Which is the best metric to use to answer my science question?

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The Validation with Observations: 1. Annual and seasonal means for bias and spatial correlation

What do I need??

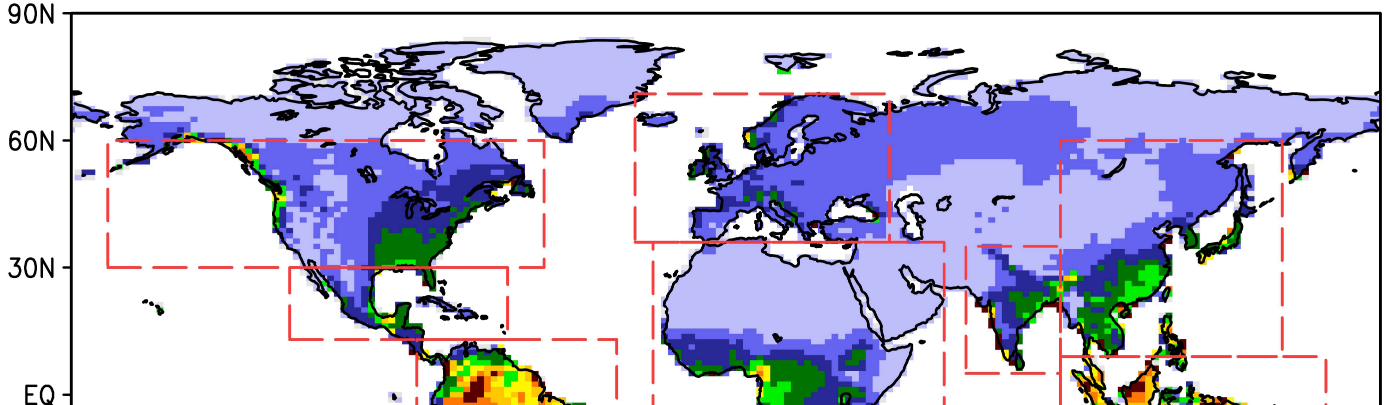
- MONTHLY time series of the model and the observed values

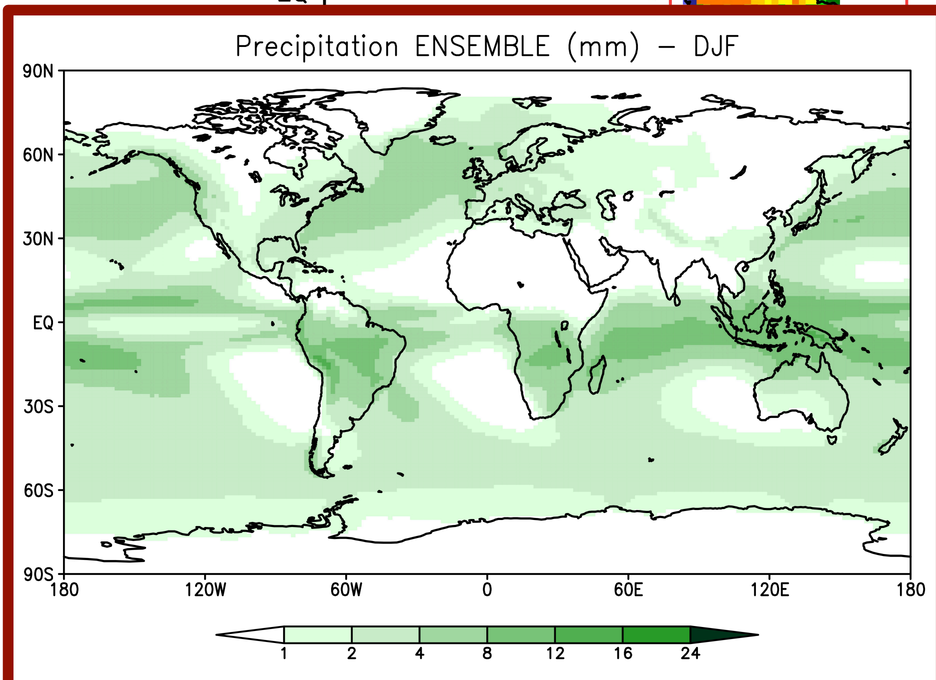
How should I process the data ??

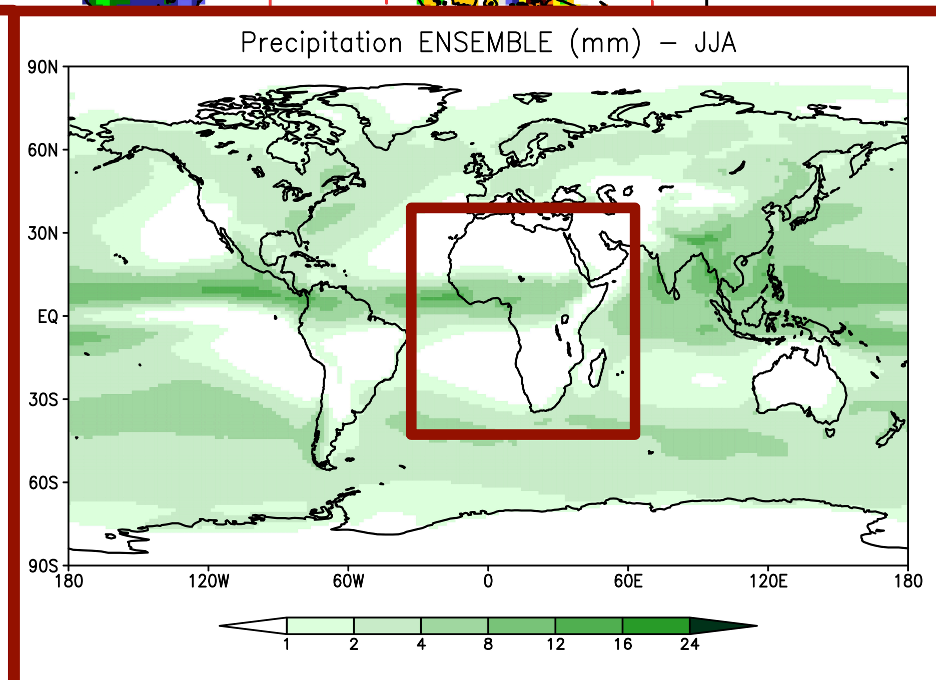
- selection of the 4 seasons and than average over time
- selection of sub-domains and average over space > annual cycle

Mean Validation

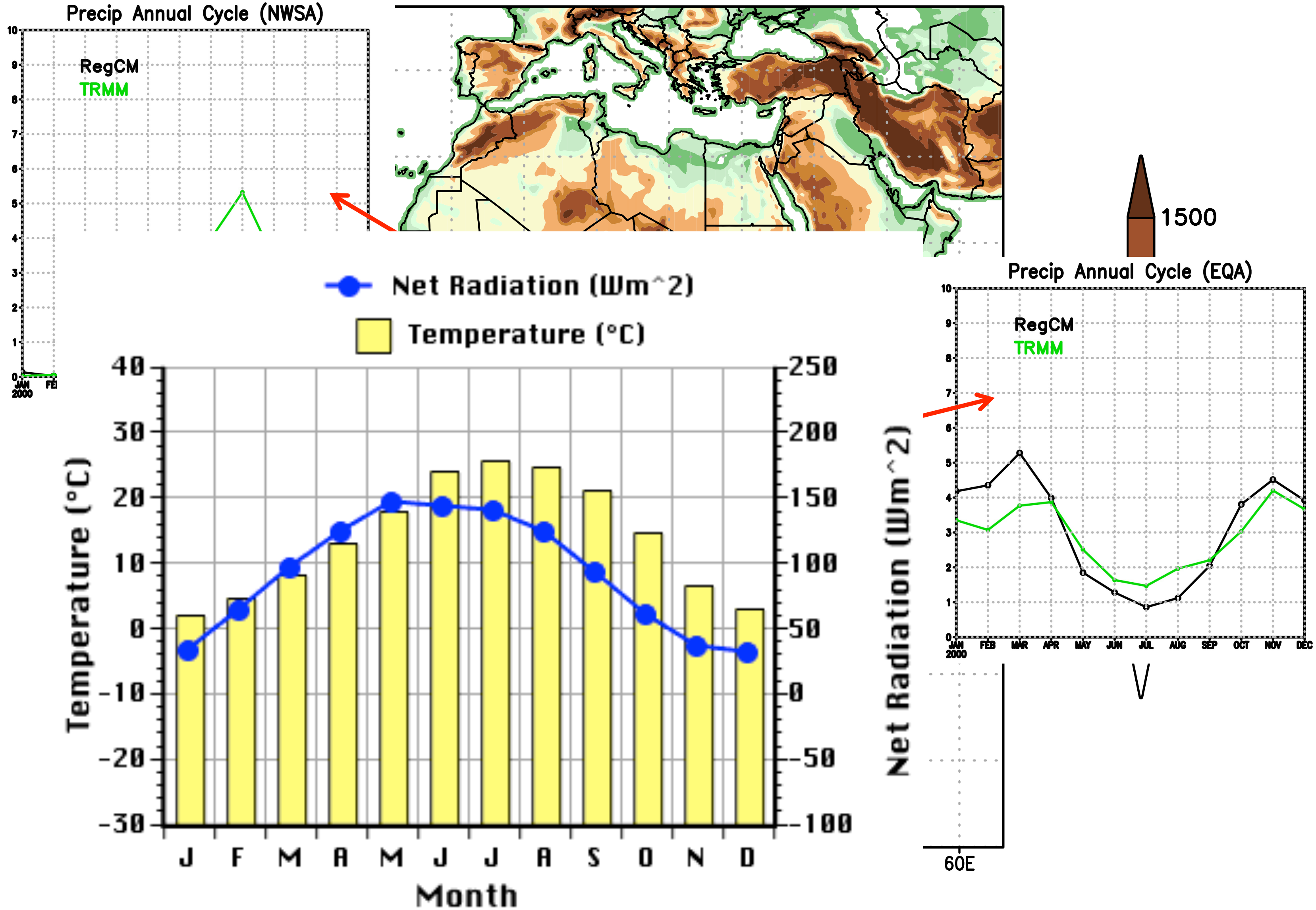
Annual Precipitation (mm/day)







