Climate extremes in reanalysis and observational products

Markus Donat (Barcelona Supercomputing Center),
with input from Robert Dunn, Lisa Alexander, Alvise Aranyossy, and many others

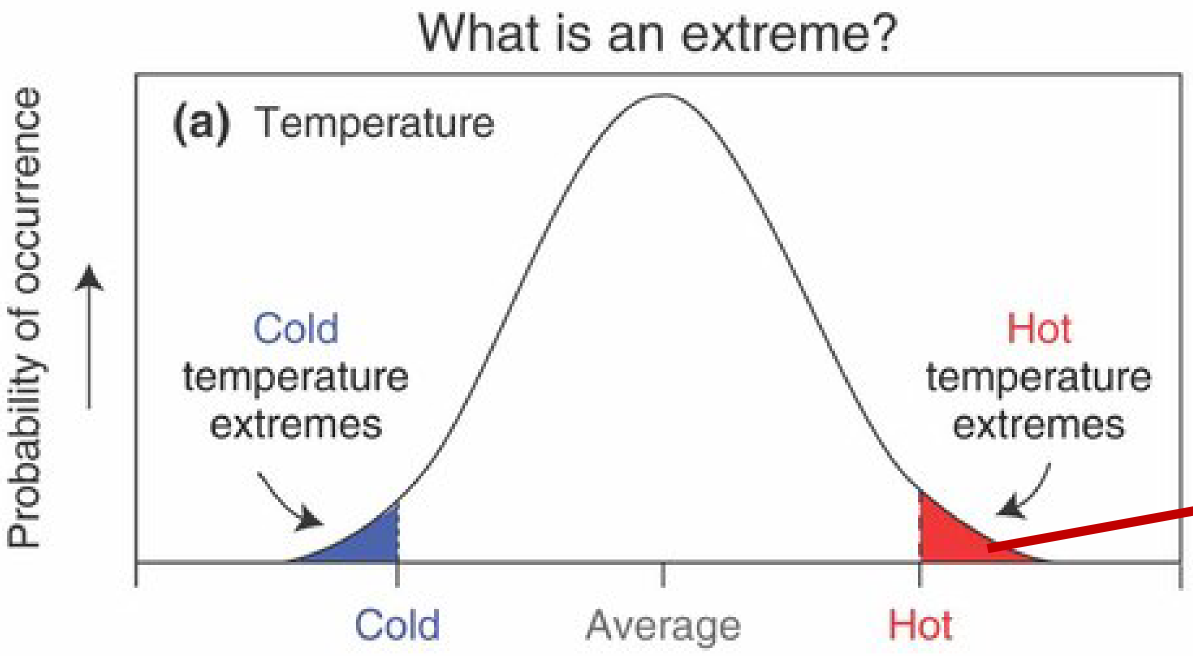
07 Sep 2023

ECMWF Annual Seminar 2023, Reading

Climate extremes in reanalysis and observational products

1. Intro: Climate extremes and observations-based data
2. Temperature Extremes
3. (Heavy) precipitation Extremes
4. Drought
5. Storms
6. Challenges

Climate Extremes



Measure extremes e.g. as

- Intensity
- Frequency
- Duration

of threshold exceedence

IPCC AR2 (1996); Zhang et al. (2011) WIREs Climate Change

Measures of Climate Extremes

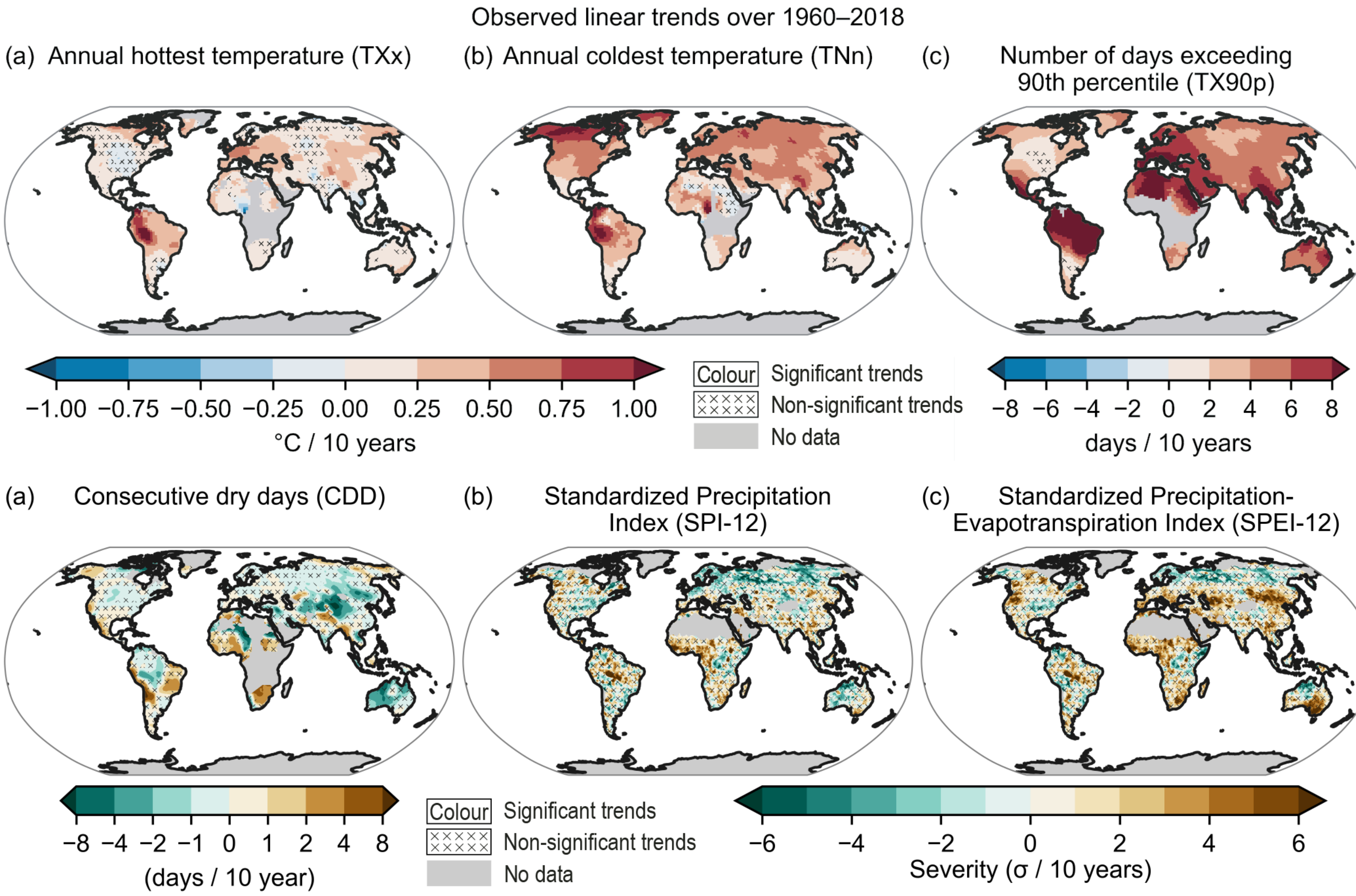
Alexander *et al* 2019 *Environ. Res. Lett.*, DOI 10.1088/1748-9326/ab51b6

ETCCDI indices to measure temperature and precipitation extremes

WMO-ETCCDI recommended 27 simple climate indices based on temperature and precipitation data, e.g.:

	Index	Name	Definition
temperature	TXx	max Tmax	Warmest daily maximum temperature
	TNn	min Tmin	Coldest daily minimum temperature
	TX10p	Cool days	Share of days when Tmax < 10th percentile
	TN10p	Cool nights	Share of days when Tmin < 10th percentile
	TX90p	Warm days	Share of days when Tmax > 90th percentile
	TN90p	Warm nights	Share of days when Tmin > 90th percentile
	WSDI	Warm spell duration indicator	Annual number of days with at least 6 consecutive days when Tmax > 90th percentile
precipitation	Rx1day	Max 1-day precipitation	Annual maximum 1-day precipitation
	R95p	Annual contribution from very wet days	Annual sum of daily precipitation > 95th percentile
	R10mm	Heavy precipitation days	Annual number of days when precipitation >= 10 mm

