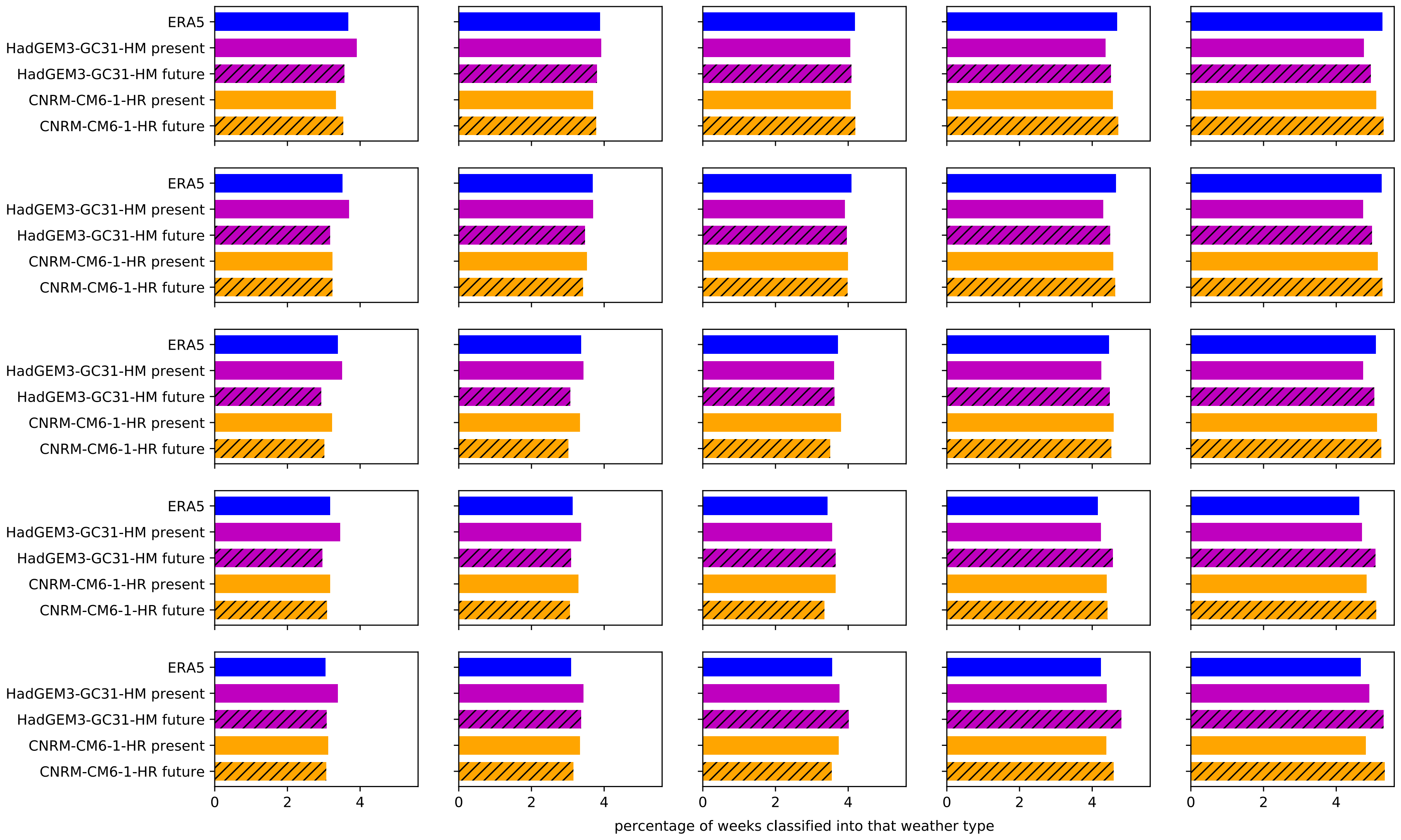
It would be nice if we could discuss these preliminary results and your thoughts on it in a poster session.
But I think it’s also nice, that you read the presentation until here. As a reward I would invite you for a drink the next time we can meet in person on a conference!

References

Jaye, A. B., Bruyère, C. L. & Done, J. M. y. *Weather Clim. Extrem.* **26**, (2019).

Roberts, M. J. *et al.* Impact of model resolution on tropical cyclone simulation using the HighResMIP-PRIMAVERA multimodel ensemble. *J. Clim.* **33**, 2557–2583 (2020).

Preliminary results: frequency of weather types



All weather types are (nearly) equally frequent in reanalysis and CNRM-CM6-1-HR and HadGEM3-GC31-HM

Preliminary results: number of TSs