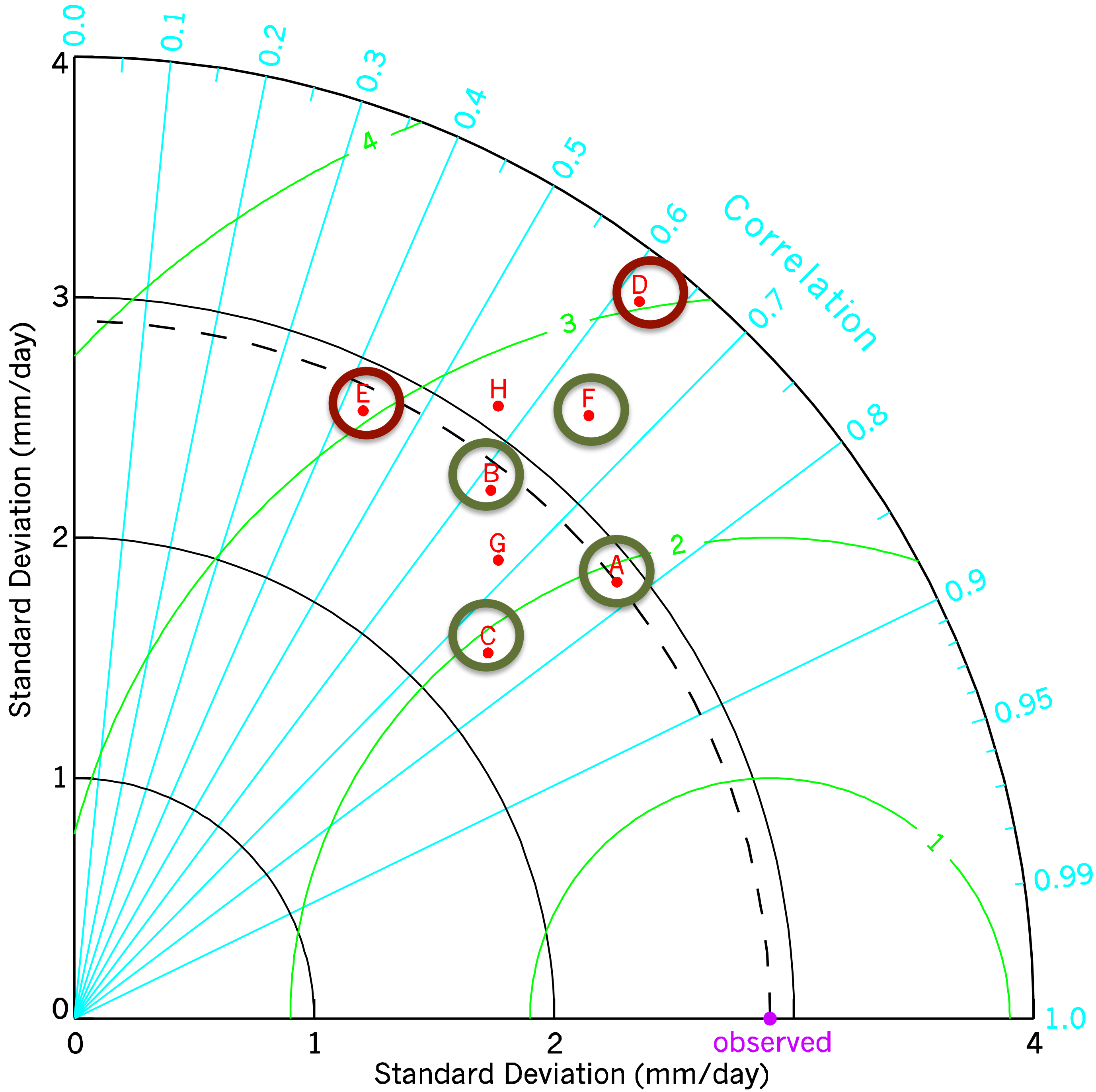
The Validation with Observations:
2. the annual cycle



3. The Taylor Diagrams: information on spatial correlation and signal variability

- Provide a way of graphically summarizing how closely a pattern (or a set of patterns) matches observations. The similarity between two patterns is quantified in terms of their correlation, their centered root-mean-square difference and the amplitude of their variations (represented by their standard deviations).

- Note that there is NO information on BIAS in aTaylor diagram, since any difference in the means is first removed, before computing the second-order statistics.



Correlation
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.95
0.99
1.0
Standard Deviation (mm/day)
Standard Deviation (mm/day)
0
1
2
3
4
4
3
2
1
observed
A
B
C
D
E
F
G
H

3. The Taylor Diagrams: information on spatial correlation and signal variability

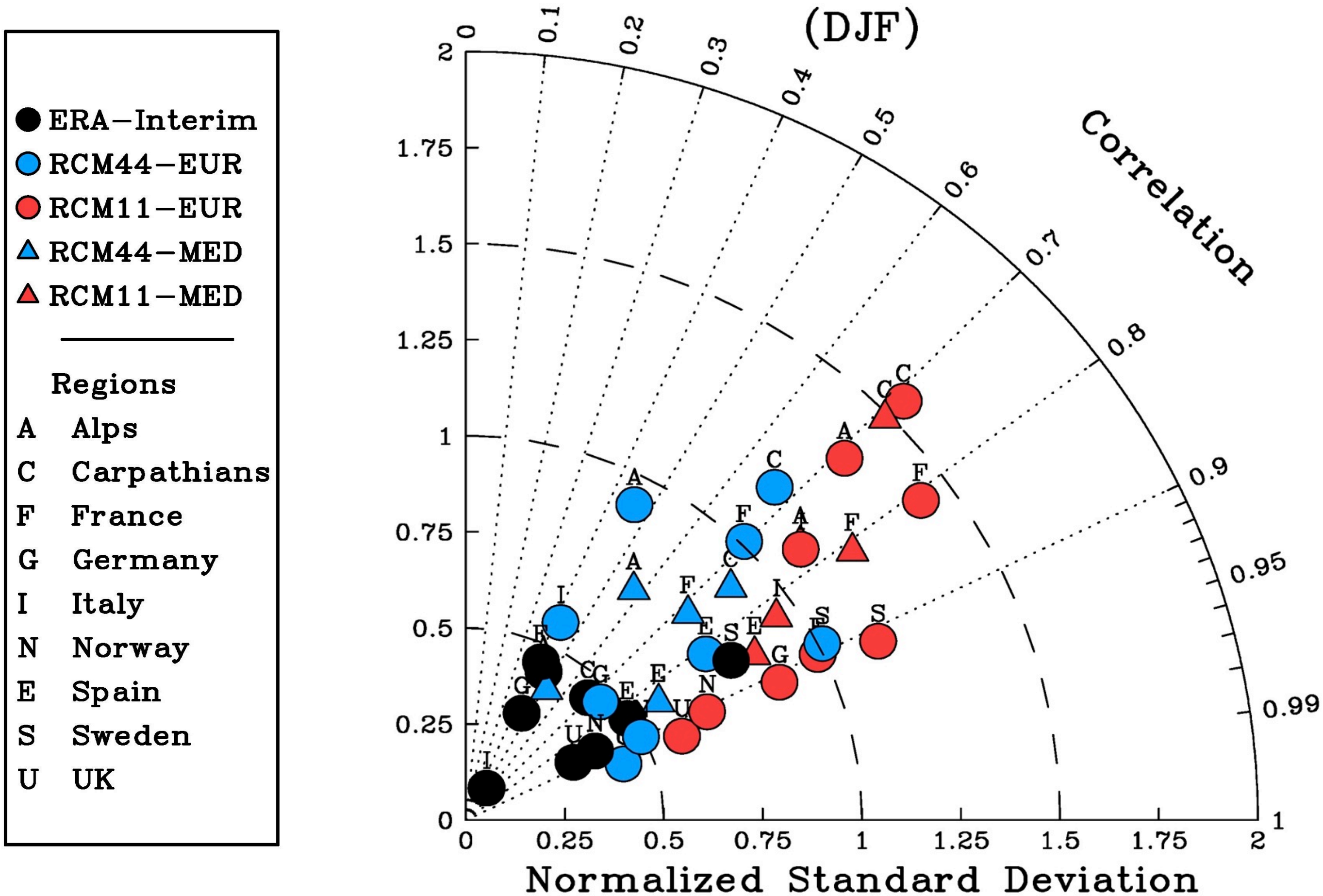


Figure 3. Taylor diagrams of the ensemble mean seasonal precipitation in the different analysis regions for the ERA-Interim, RCM44 and RCM11 (both All Models and Med-CORDEX models) ensembles with respect to the corresponding regional observation datasets. The distance from the point 1 measures the centered (bias removed) RMSE and the mean is taken over the different regional analysis periods.