Monitoring/observing changes in climate extremes

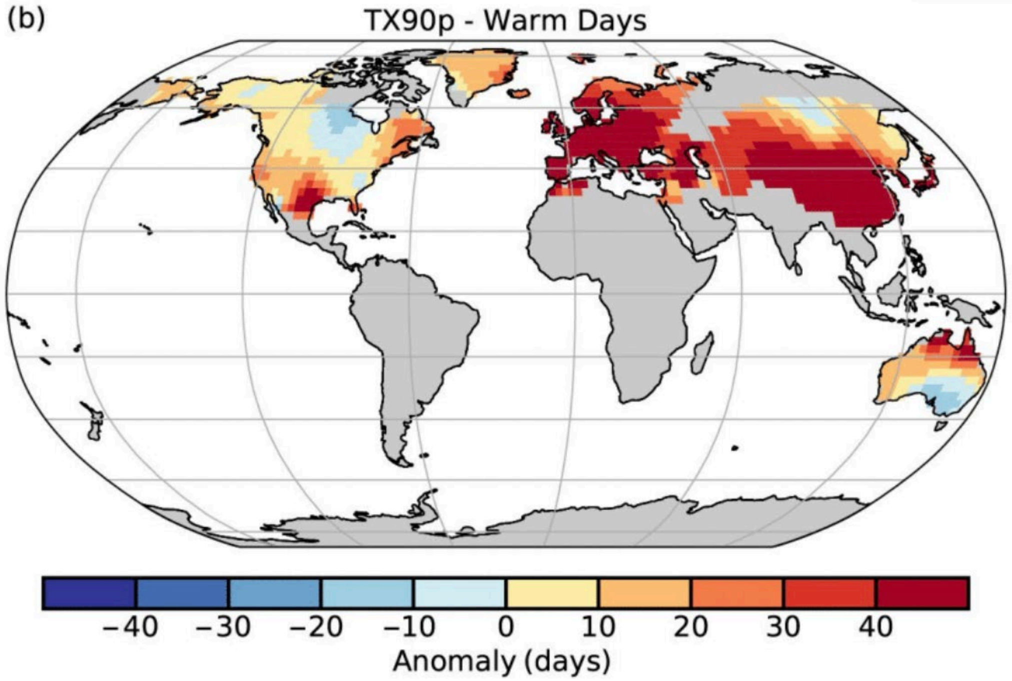


IPCC AR6 (2023) Chapter 11, Figs. 11.9, 11.17

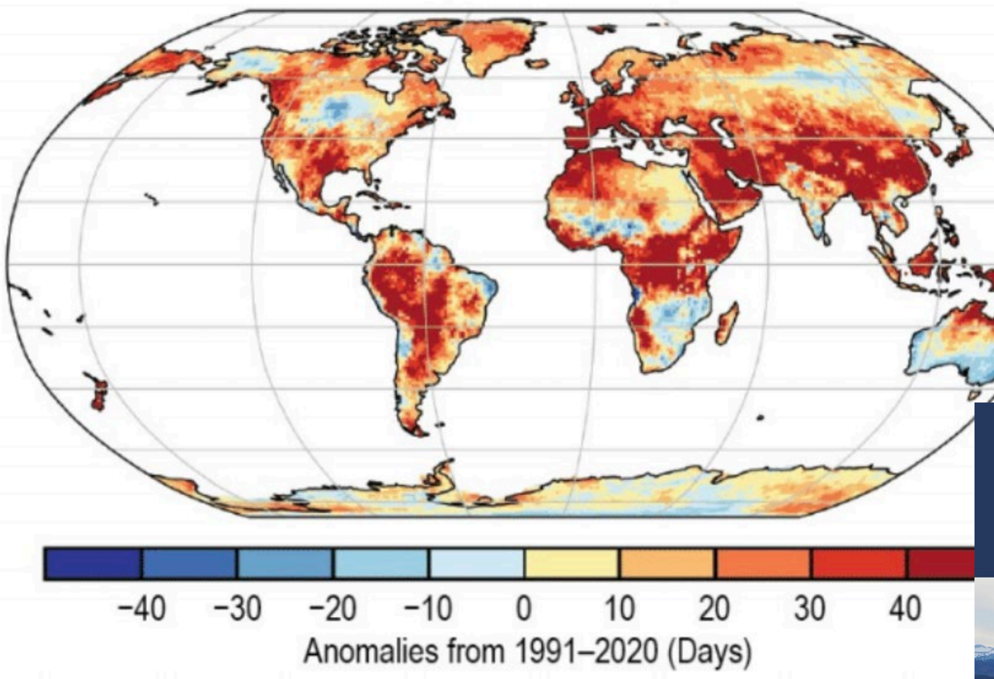
Monitoring changes in climate extremes

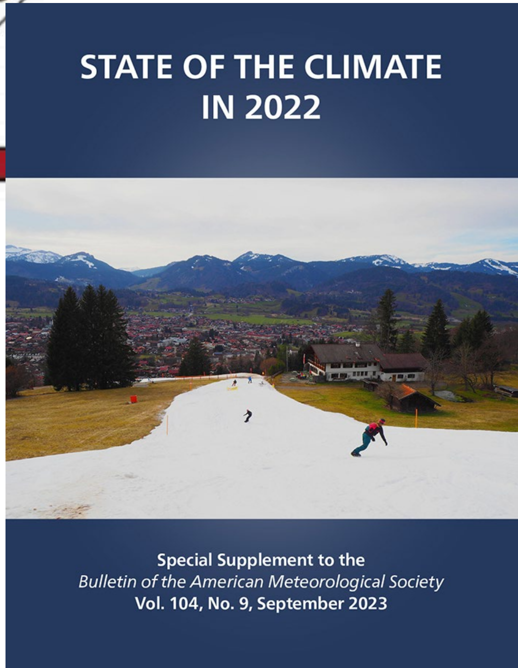
Observed anomaly in 2022

using GHCNDEX



ERA5





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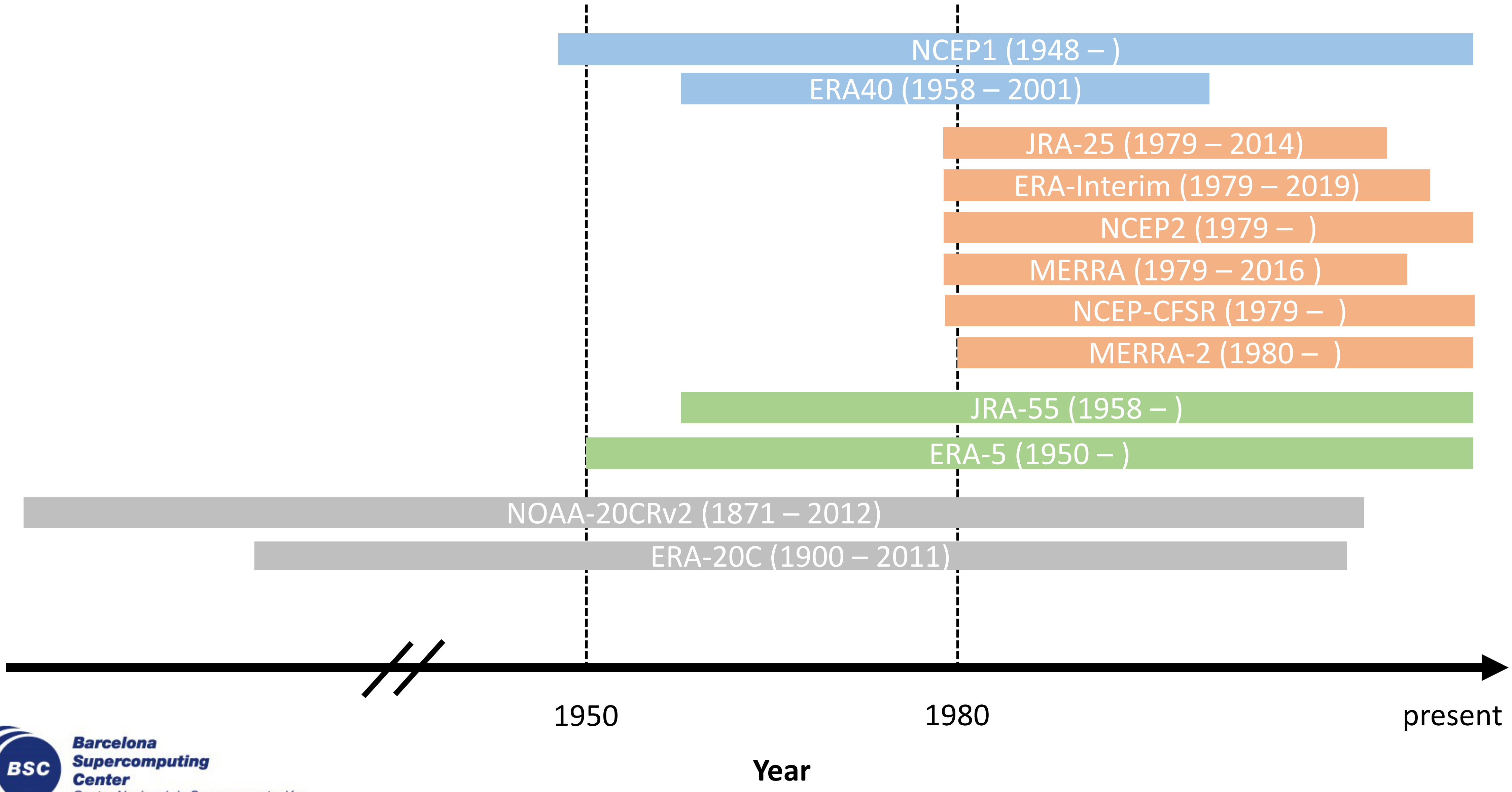
“State of the Climate in 2022“ report (BAMS, 2023)

Different generations of global atmospheric reanalsyes



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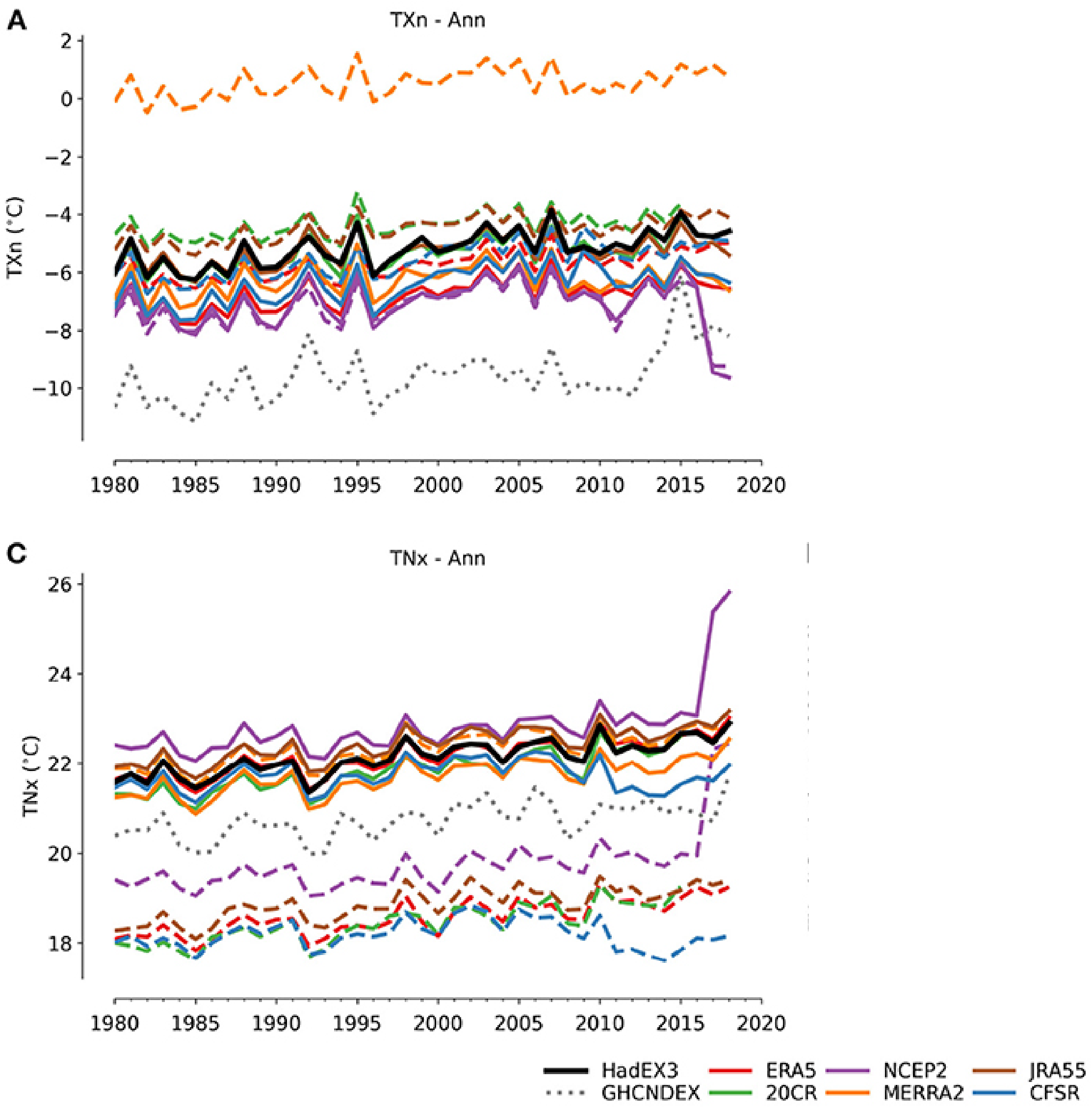
Temperature Extremes

Extremes across different datasets

e.g. annually coldest day (TXn)

e.g. annually warmest night (TNx)



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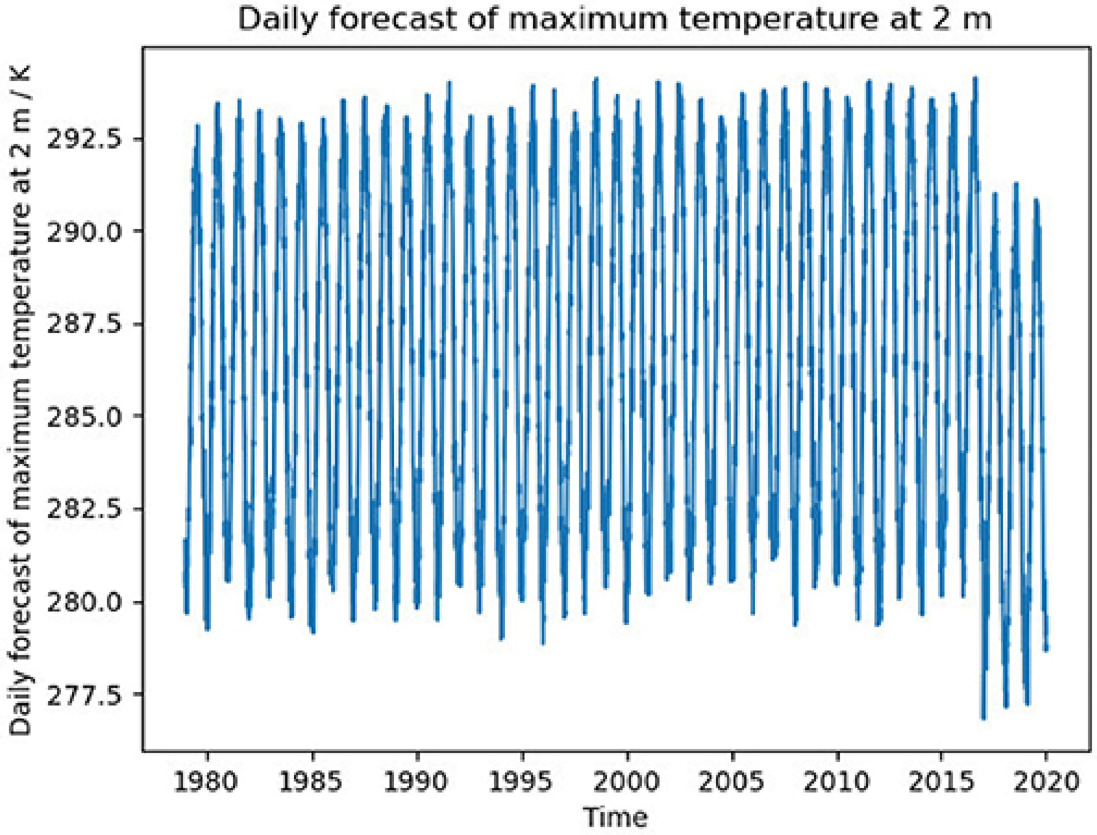
Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

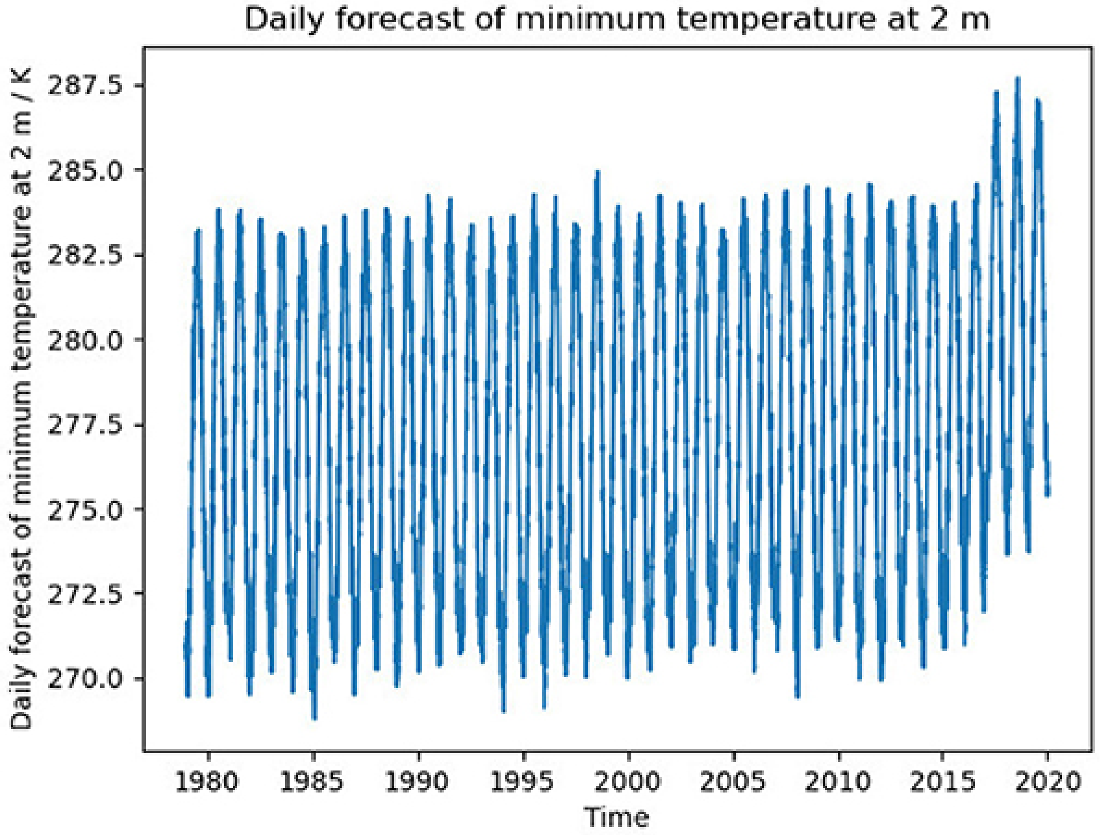
Discontinuities hamper analyses of long-term changes or anomalies

Example: temperature discontinuity NCEP2

Daily Tmax



Daily Tmin



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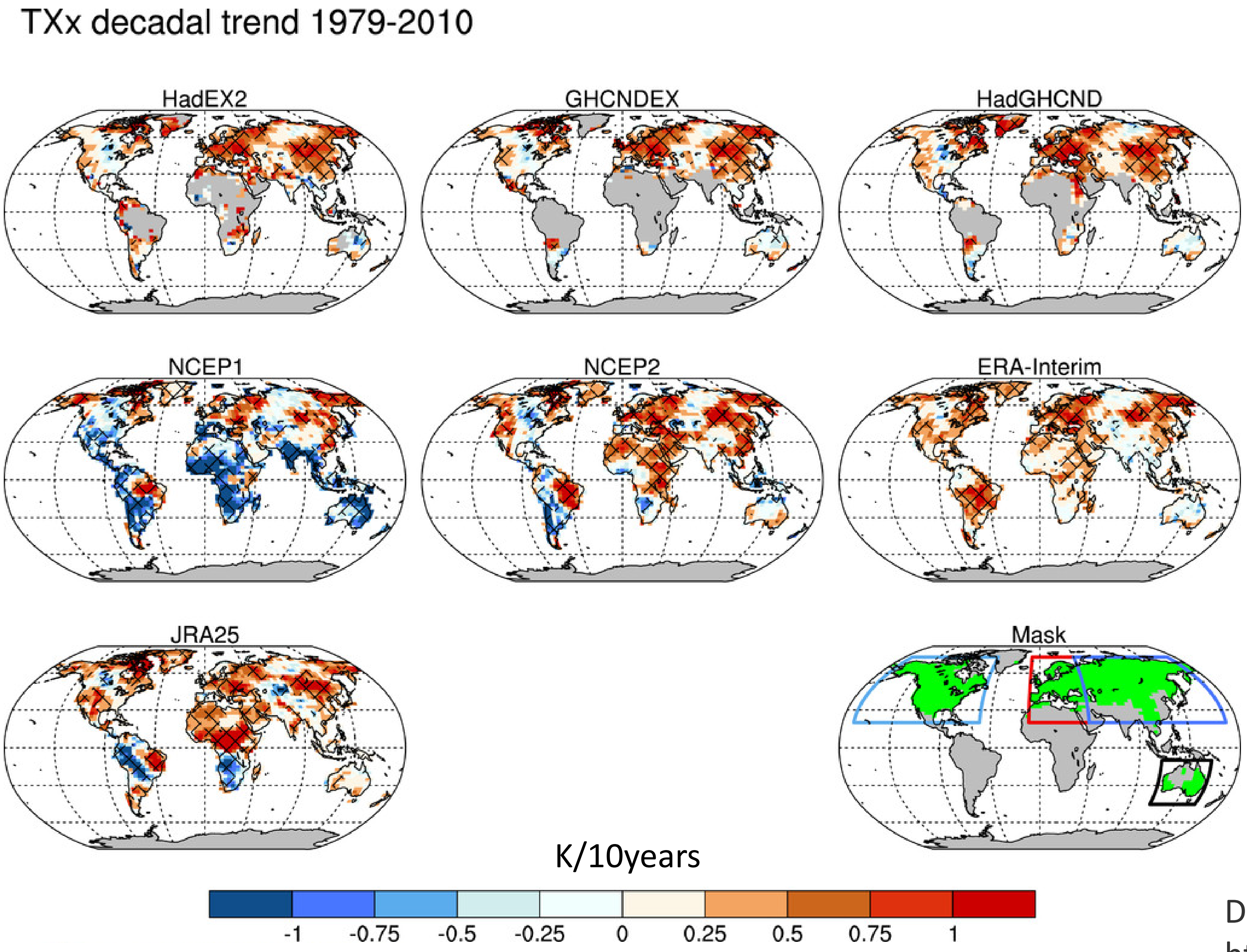
Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