4. Interannual Variability

The ability of a climate model to capture realistic **interannual** variability is an important measure of its performance.

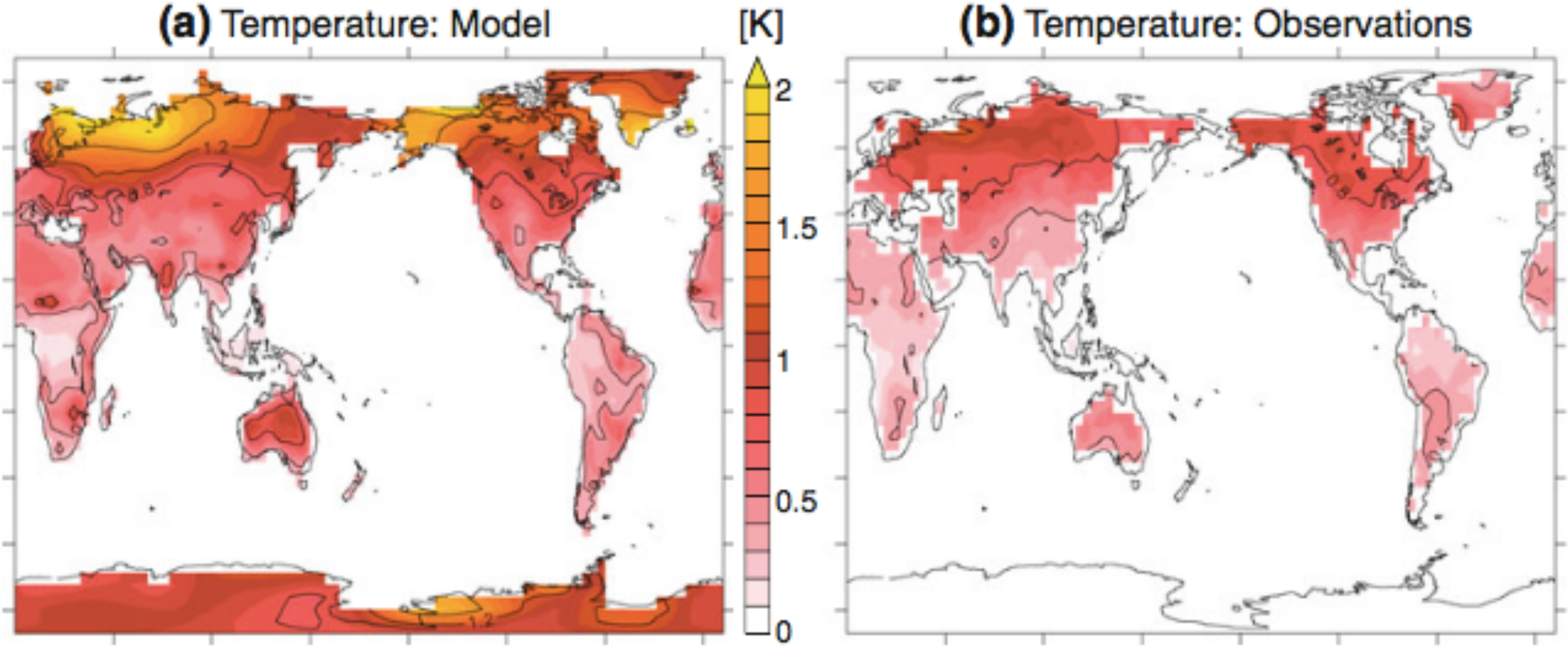
- **<u>The interannual standard deviation</u>** (for temperature): it is a measure of how much a model is able to reproduce the year by year variability of temperature compared for example to the observations. It is calculated as standard deviation.

the value of a single year

mean value of temp (for example) for the period considered

$$\sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{n}}$$

number of years



Simulated versus observation-based interannual variability over land. (a) Simulated interannual variability in surface temperature obtained by computing the standard deviation of annual mean values from the unforced control simulation.

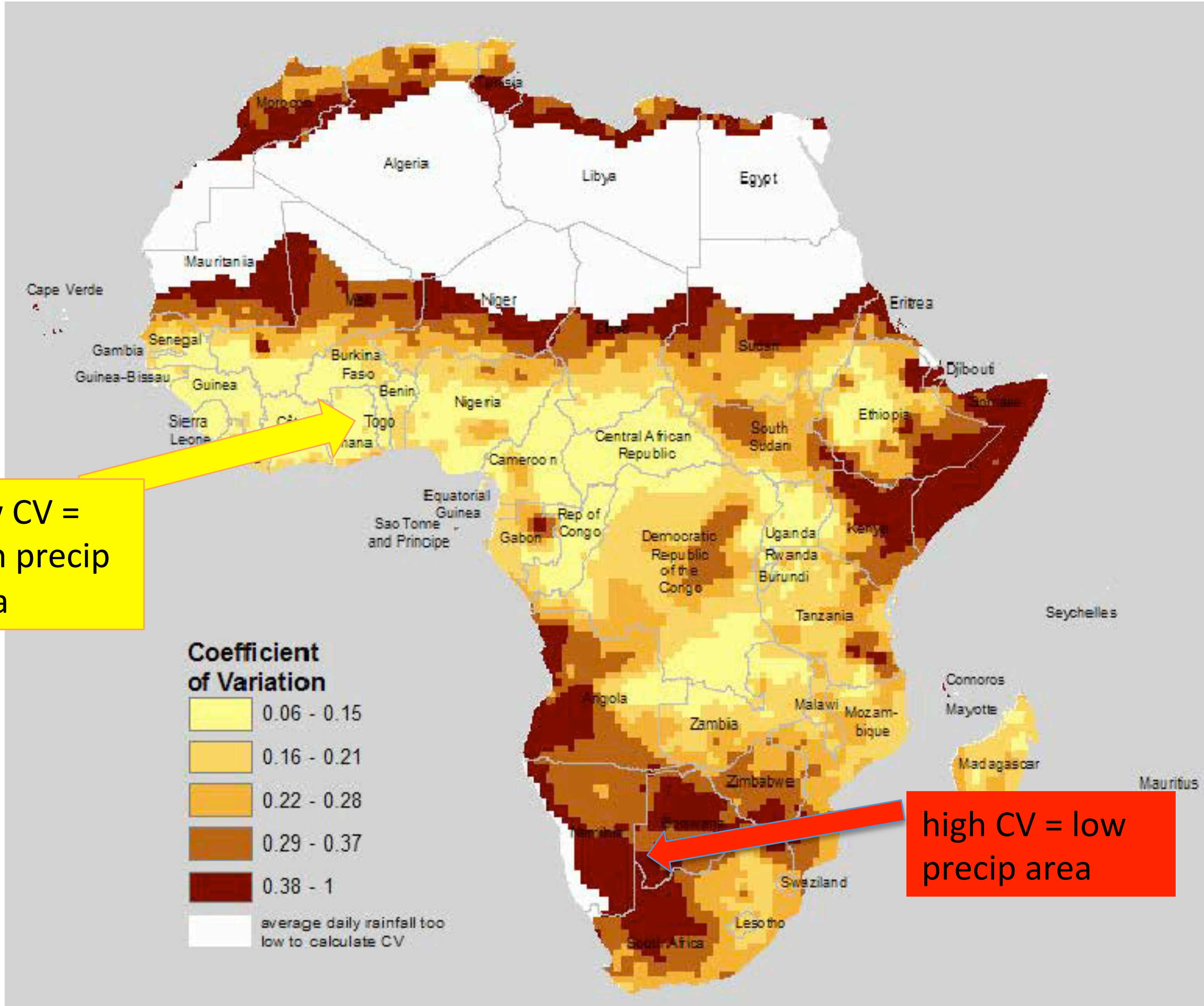
4. Interannual Variability

- **<u>The coefficient of variation</u>** (for precipitation): it is a measure of relative **variability**. It is the ratio of the standard deviation to the mean (average):

Coefficient of Variation = (Standard Deviation / Mean) * 100

The coefficient of variation is useful because the standard deviation of precipitation data must always be compared to the mean value. This because of the large variability of precipitation values. Moreover, the actual value of the CV is a dimensionless number, thus it’s perfect for comparison between data sets with different units or widely different means.

Typical values of CV in Africa



Low CV = high precip area

high CV = low precip area

Extremes Validation:

What do I need??

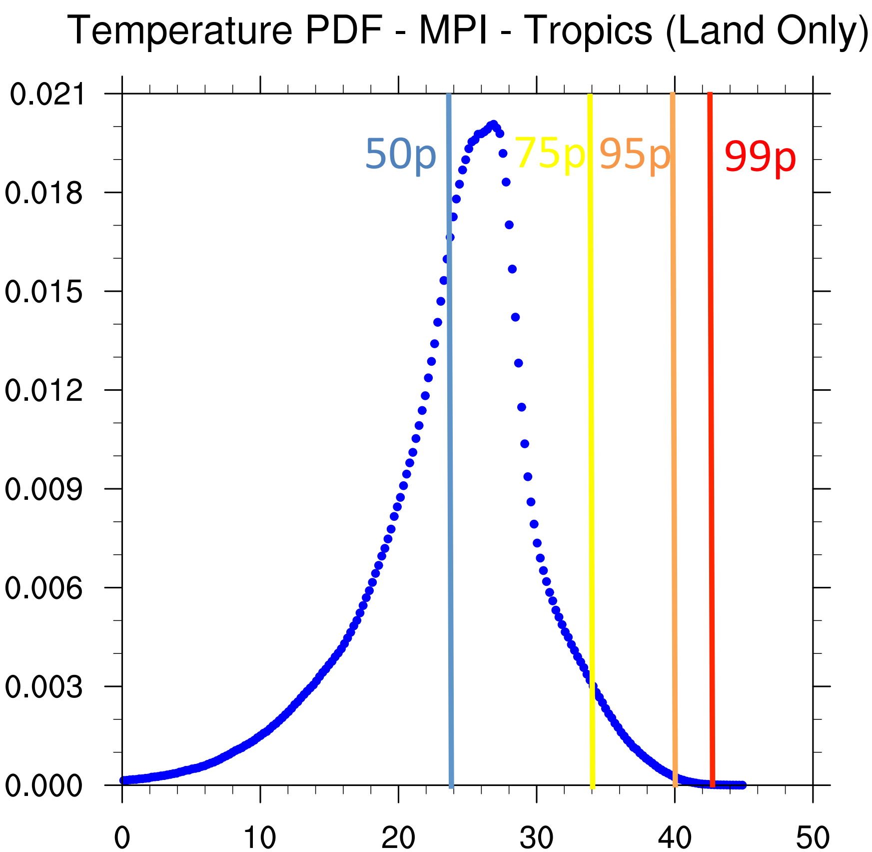
- DAILY (or sub-daily) time series of the model and the observed values

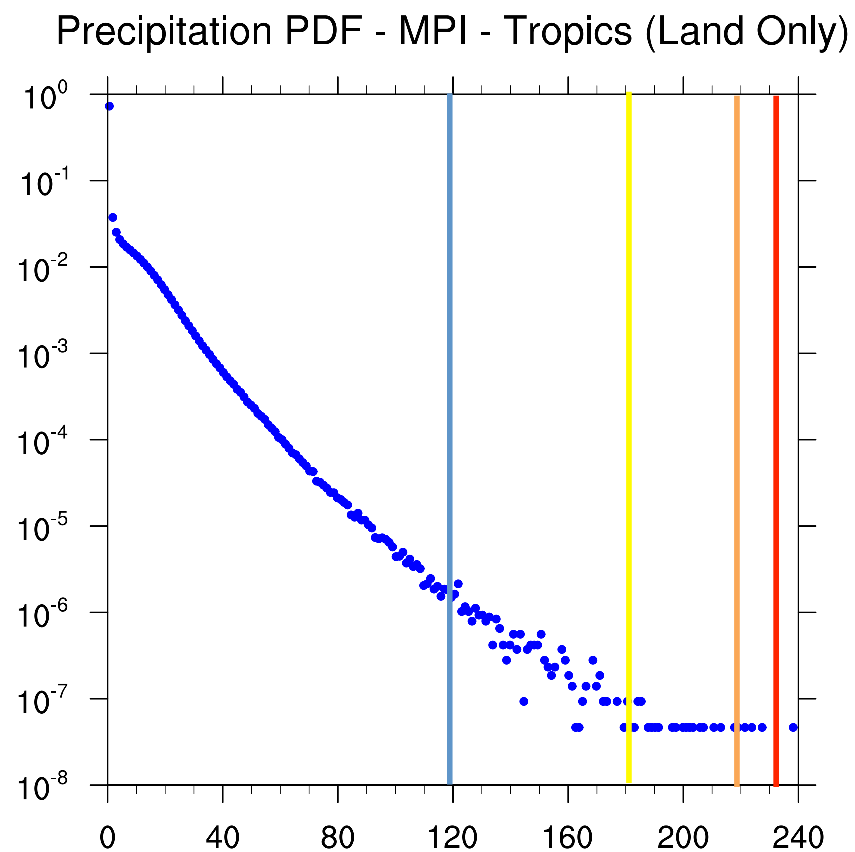
For example: if I have a 10-year period, my daily time series will have 3650 time steps.

- at a grid point level, without averaging over space

I need to keep BOTH the SPACE and TIME resolution high!!

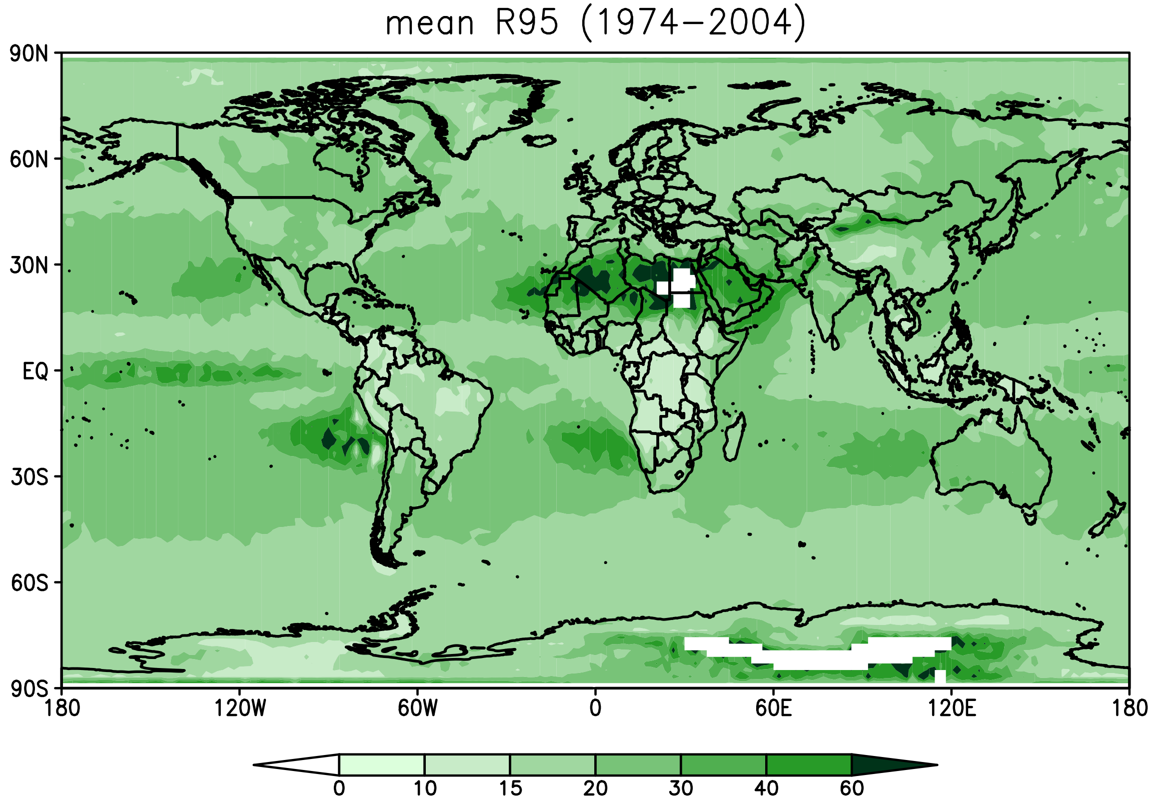
Extremes Validation:
1. the Probability Distribution Function