Temporal Changes across datasets



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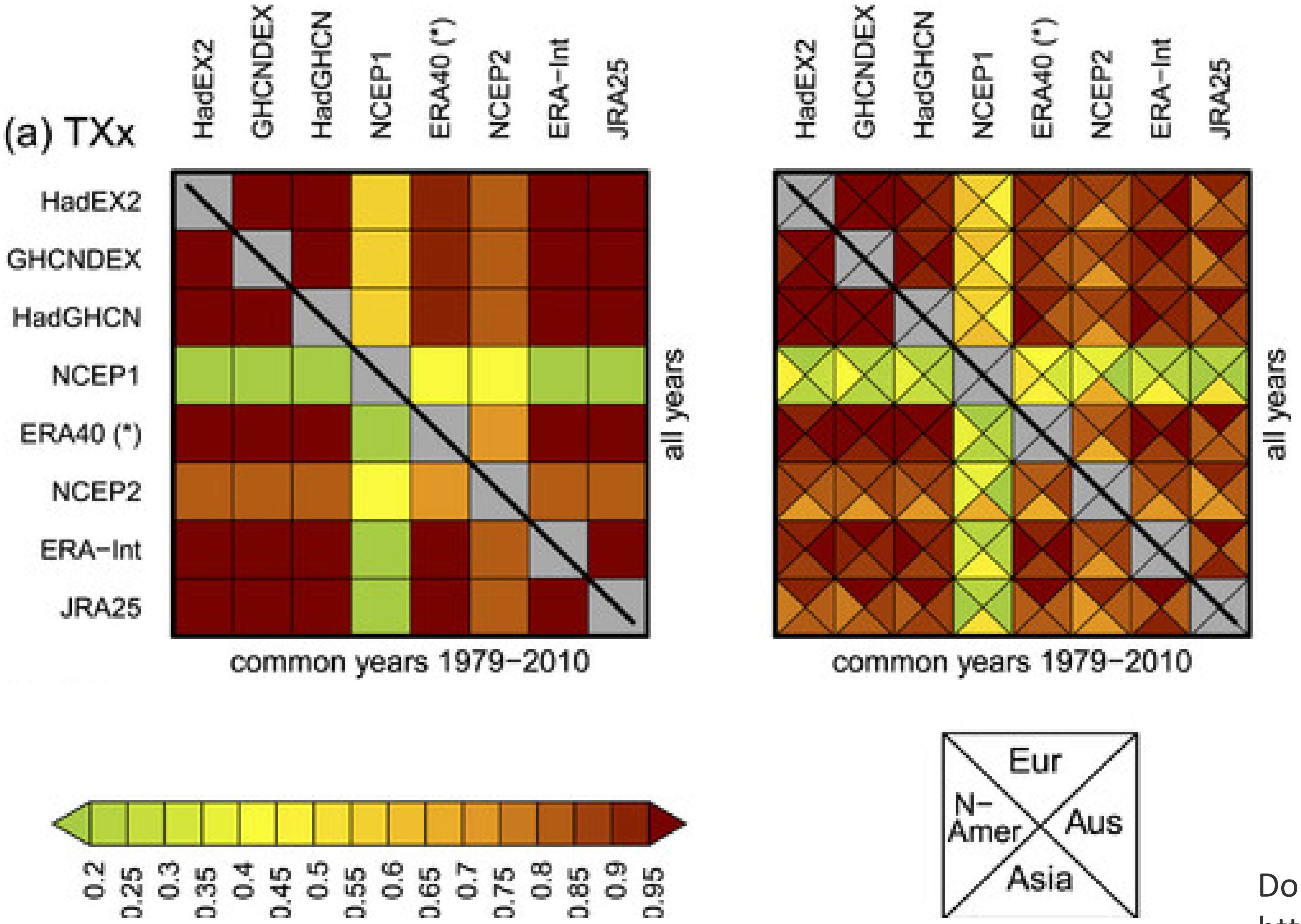
Temporal Changes across datasets



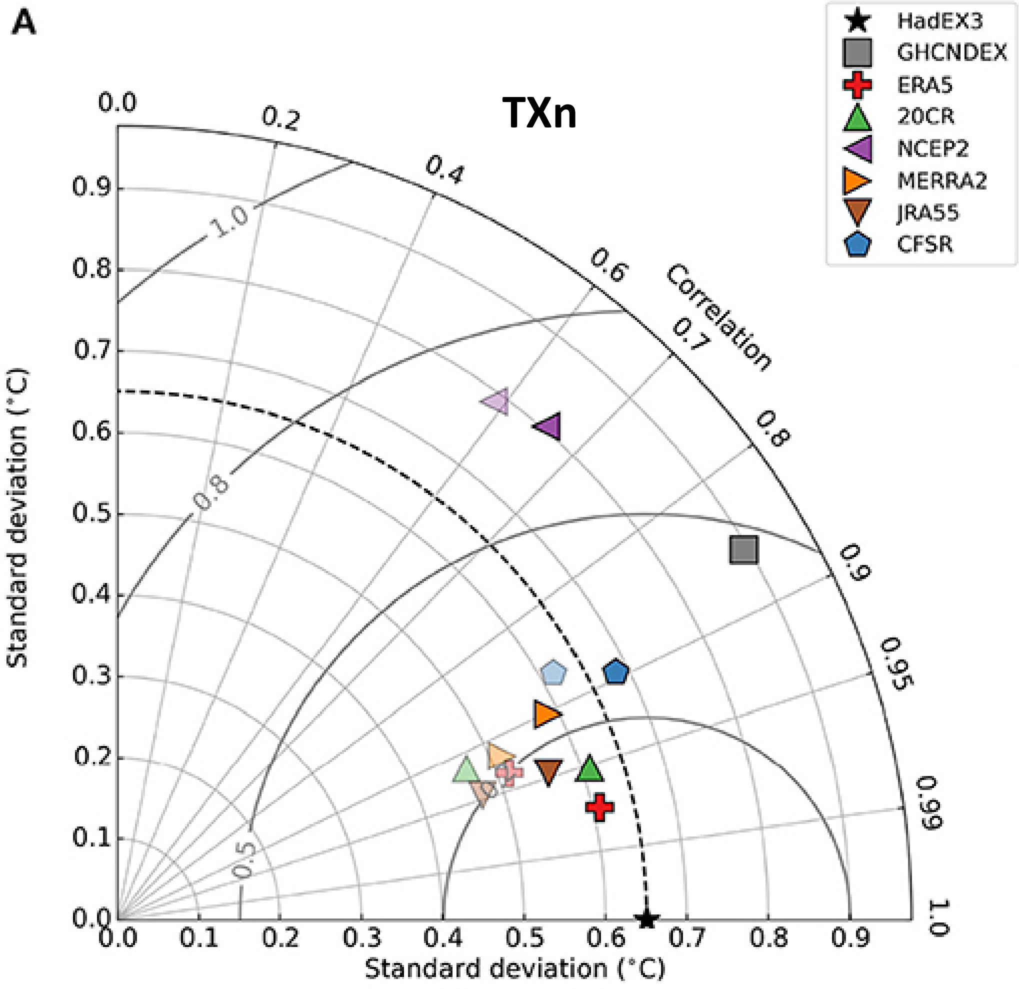
Donat *et al* 2014, J. Climate, https://doi.org/10.1175/JCLI-D-13-00405.1.

Extremes across different datasets

Taylor Diagram:

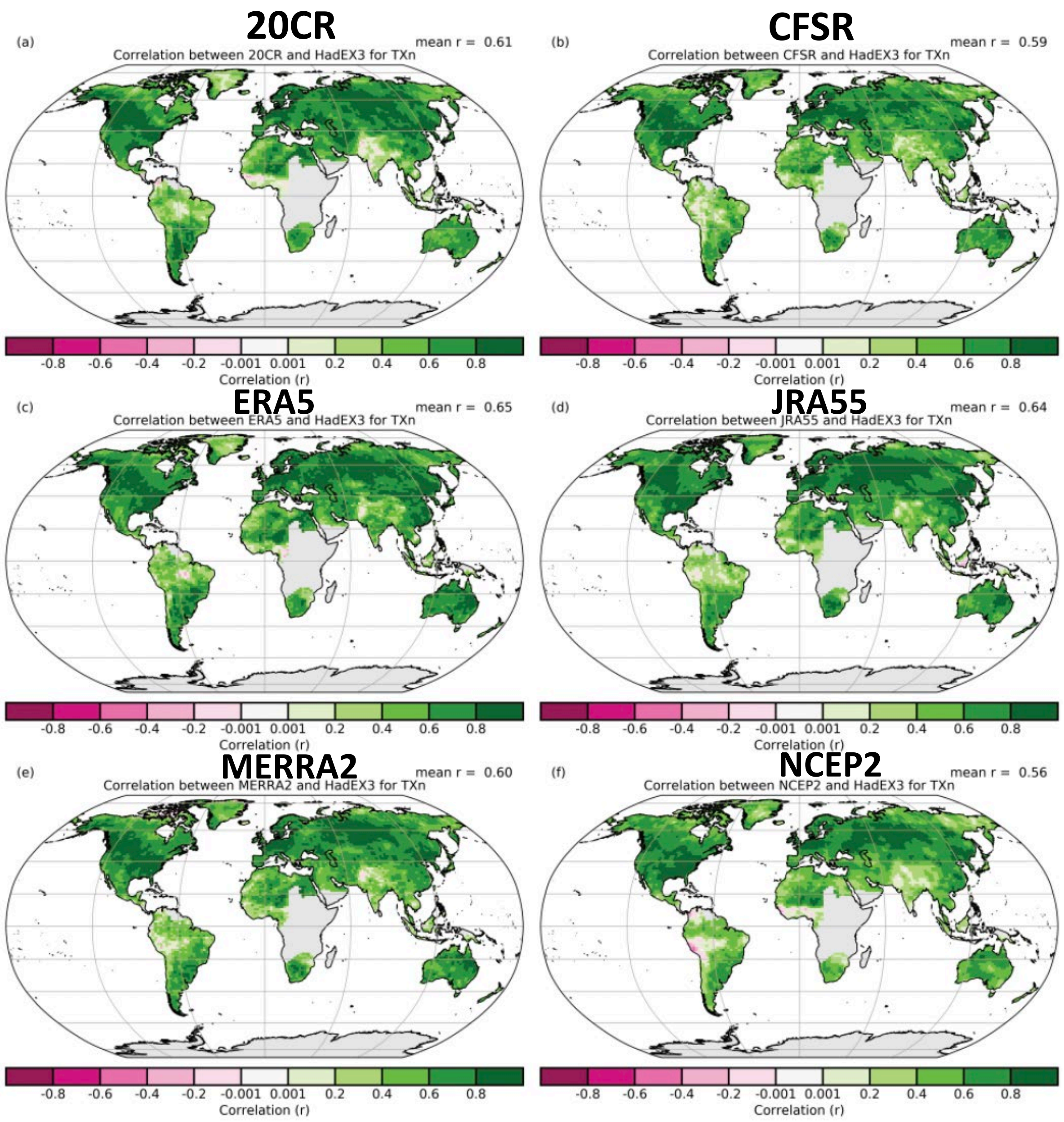
x and y axes: standard deviation of the time series for each dataset; polar axis: correlation with the reference dataset (HadEX3); semi-circles centered on HadEX3: values of the root-mean-square difference.

fainter symbols: reanalyses using complete global land coverage, darker symbols: spatio-temporal coverage matched to HadEX3.



Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

Temporal correlation of extremes with observations (HadEX3), e.g. TXn



Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

Precipitation Extremes

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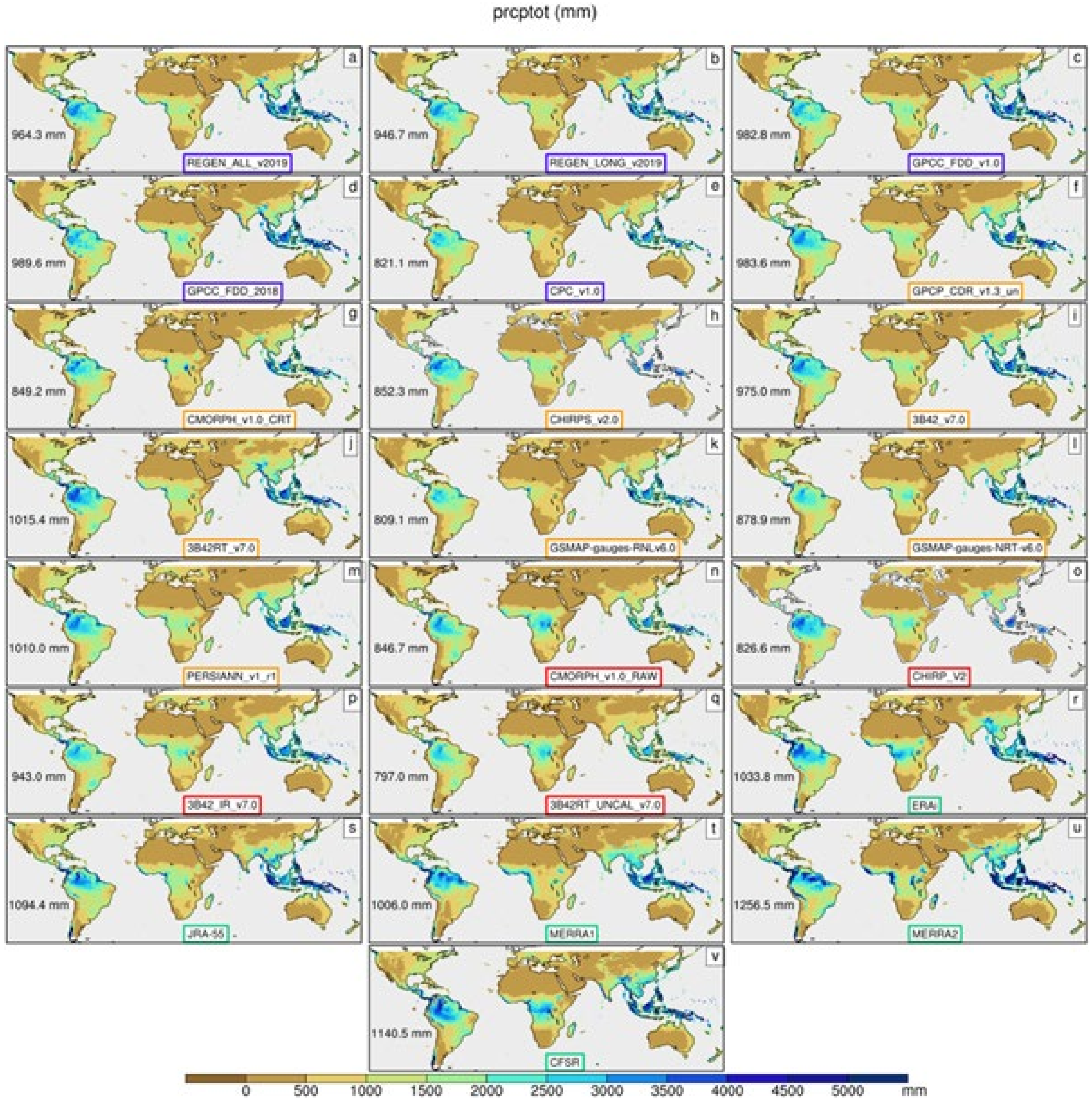
Extremes Climatology across Observations-Based Datasets