Extremes Validation:
2. R95 and R99

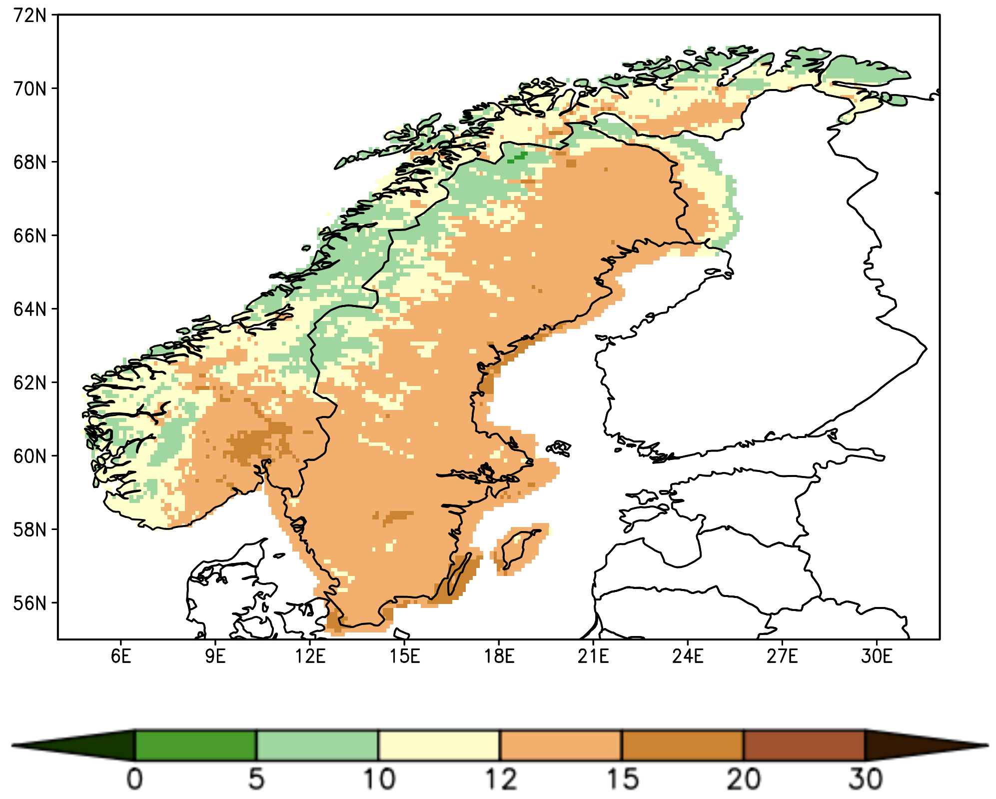
DEFINITION:
Precipitation percent due to the sum of those days > 95th (or 99th) percentile of the daily precipitation amount at WET days (precip >= 1 mm) for any period used as reference. (%)



Extremes Validation:
3. Consecutive Dry Days (CDD)

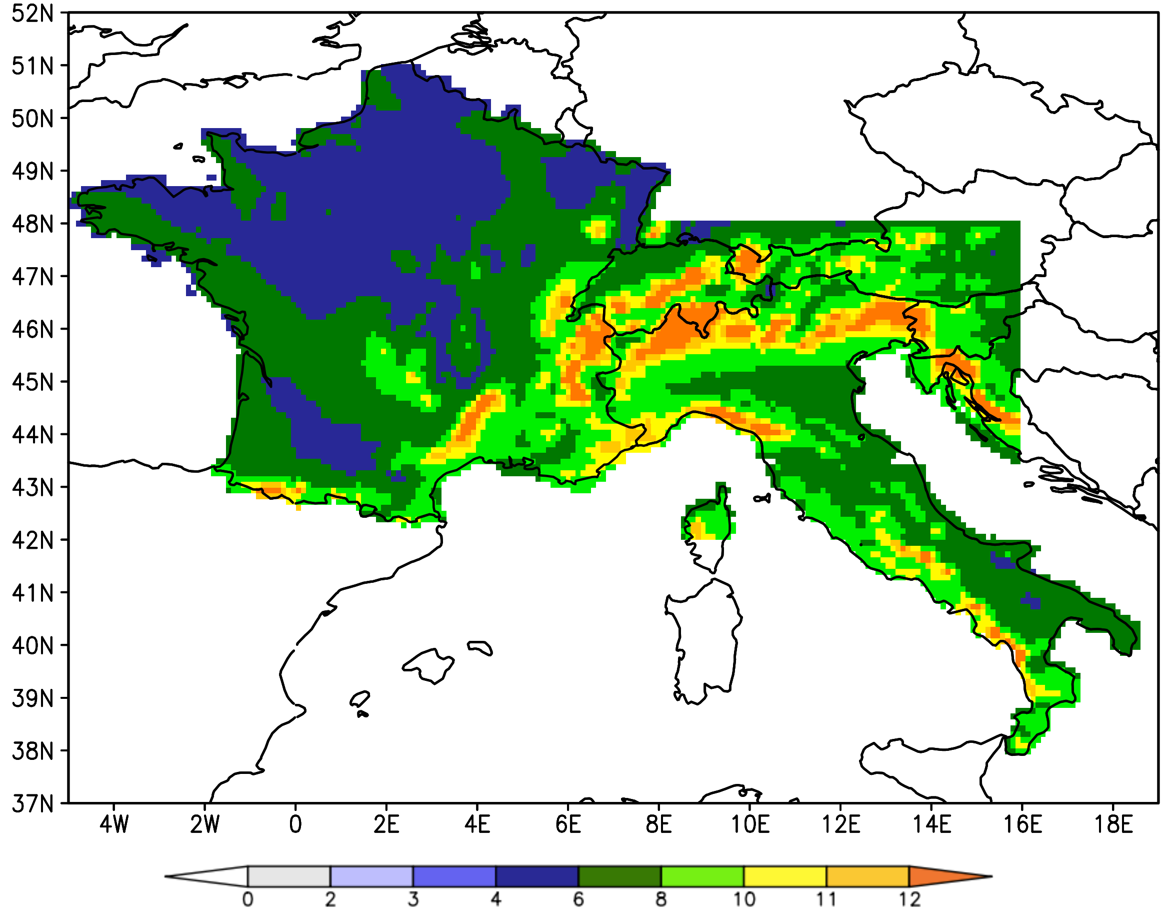
DEFINITION: Consecutive dry index per time period.

CALCULATION:
Given a daily time series of precipitation, the largest number of consecutive dry days (where precip < 1 mm) is counted. Units are No. of days.



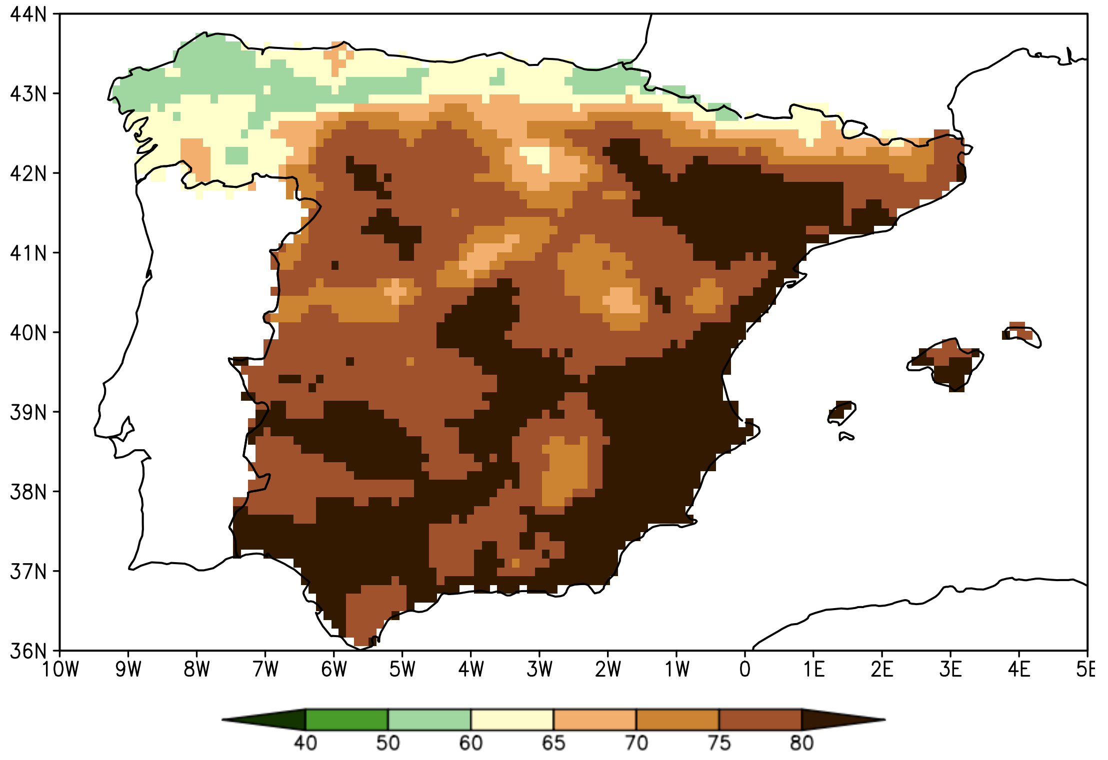
Extremes Validation:
4. Simple Daily Intensity Index (SDII)

DEFINITION: Simple daily intensity index per time period, that is the mean precipitation amount at wet days (precip >= 1 mm). Units are mm/day



Extremes Validation:
5. WET/DRY Frequency

CALCULATION:
The number of wet (or dry) days are summed up and divided for the total number of days in the period considered. Units are %.

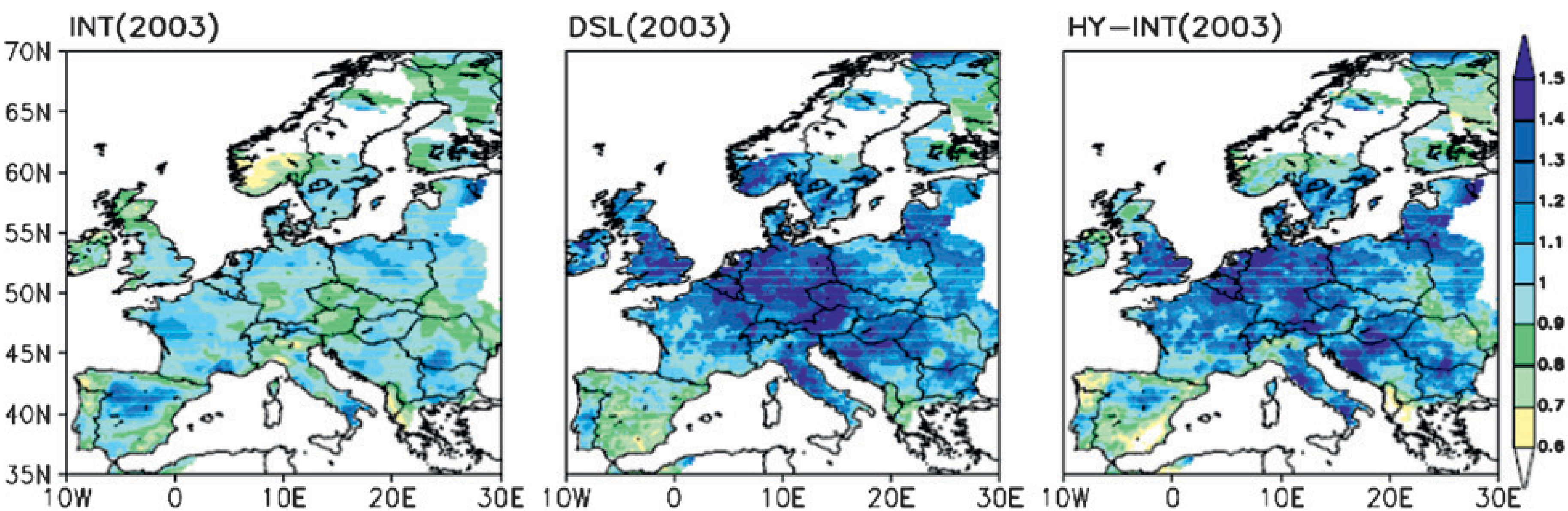


Extremes Validation:
6. Hydro-climatic Index (Hy-int)

DEFINITION: Product of normalized mean precipitation intensity (SDII) and normalized mean dry spell length (DSL). It is a measure of change in hydroclimatic regimes, with increasing HY-INT implying a shift towards a regime of more intense and less frequent precipitation events.

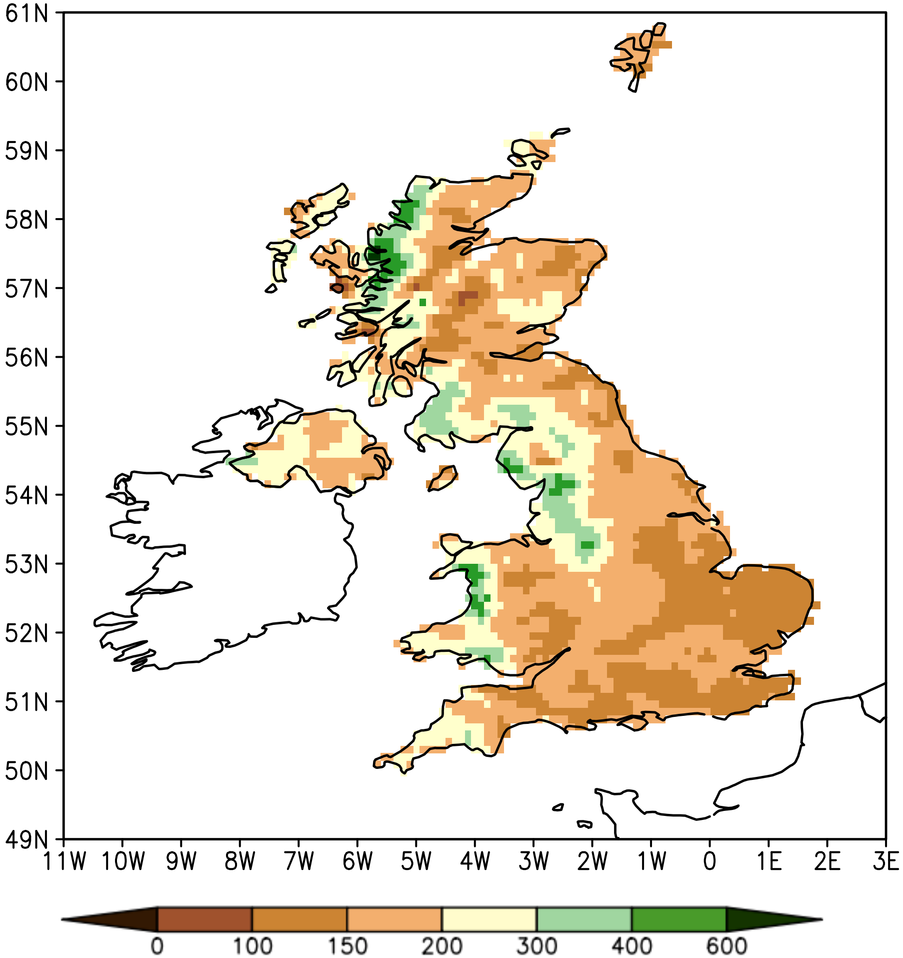
CALCULATION:

- given a daily time series of precipitation, the mean CDD for each year and the mean CDD for all the period are computed.
- dividing CDDyearly / meanCDD = normalized CDD
- the same is done for SDII



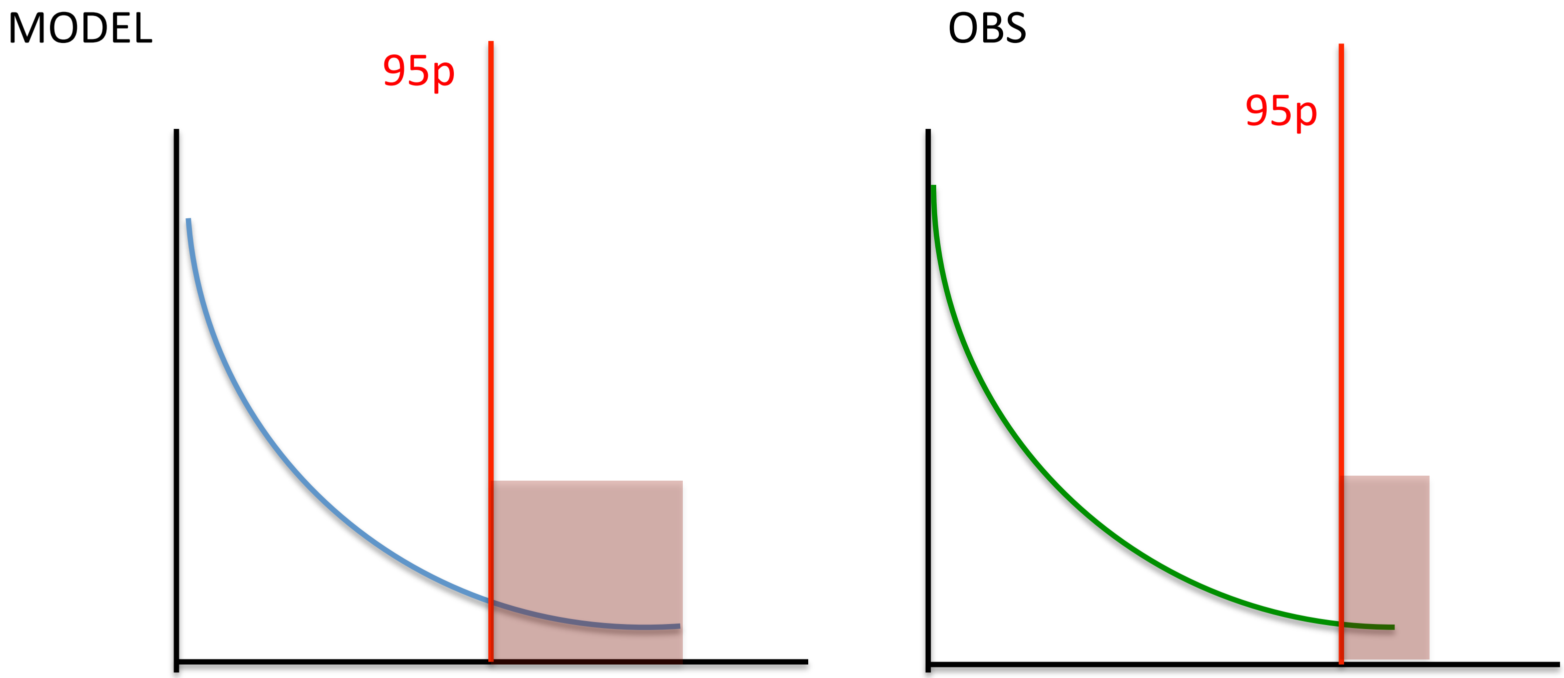
Extremes Validation:
7. Psum>R95obs

DEFINITION: The total precipitation above the reference 95th percentile of OBSERVED DAILY precipitation. Units are mm.