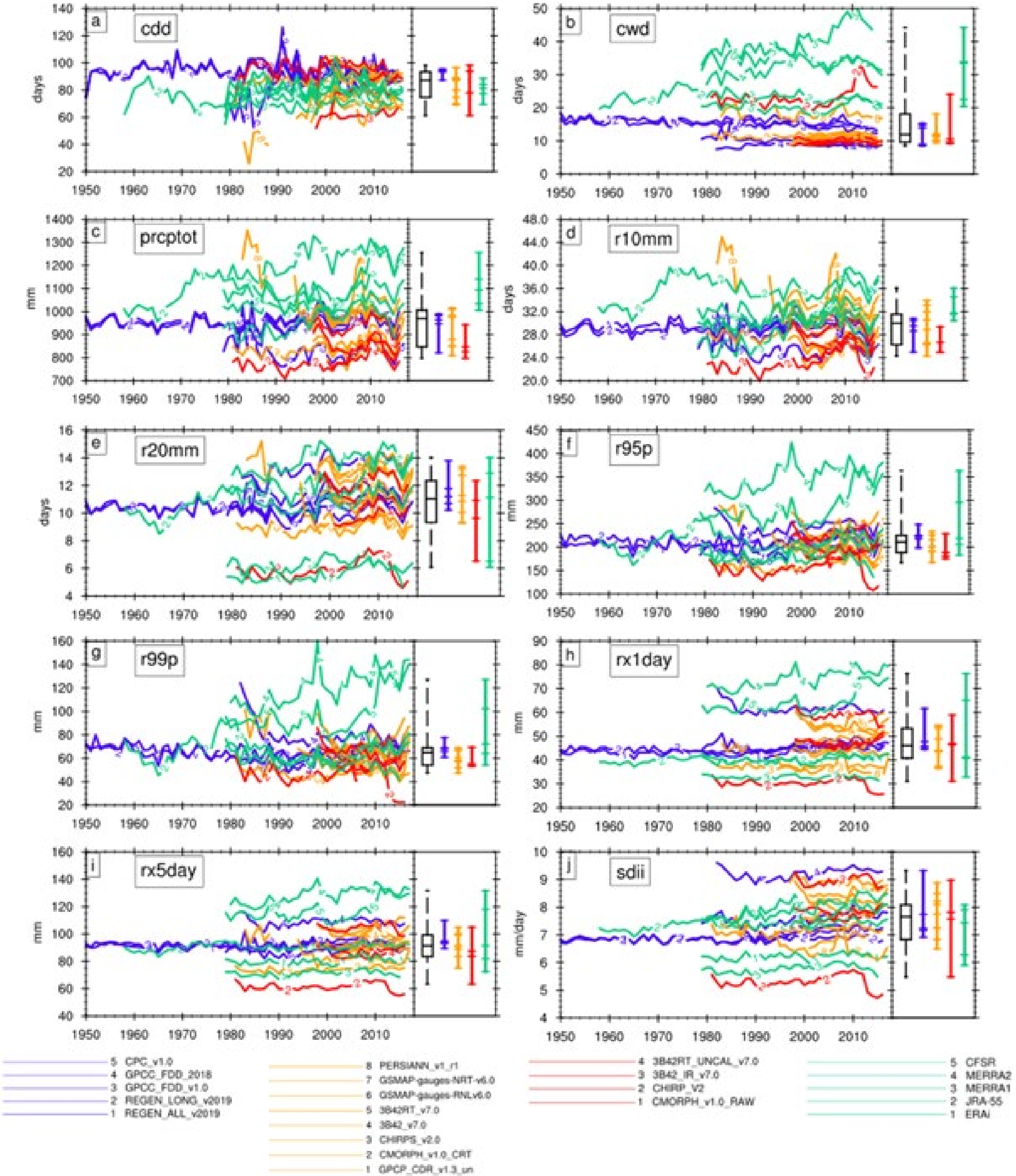


Intercomparing precipitation indices across a collection of (daily) precipitation products in the FROGS database (Roca *et al* 2019):

- gridded *in situ* data
- Satellite estimates with correction to *in situ*
- Satellite estimates w/o correction
- reanalysis

Alexander *et al* 2020 *Environ. Res. Lett.* **15** 055002
DOI 10.1088/1748-9326/ab79e2

Global land (50°S–50°N) average timeseries



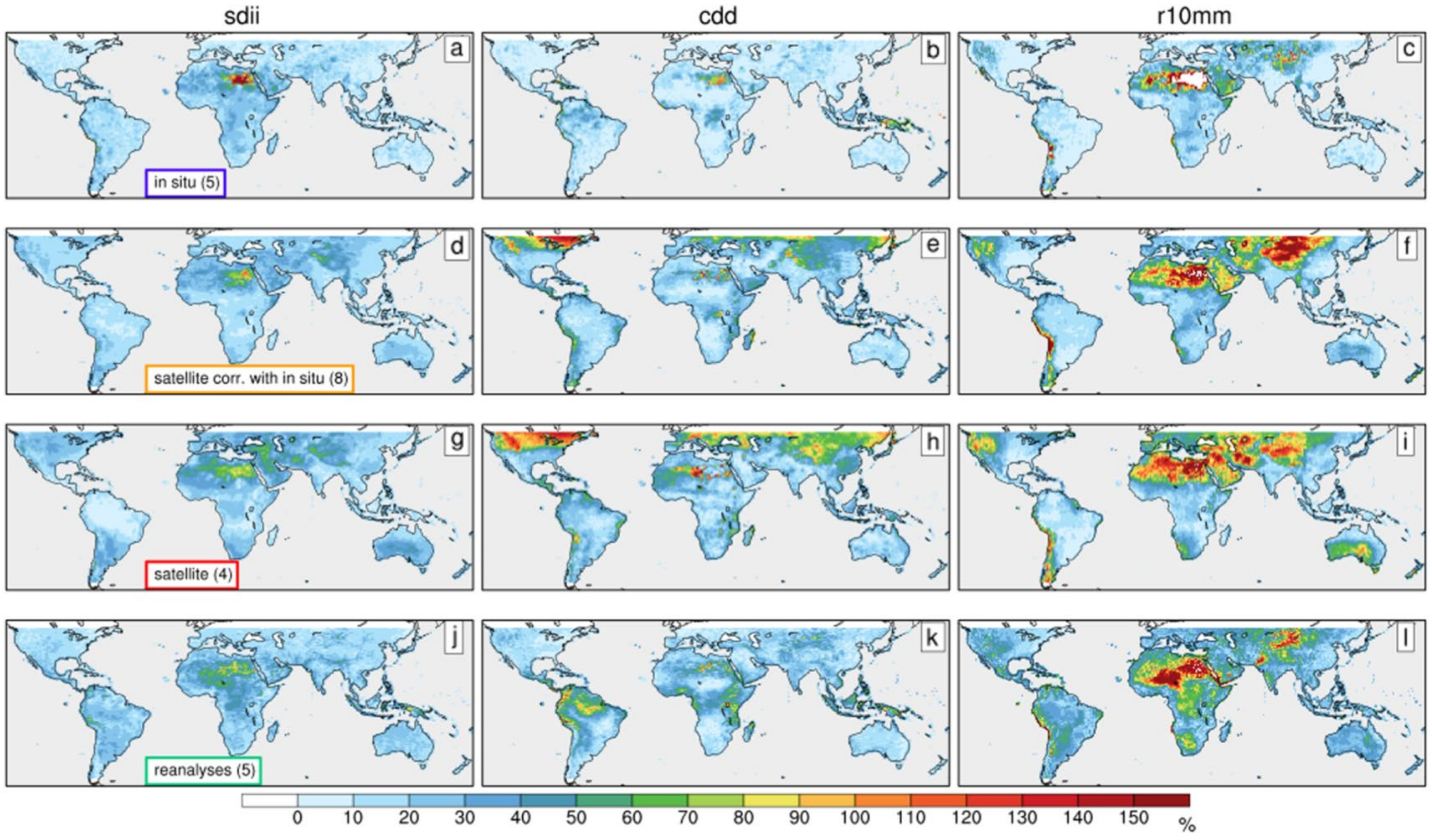
	Dataset name	SDII	PRCPTOT	Rx1day	Rx5day	R95p	R99p	R10mm	R20mm	CDD	CWD
in situ-based	REGEN_ALL_v2019	7	11	9	13	13	12	12	13	6	14
	REGEN_LONG_v2019	6	10	10	14	15	16	8	9	4	15
	GPCC_FDD_v1.0	8	13	11	15	16	15	15	15	1	13
	GPCC_FDD_2018	22	15	20	20	20	20	11	21	7	1
	CPC_v1.0	12	3	14	9	8	10	4	8	11	2
satellite with correction to *in situ*	GPCP_CDR_v1.3_un	20	14	7	11	6	2	20	19	21	4
	CMORPH_v1.0_CRT	13	6	15	10	9	9	5	10	3	7
	CHIRPS_v2.0	9	7	4	3	1	1	9	5	8	10
	3B42_v7.0	18	12	16	16	17	14	14	17	15	9
	3B42RT_v7.0	19	18	18	18	19	17	18	20	18	12
	GSMAP-gauges-RNLv6.0	5	2	8	8	7	8	1	4	12	11
	GSMAP-gauges-NRT-v6.0	17	8	17	17	12	13	6	14	10	6
	PERSIANN_v1_r1	4	17	3	5	10	7	19	7	19	16
Satellite uncorrected	CMORPH_v1.0_RAW	14	5	13	7	5	6	7	11	5	8
	CHIRP_V2	1	4	1	1	2	3	3	3	2	19
	3B42_IR_v7.0	21	9	19	19	18	18	10	16	22	3
	3B42RT_UNCAL_v7.0	11	1	12	6	3	4	2	6	16	5
reanalyses	ERAi	3	19	6	4	11	19	17	1	13	20
	JRA-55	10	20	5	12	14	11	22	12	17	18
	MERRA1	2	16	2	2	4	5	13	2	20	22
	MERRA2	16	22	22	22	22	22	16	22	14	21
	CFSR	15	21	21	21	21	21	21	18	9	17

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

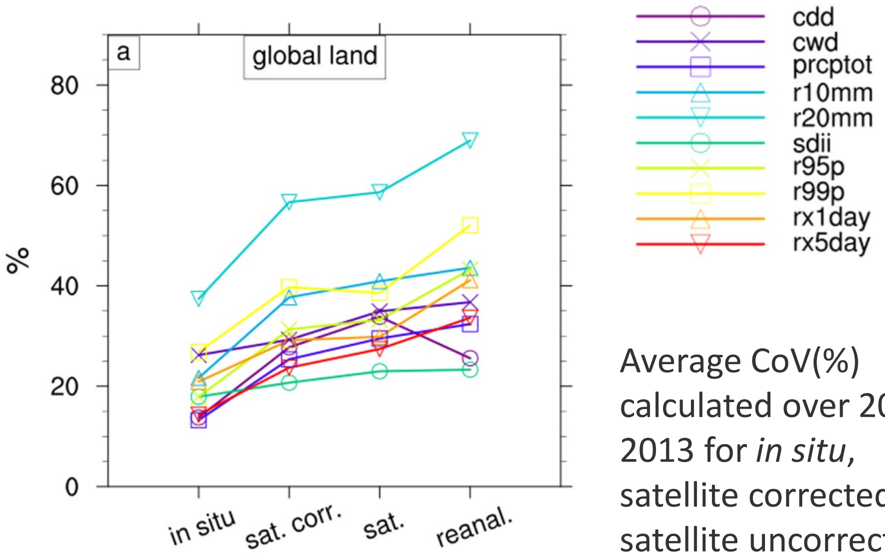
Driest --Wettest

Alexander *et al* 2020 *Environ. Res. Lett.* **15** 055002 **DOI** 10.1088/1748-9326/ab79e2

Large uncertainties in data sparse regions irrespective of product type



CoV (%) calculated over the 2001–2013 climatologies from the different datasets for SDII, CDD and R10mm across precipitation products arranged by product type: *in situ*, satellite corrected, satellite uncorrected and reanalyses. The number of products considered within each cluster is indicated.



Average CoV(%) calculated over 2001–2013 for *in situ*, satellite corrected, satellite uncorrected and reanalyses) for precipitation indices

Frequency-based indices are more sensitive to product than intensity-based indices

Reanalyses generally have largest inter-product spread

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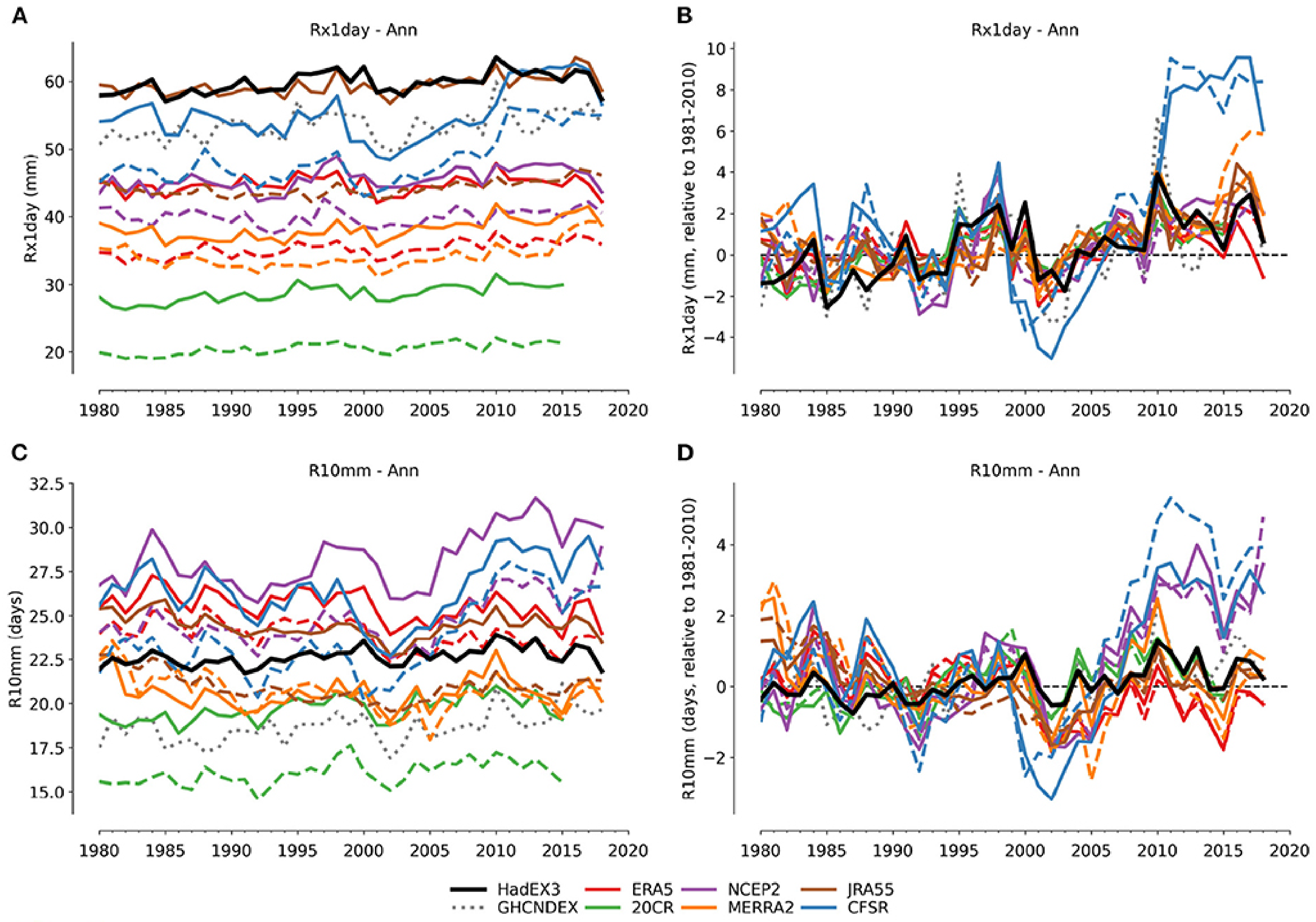
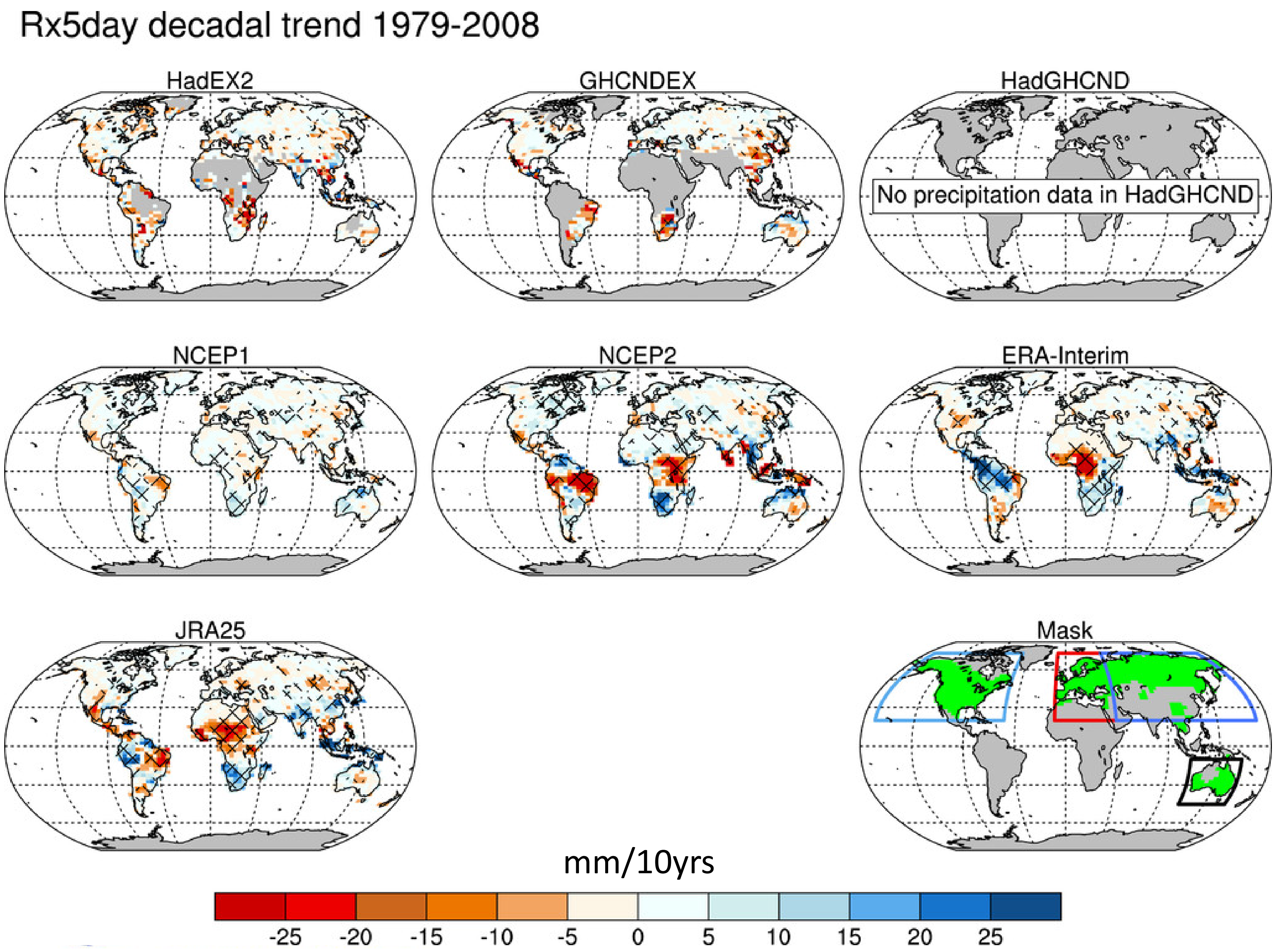
Precipitation Extremes



Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

Temporal Changes across datasets



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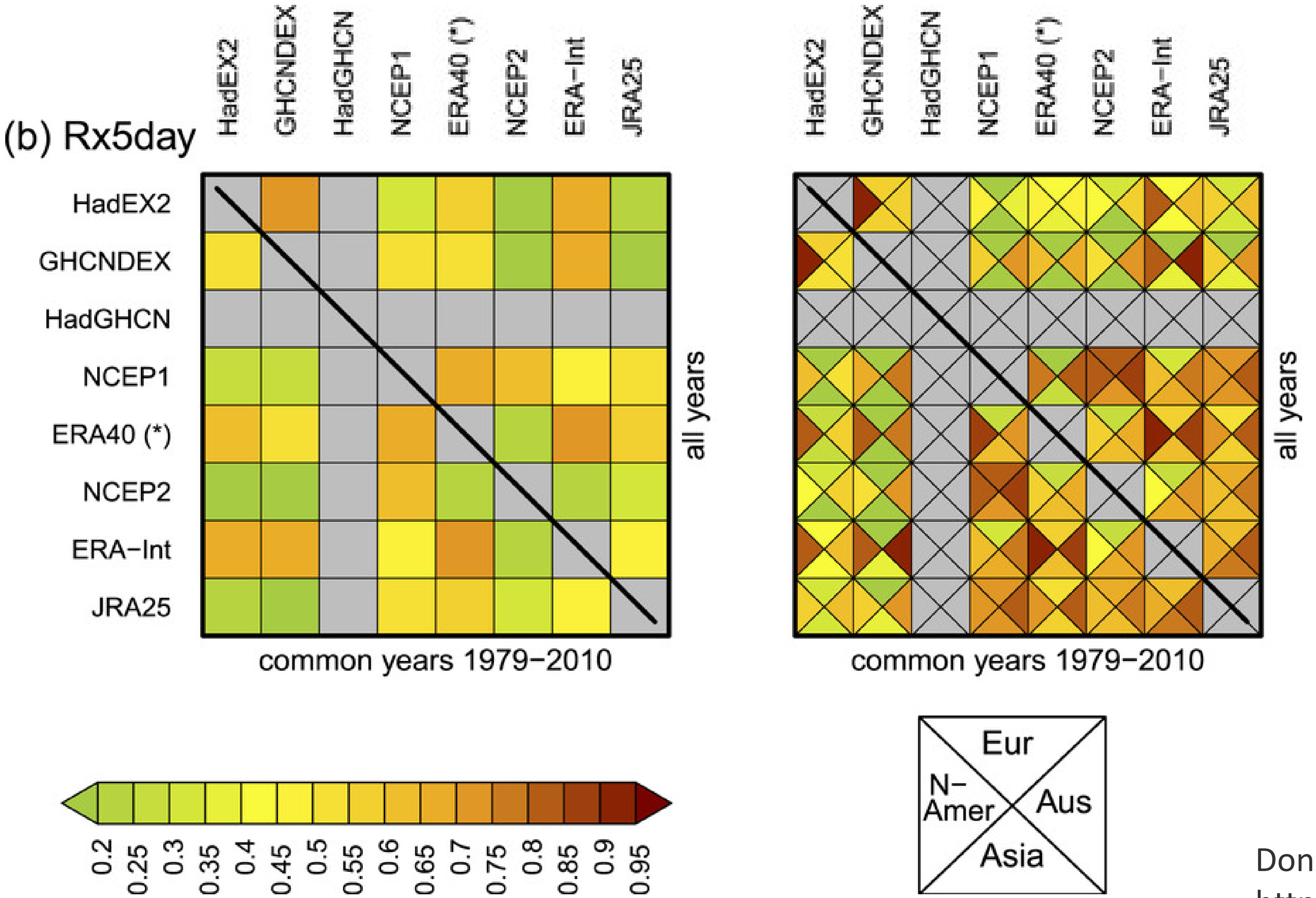

Correlations lower than for temperature extremes

Clustering of reanalysis ‘families’ (ERA*, NCEP*)

Donat *et al* 2014, J. Climate, https://doi.org/10.1175/JCLI-D-13-00405.1.

Precipitation Extremes

Taylor Diagram:

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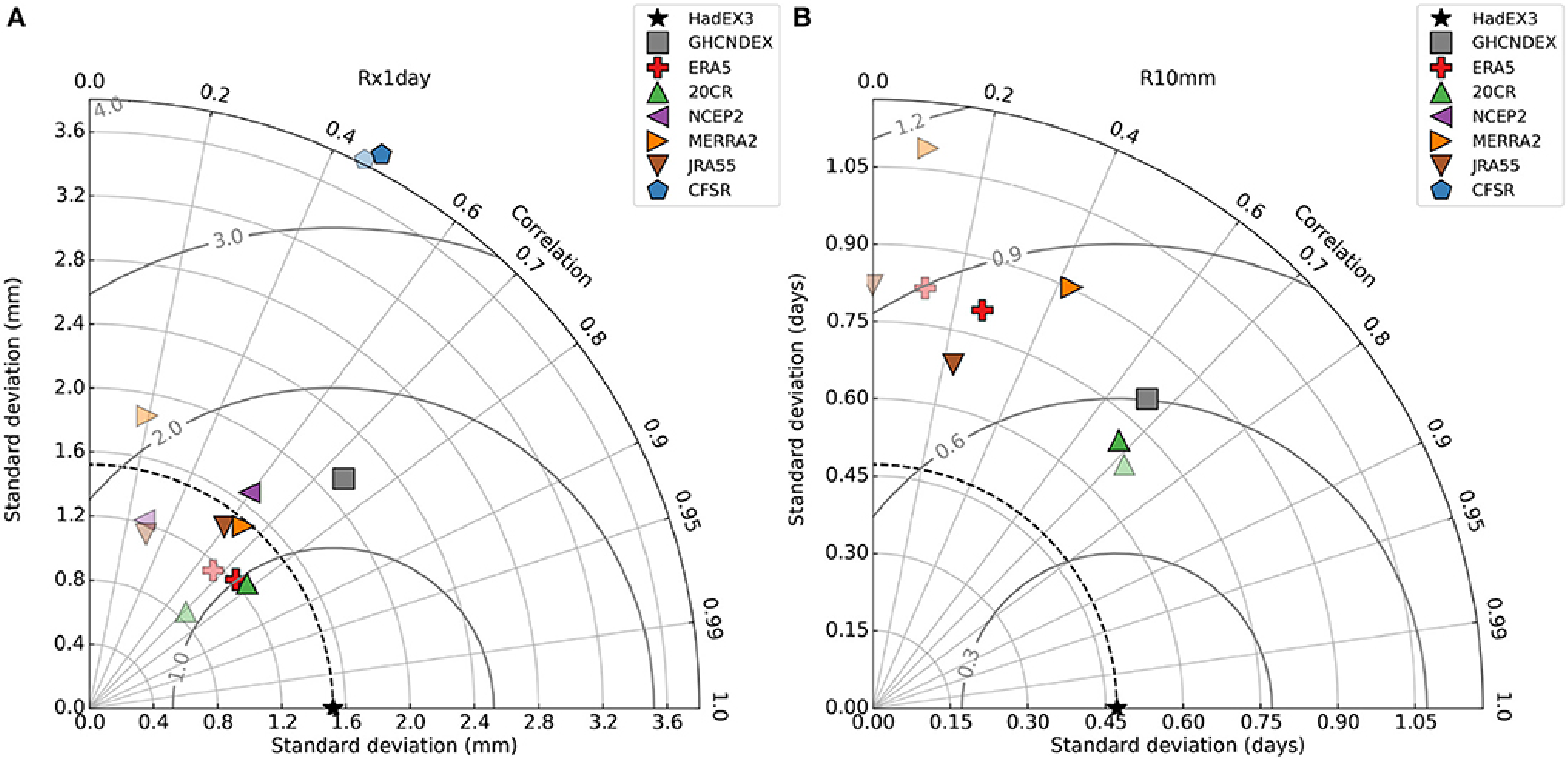