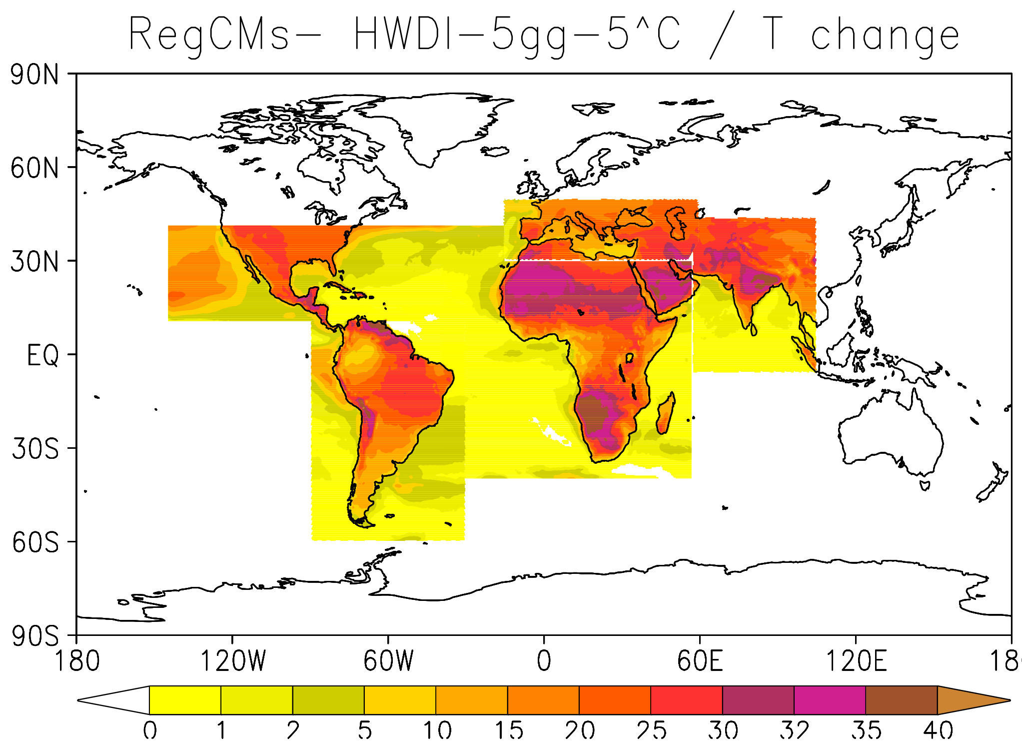
CALCULATION:

- given a daily time series of OBSERVED precipitation, the 95th percentile is calculated.
- each day of the model precipitation time series is compared with this threshold and is taken into account only if it exceeds it.
- the total precipitation is then calculated summing up the precipitation of all the selected days.


MODEL
95p
OBS
95p

Extremes Validation:
8. Heat waves

DEFINITION: Heat wave duration index, that is the number of heat wave days, where a heat wave occurs when for at least Nd consecutive days the daily maximum temperature exceeds the long term average (TXnorm) by at least Nt degrees.

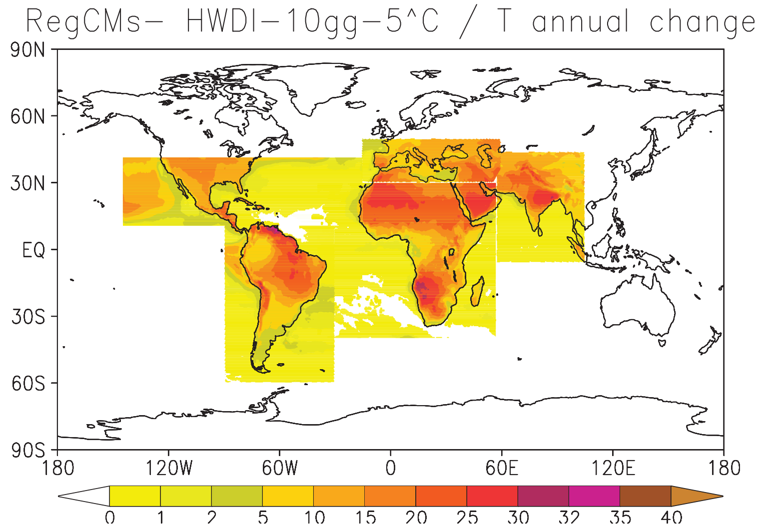


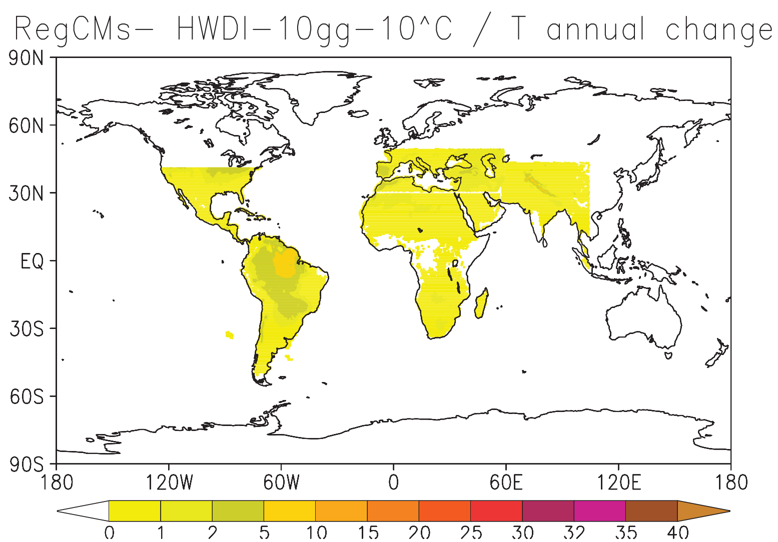
The ensemble average change in number of heat wave days (HWD) per year per degree of (local) warming, when both Nd and Nt are equal to 5

CALCULATION (of TXnorm):

- given a time series of daily maximum temperature, the mean of maximum temperature of a 5 day window centered on each calendar day of a given climate reference period is computed. (the so-called running mean)

Extremes Validation:
8. Heat waves





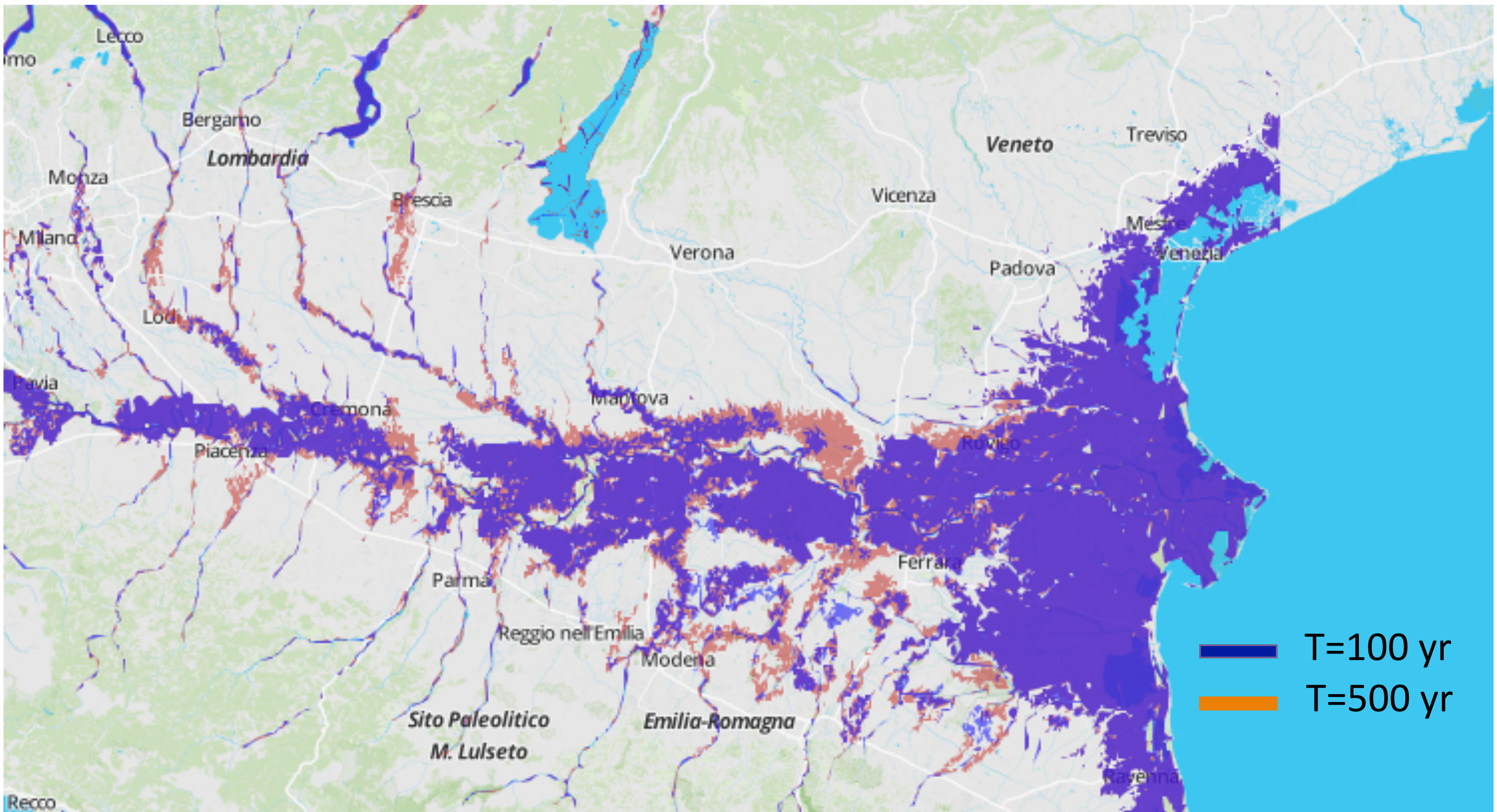
The last case would be indicative of the occurrence of extremely severe heat waves in which anomalies of at least 10°C would persist for at least 10 days. When only Nd is increased to 10 days, we do not find strong differences with respect to the first figure, while the increase in HWD is inhibited when Nt is increased to 10°C with change values HWD/year.