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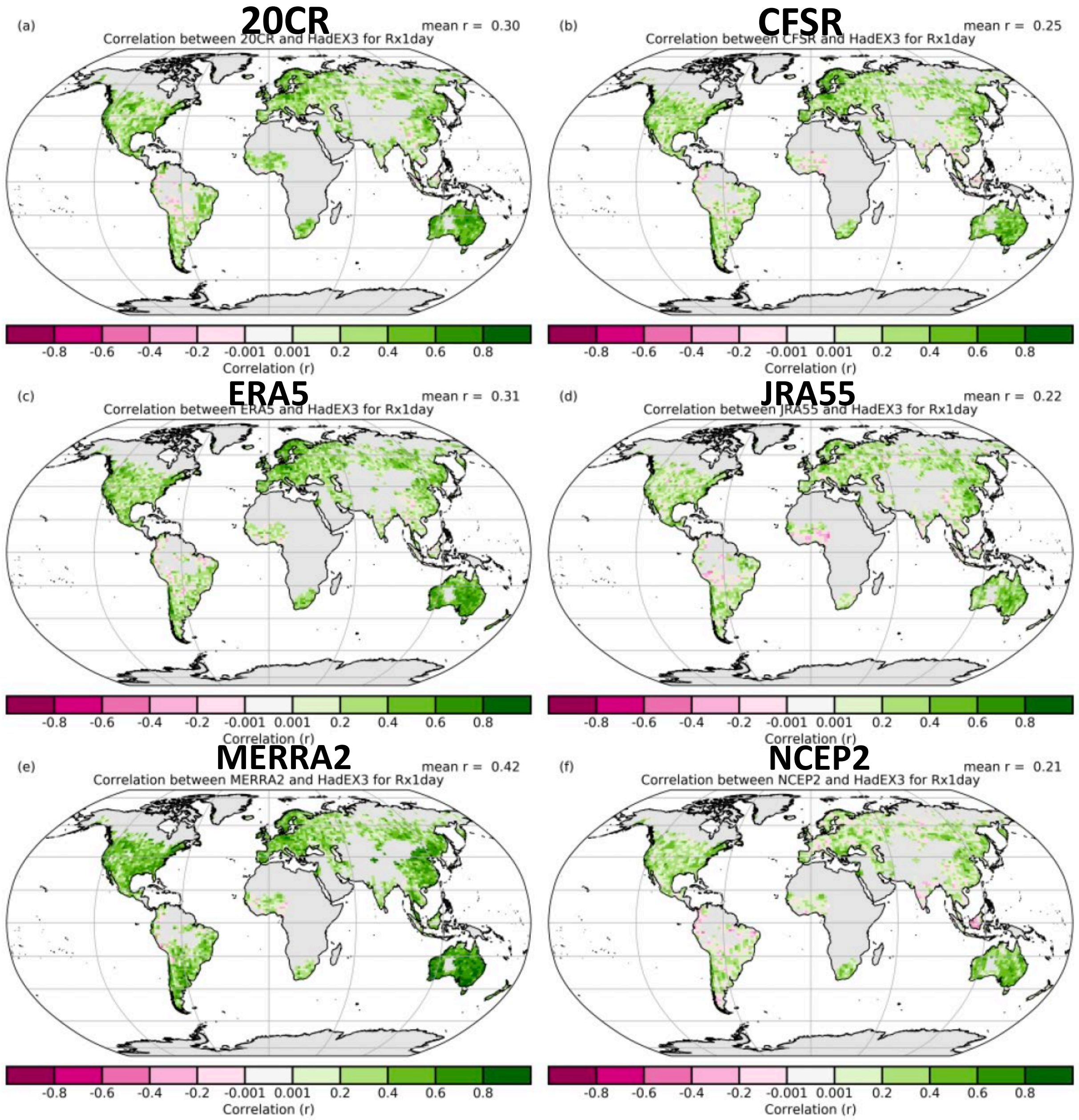
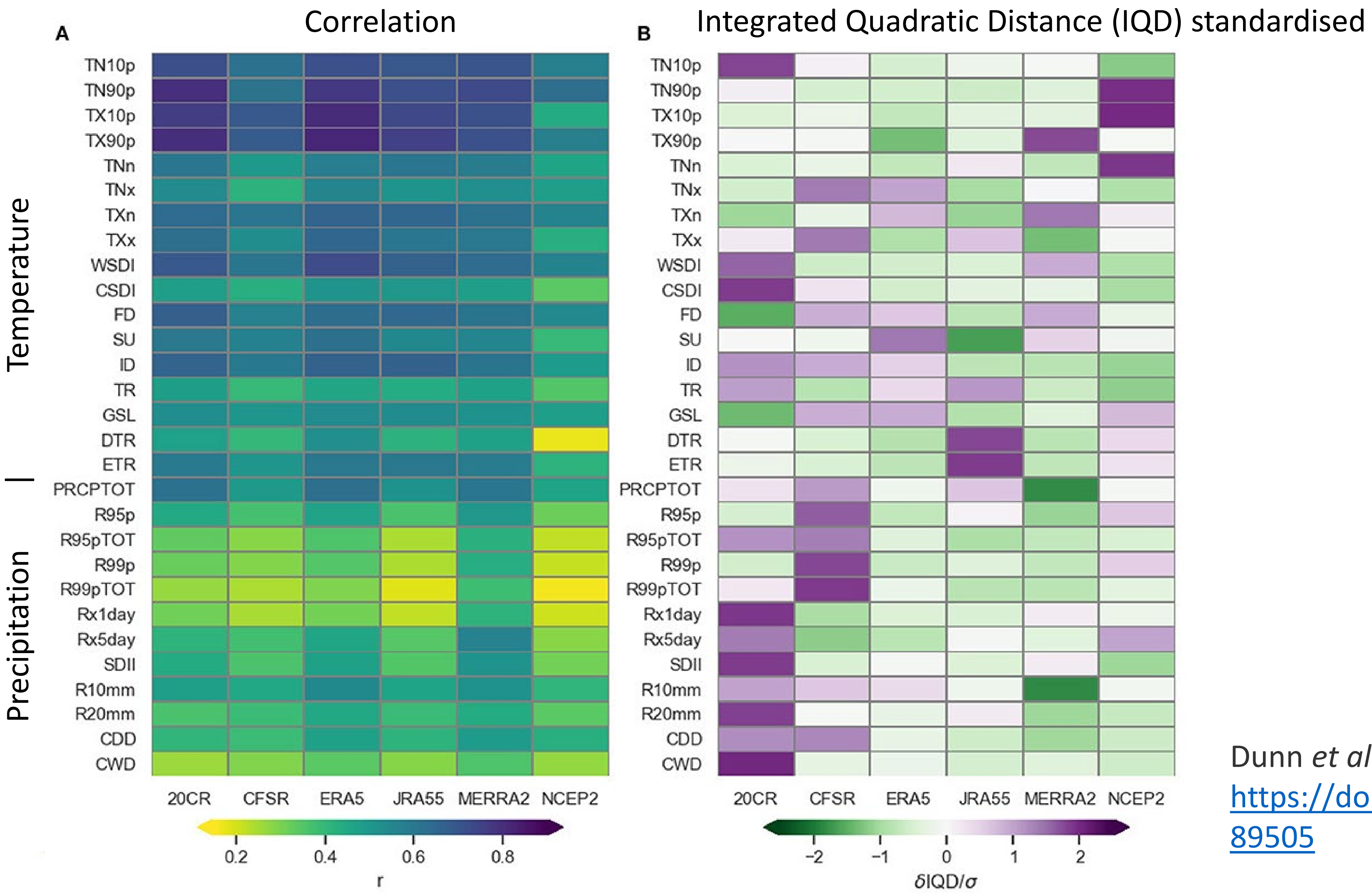
Temporal correlation of extremes with observations (HadEX3),e.g. Rx1day



Dunn *et al* 2022 Front. Clim.;
https://doi.org/10.3389/fclim.2022.989505

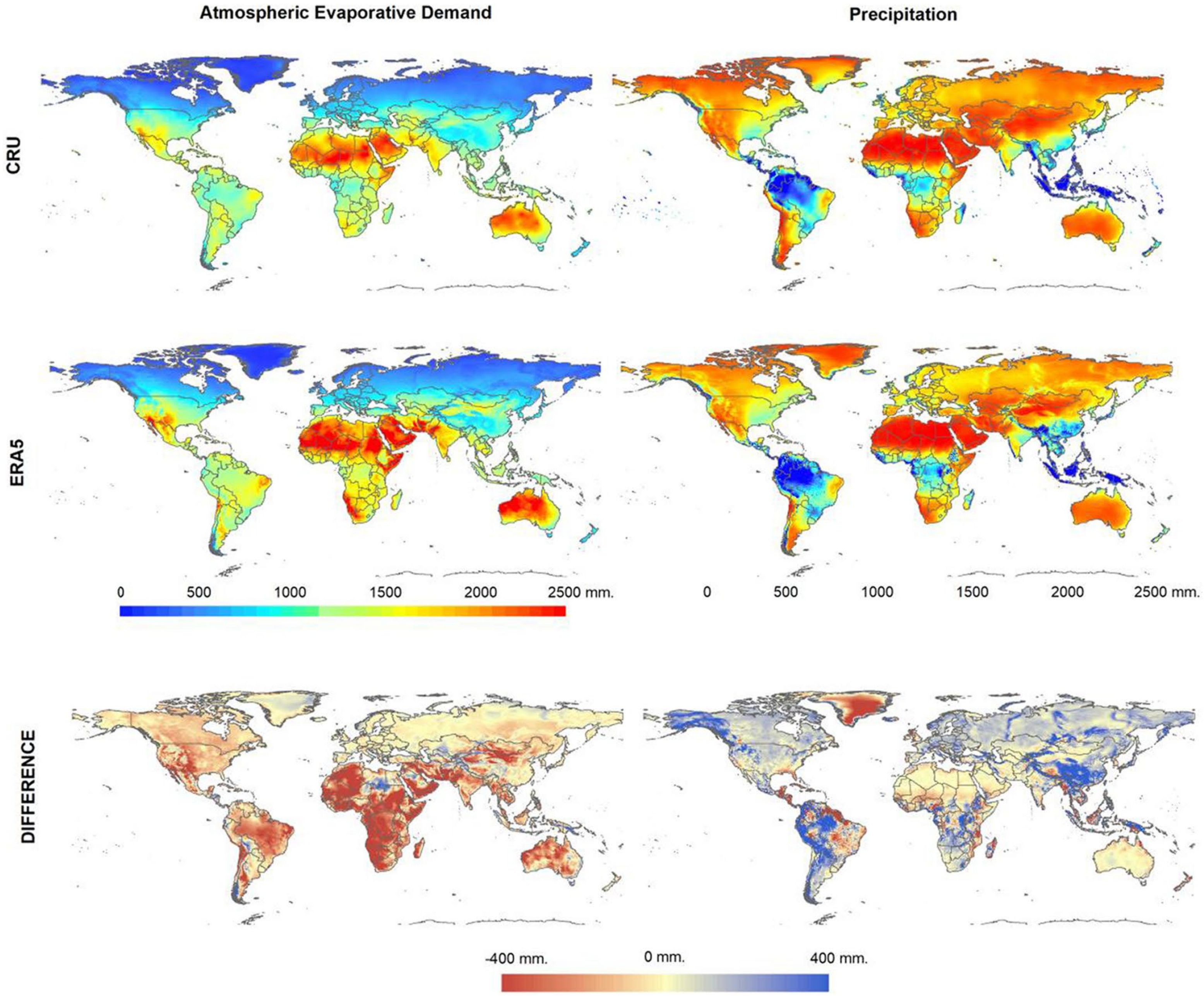
Summary for 29 extremes indices



Dunn *et al* 2022 Front. Clim.; https://doi.org/10.3389/fclim.2022.989505

Drought

Drought-related variables

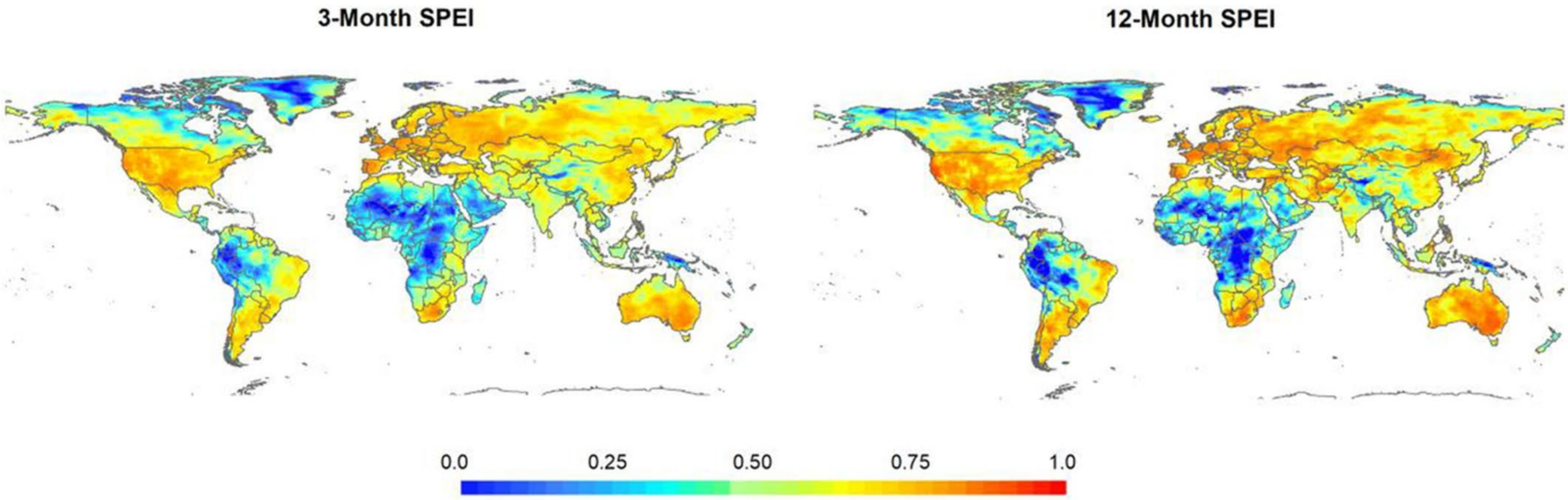


Evaporative Demand (PET) calculated following the FAO-56 Penman-Monteith approximation,
based on daily data of 2-m maximum and minimum air temperature, downward surface solar radiation, 10-m wind speed and 2-m dewpoint temperature.

Vicente-Serrano *et al* 2022 Geoscience Data Journal https://doi.org/10.1002/gdj3.178

Correlation of SPEI (CRU – ERA5)

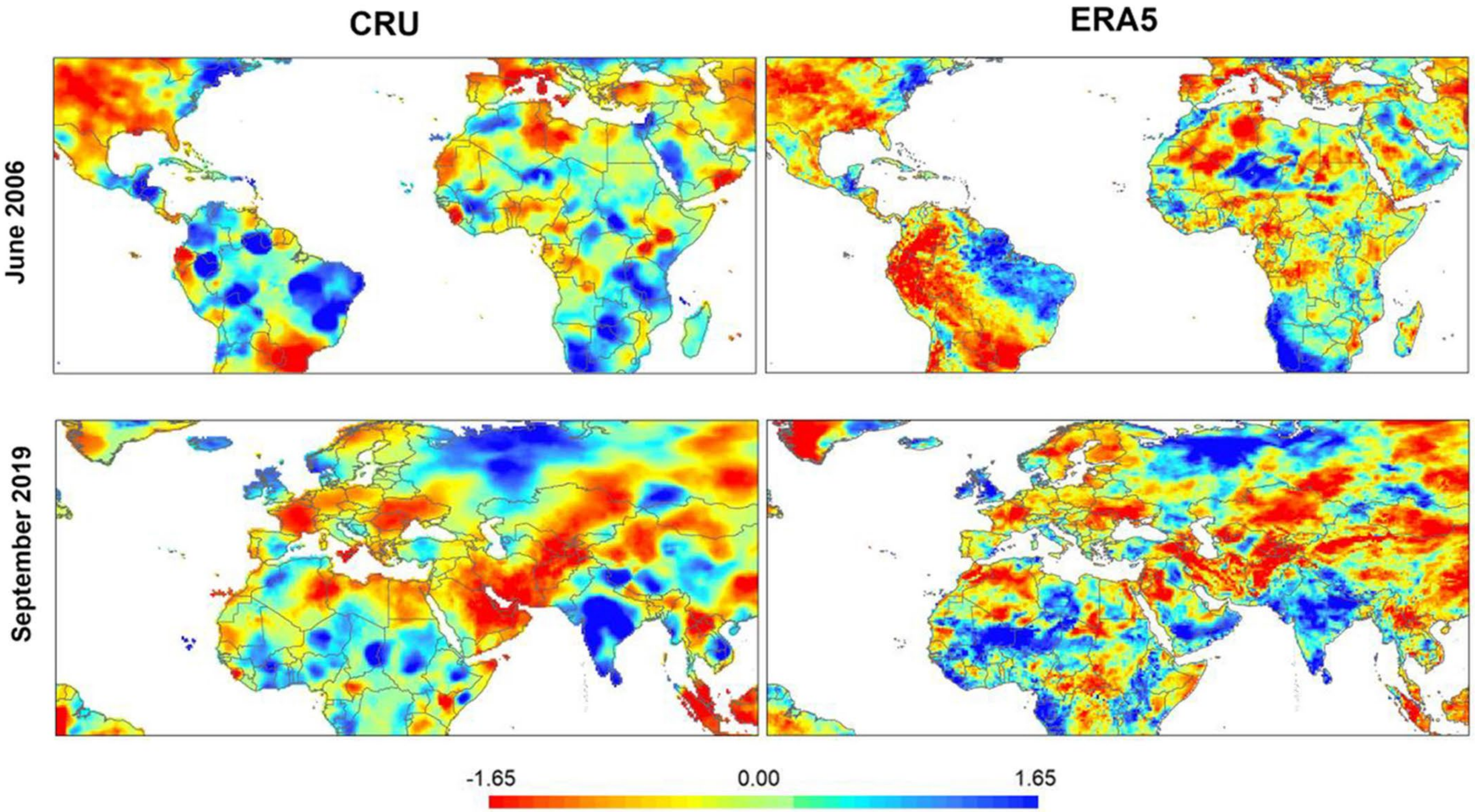
Standardised Precipitation-Evapotranspiration Index (SPEI)



Pearson's r correlation

Vicente-Serrano *et al* 2022 Geoscience Data Journal https://doi.org/10.1002/gdj3.178

Spatial fields of SPEI3 for specific dates



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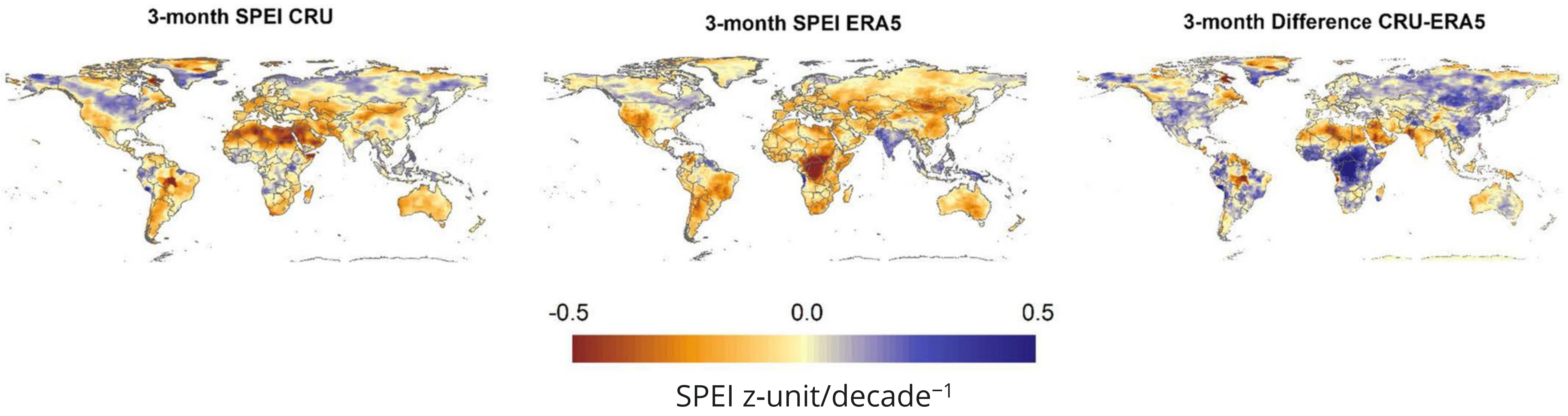
Vicente-Serrano *et al* 2022 Geoscience Data Journal https://doi.org/10.1002/gdj3.178

Trends



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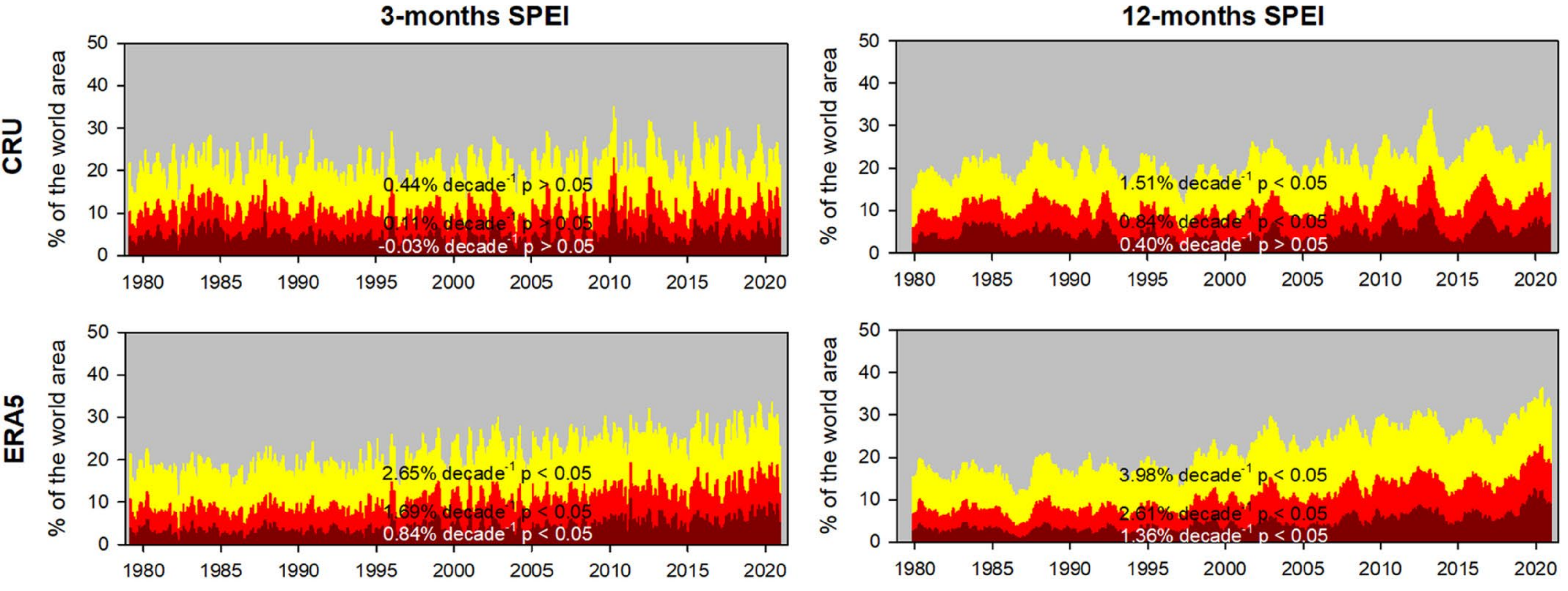
Vicente-Serrano *et al* 2022 Geoscience Data Journal https://doi.org/10.1002/gdj3.178

Time series of global area in drought conditions



Pearson's r correlations:
3-months: *Mild:* 0.48, *Moderate:* 0.52, *Extreme:* 0.56
12-months: *Mild:* 0.52, *Moderate:* 0.60, *Extreme:* 0.67

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Vicente-Serrano *et al* 2022 Geoscience Data Journal https://doi.org/10.1002/gdj3.178

Storms

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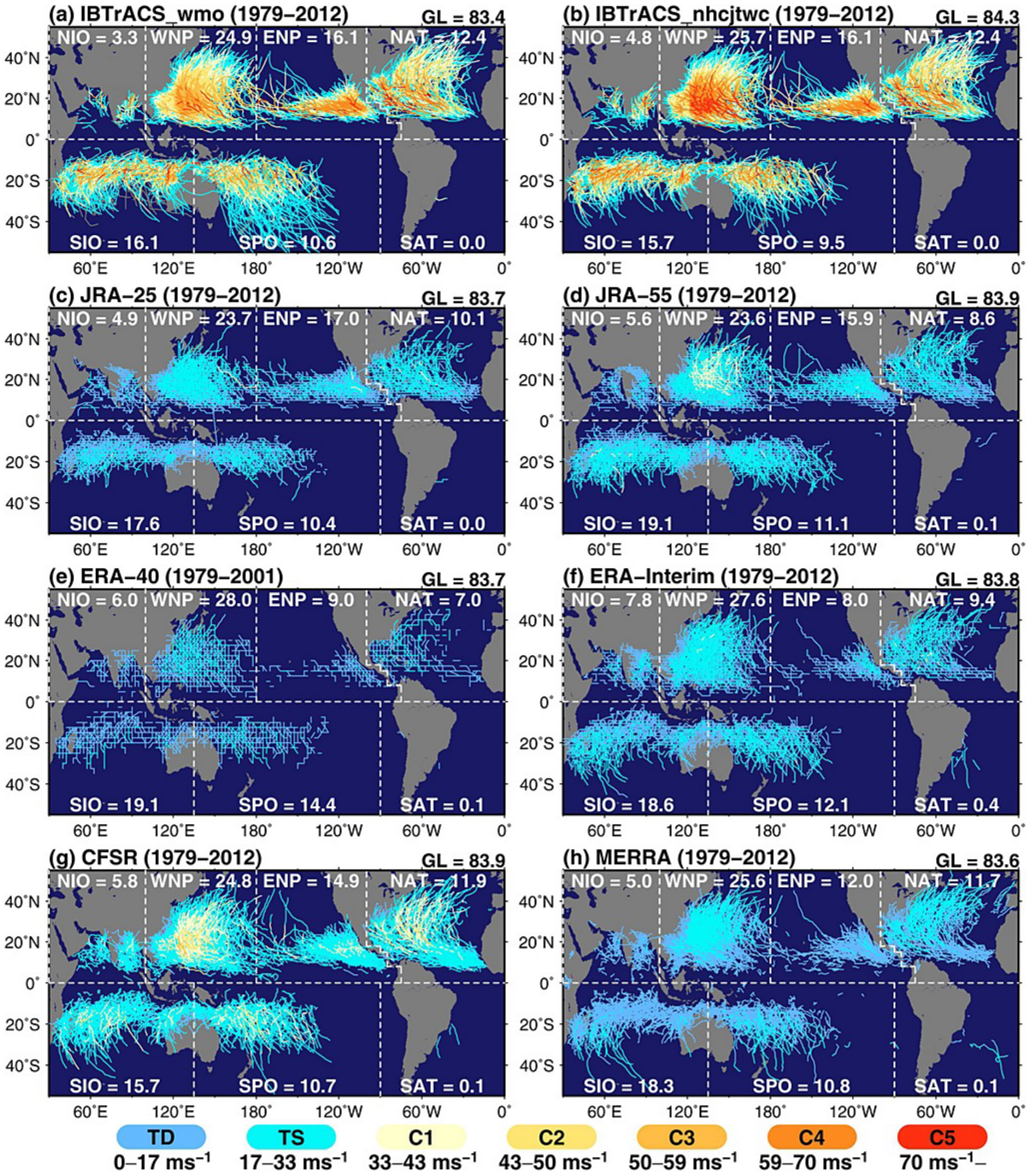
Tropical Cyclones Climatology



Most of the reanalyses reproduce a reasonable global spatial distribution of observed TCs and temporal interannual variation of total TC frequency

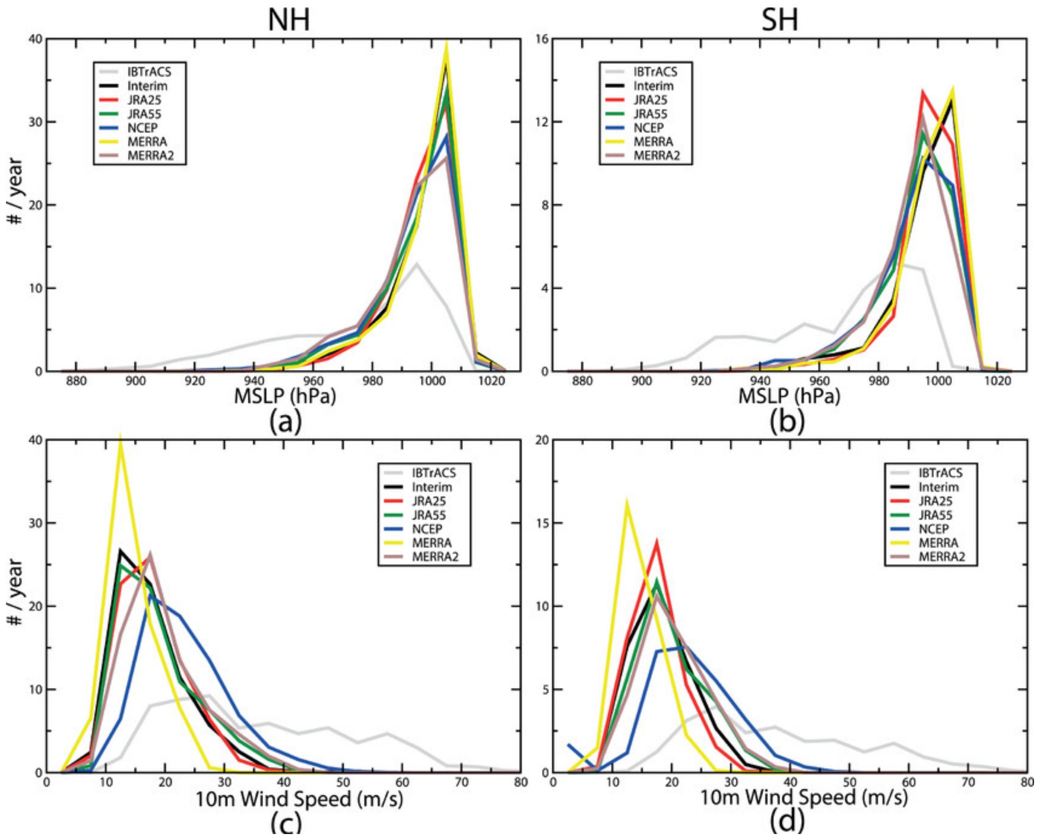
Of the six reanalysis data sets, JRA-55 appears to be the best in terms of

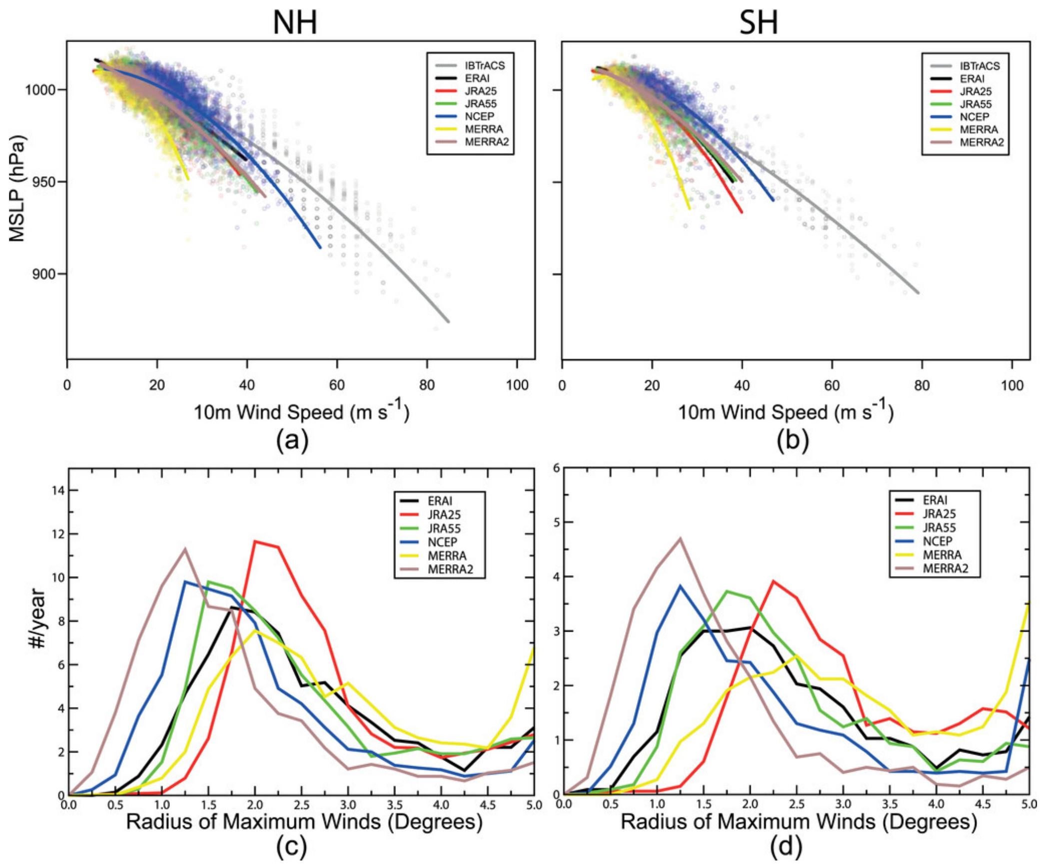
- highest skill for spatial and temporal distribution of TC frequency of occurrence,
- highest TC hitting rate, lower false alarm rate, reasonable TC structure in terms of the relationship between maximum surface wind speed and sea level pressure,
- higher correlation coefficients for interannual variations of TC frequency.

These results also suggest that the finest-resolution reanalysis (MERRA) are not always the best in terms of TC climatology.

Murakami 2014 GRL https://doi.org/10.1002/2014GL059519

Tropical Cyclones Climatology



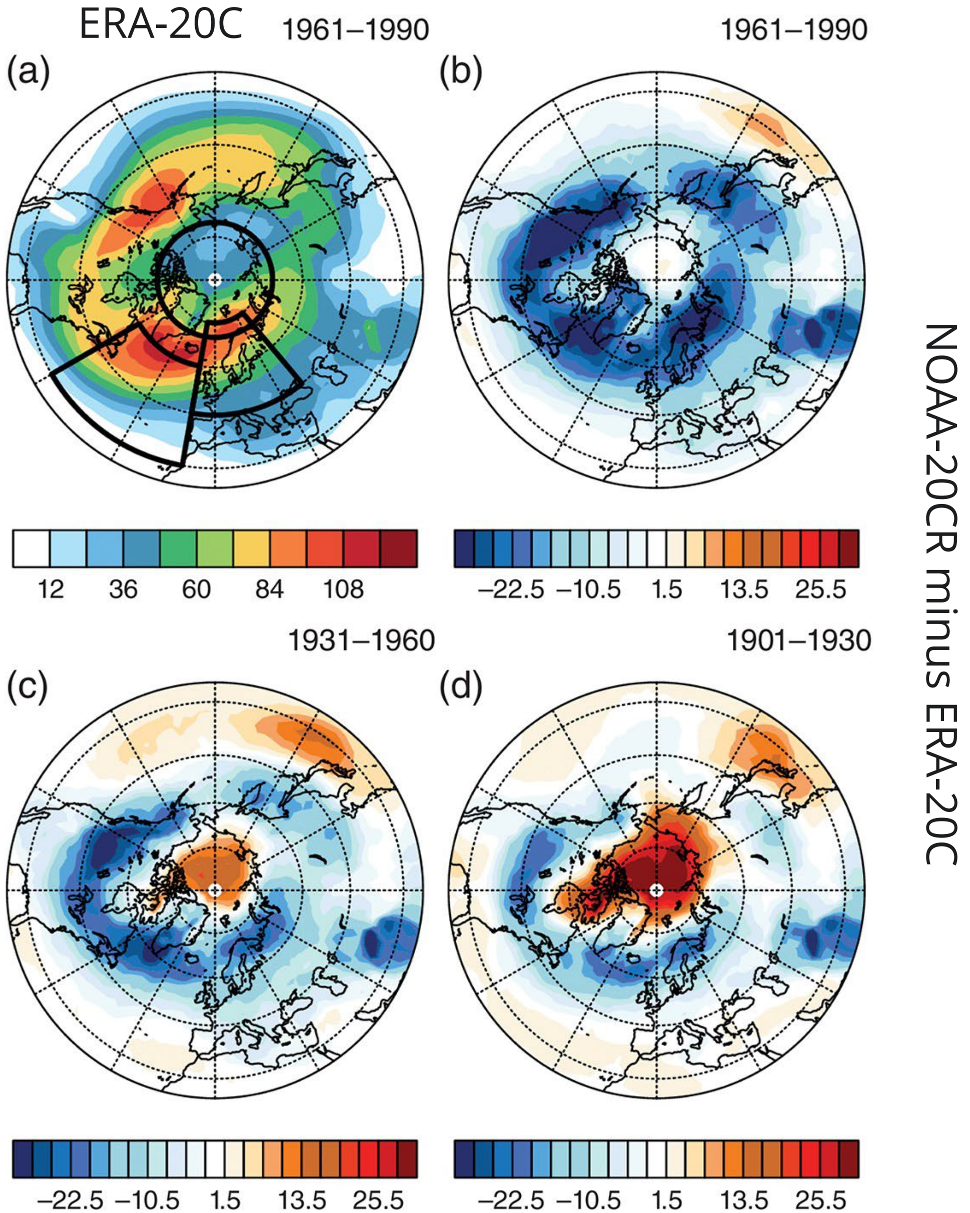


- nearly every cyclone present in IBTrACS over the period 1979–2012 can be found in all six reanalyses
- TC intensities are significantly underrepresented in the reanalyses compared to the observations
- largest uncertainties in TC identification occur for the weaker storms (exacerbated by uncertainties in the observations for weak storms and lack of consistency in operational procedures)
- definite improvements in how well TCs are represented in more recent, higher-resolution reanalyses (e.g. MERRA-2 is comparable with the NCEP-CFSR and JRA-55 reanalyses)

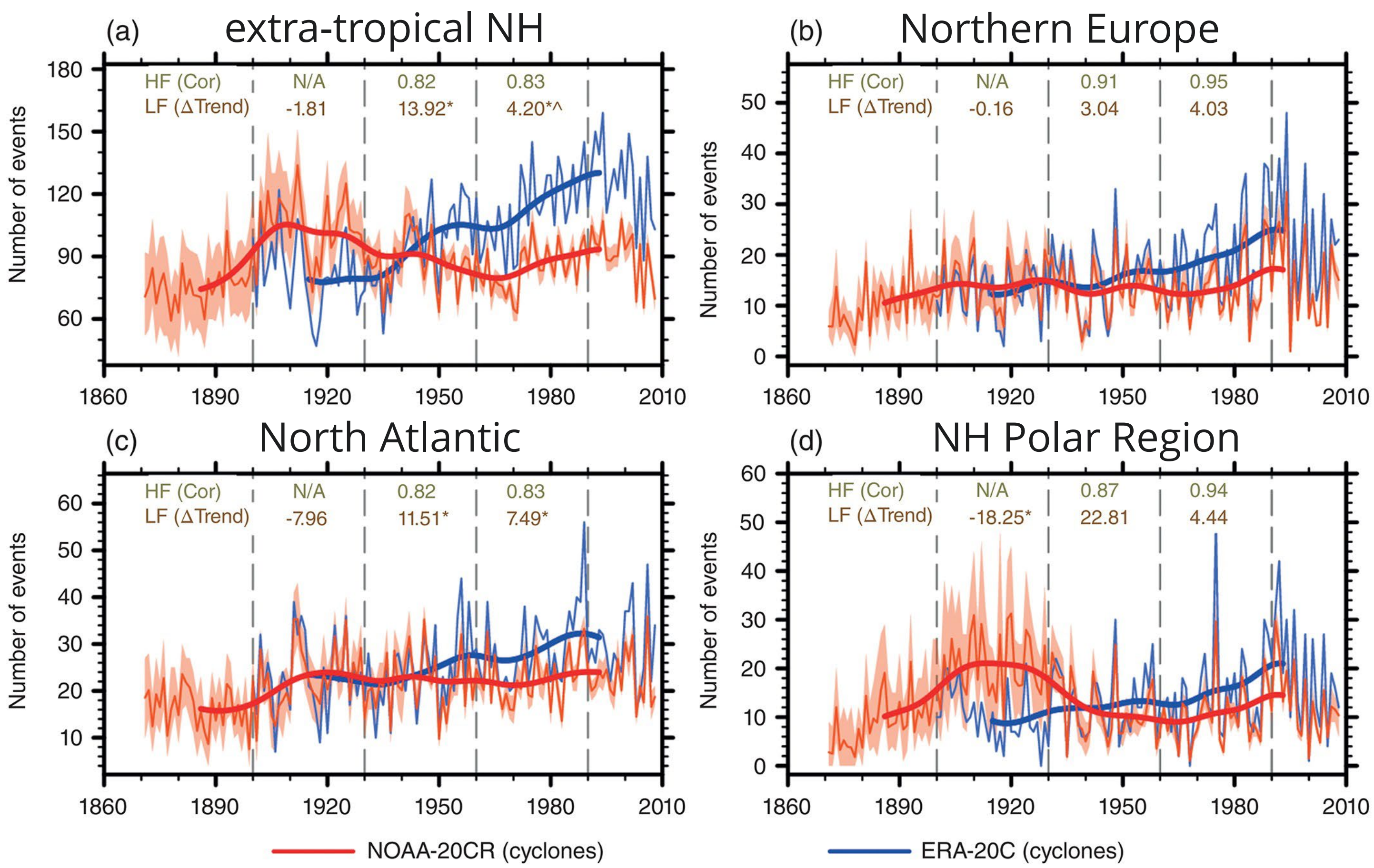
Hodges *et al* 2017 J of Climate https://doi.org/10.1175/JCLI-D-16-0557.1

Extra-Tropical Cyclones in long-term reanalyses

Track densities



Regional changes in extreme cyclones (<970hPa)



Befort *et al* 2016 Atm Science Letters, https://doi.org/10.1002/asl.694

Processes driving or amplifying extremes

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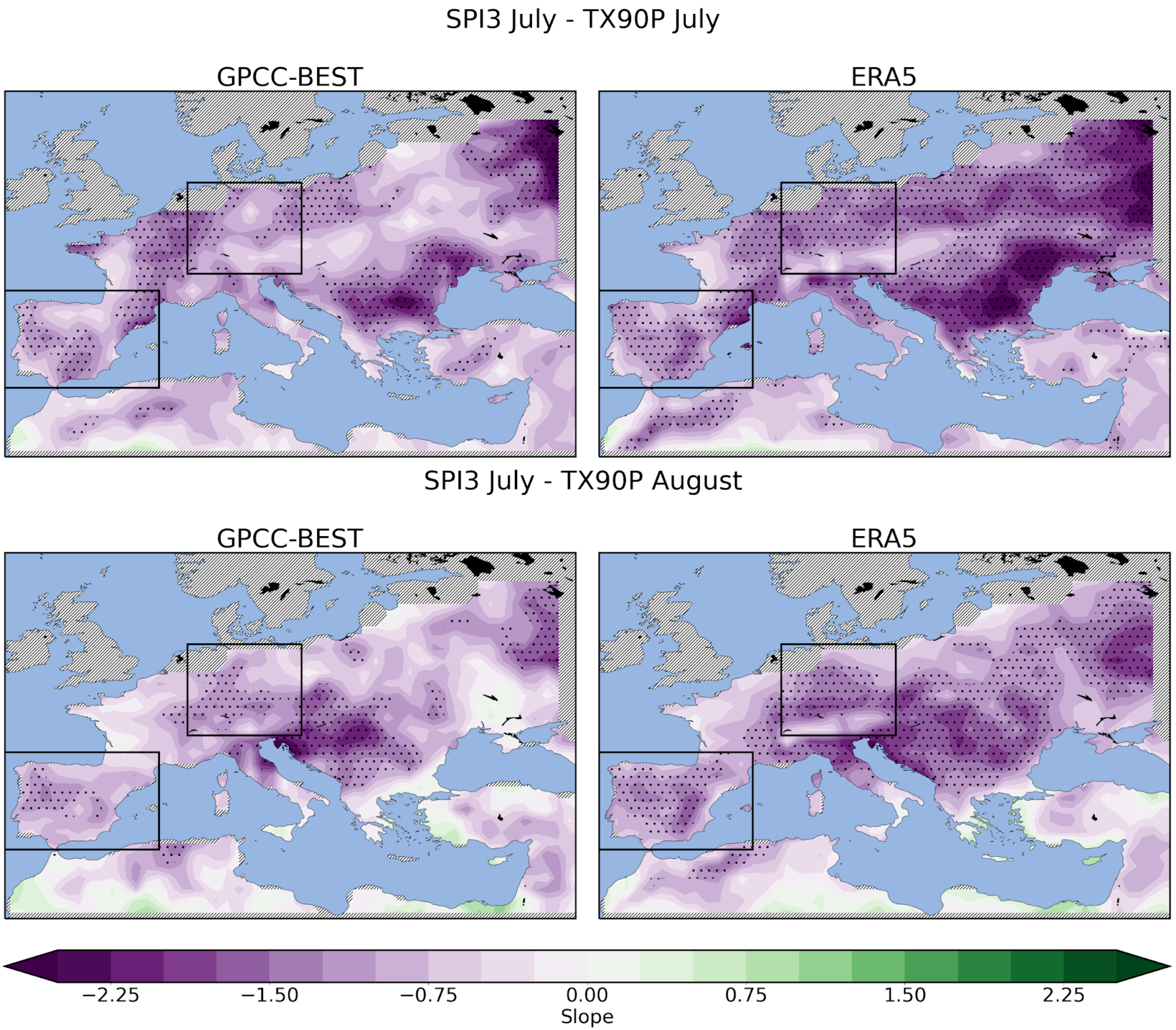
Relationship between moisture availability and hot extremes



ERA5 shows stronger relationship between moisture availability (measured as e.g. SPI or SPEI) and the number of warm days in summer compared to observations in large parts of Europe

CopERnIcus climate change Service Evolution

Courtesy Alvise Aranyossy, BSC

Summary and concluding remarks

Summary

There is often a large spread across different reanalyses and observational products with regards to measuring different aspects of extremes, and their temporal variations

- Reasonable agreement for temperature extremes, and reasonably robust assessment of long-term changes in well-observed regions (caution: inhomogeneities / data discontinuities)

- Large inter-product spread for precipitation extremes (in particular frequency measures), and regionally different long-term trends

- Regionally inconsistent drought changes between reanalysis and gridded observation

- Accurate representation of TCs and their tracks since 1979, but intensities too low

- Shortcomings and biases with process-representation in particular at small/local scales

Challenges

Reanalysis is only as good as the model and observations used to generate it!

- **Disagreement in regional trends / long-term context**
    - Large spread/uncertainty across different reanalysis products
    - Reanalyses probably not ready to look at long-term trends in precipitation extremes on climate timescales especially in regions where we have no (other, ground) data.
    - efforts needed on "ground truthing" reanalyses: has to include long-term, homogenous ground stations; need to focus on data sparse areas

- **Temporal inhomogeneities**
    - difficulties in obtaining clear information as to the inhomogeneities in any of the reanalyses: when do satellites or networks start to (or stop) being assimilated?

- **Process representation relevant to extremes**
    - E.g. resolving processes at higher resolution (storms, convection, etc.)
    - Represent and assimilate relevant earth system components (e.g. land surface)

- **Useability**
    - Pre-calculated extremes products would help broader pick-up by researchers with limited computational/data facilities

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ICREA

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Thank you.

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Pattern correlations