The main factor affecting the increase of HWD (with respect to present day climatology) is the mean warming, rather than the occurrence of peak temperature anomalies.

(Giorgi et al., 2014)

Extremes Validation:
9. Return Period and Flood Maps

DEFINITION:
The probability that the event will be equalled or exceeded in any one year. This does not mean that a 100-year flood will happen regularly every 100 years, or only once in 100 years. Despite the connotations of the name "return period". In any given 100-year period, a 100-year event may occur once, twice, more or never.



The Regional Added Value: a necessary introduction regarding observations uncertanty

Gridded observed dataset

1. to move from the station based information to the grid based, we need to go trough several steps, for example:
    - quality control
    - homogenization of the data
    - statistical procedure to interpolate the data on the grid

2. Moreover between gridded observations there can be many differences due for example to:
    - the grid resolution
    - station density
    - interpolation method
    - sampling error, that for precipitation depends on the spatial variability that is influenced by the orography, season, temporal resolution, and type of precipitation (Schneider et al., 2014; Rudolf et al. 1994).

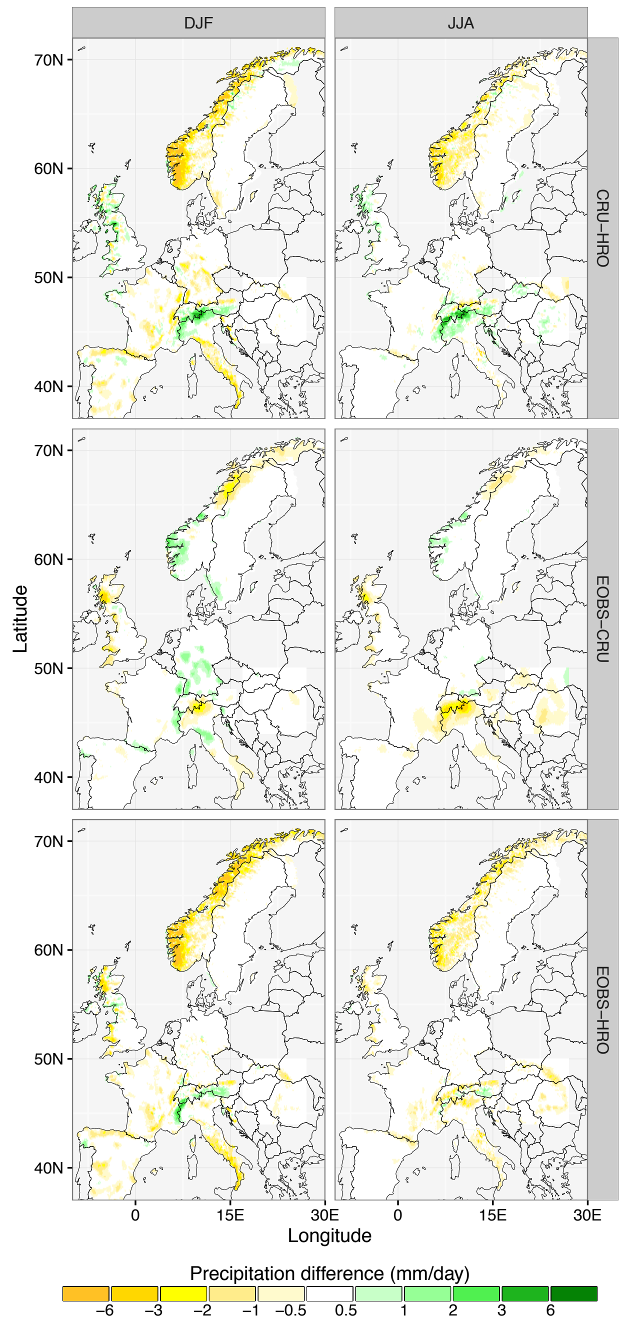


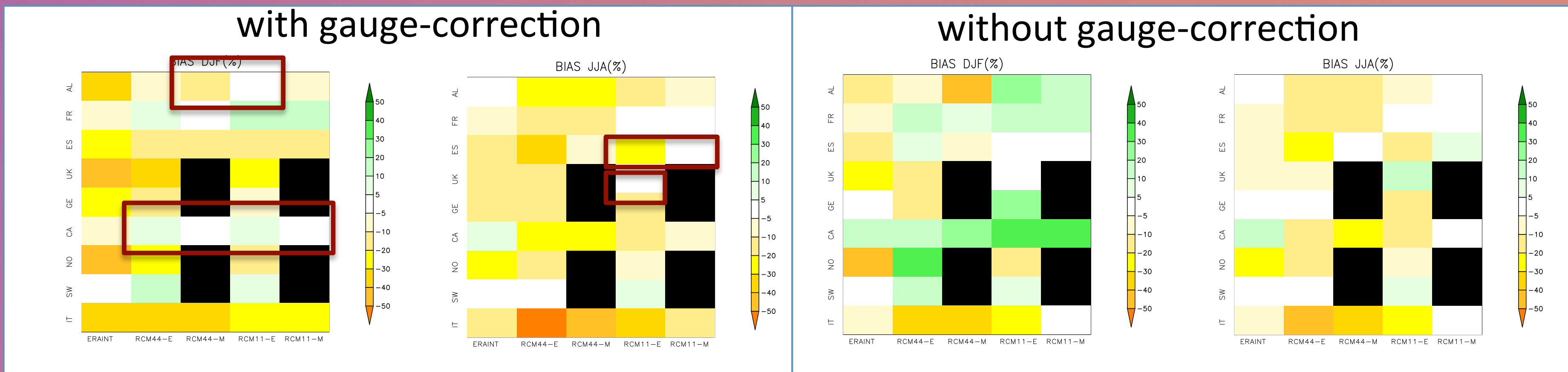
Figure 1: Seasonal average precipitation differences in DJF (left) and JJA (right) between CRU and the HRO (first row), E-OBS and CRU (second row), and E-OBS and HRO (third row).

A comparison between 3 different datasets of observed precipitation

Rain for the European area on a common 0.11 degree resolution grid. One is the High resolution Regional Observation dataset (HRO) that is composed of 9 regional observed datasets described in Fantini et al. 2016, with resolution spanning between 1 km and 12 km resolution; the E-OBS dataset (Haylock et al., 2008) of 25 km resolution and the CRU dataset (Harris et al., 2014) 0.5 degree resolution.

The main differences between these datasets are more evident in the region of complex topography like the Alps to start with, but also Norway, the Apennine in Italy, the Carpathian, the west coast of England and the Pyrenees. The magnitude of the differences are bigger and up to 6 mm/day between the HRO and CRU due to differences in resolution and station density, but also evident between E-OBS and HRO. Like for example there is a clear difference in spatial distribution of precipitation in JJA over the Alpine region where the HRO show less precipitation than E-OBS on the top of the mountain and more on the side probably due to the bigger difference in station density (Prein and Gobiet, 2016).

Another example of model validation with multiple observation dataset:
for each season (DJF and JJA) and each of the 9 European regions, we computed the average regional bias for each regional climate models ensemble.

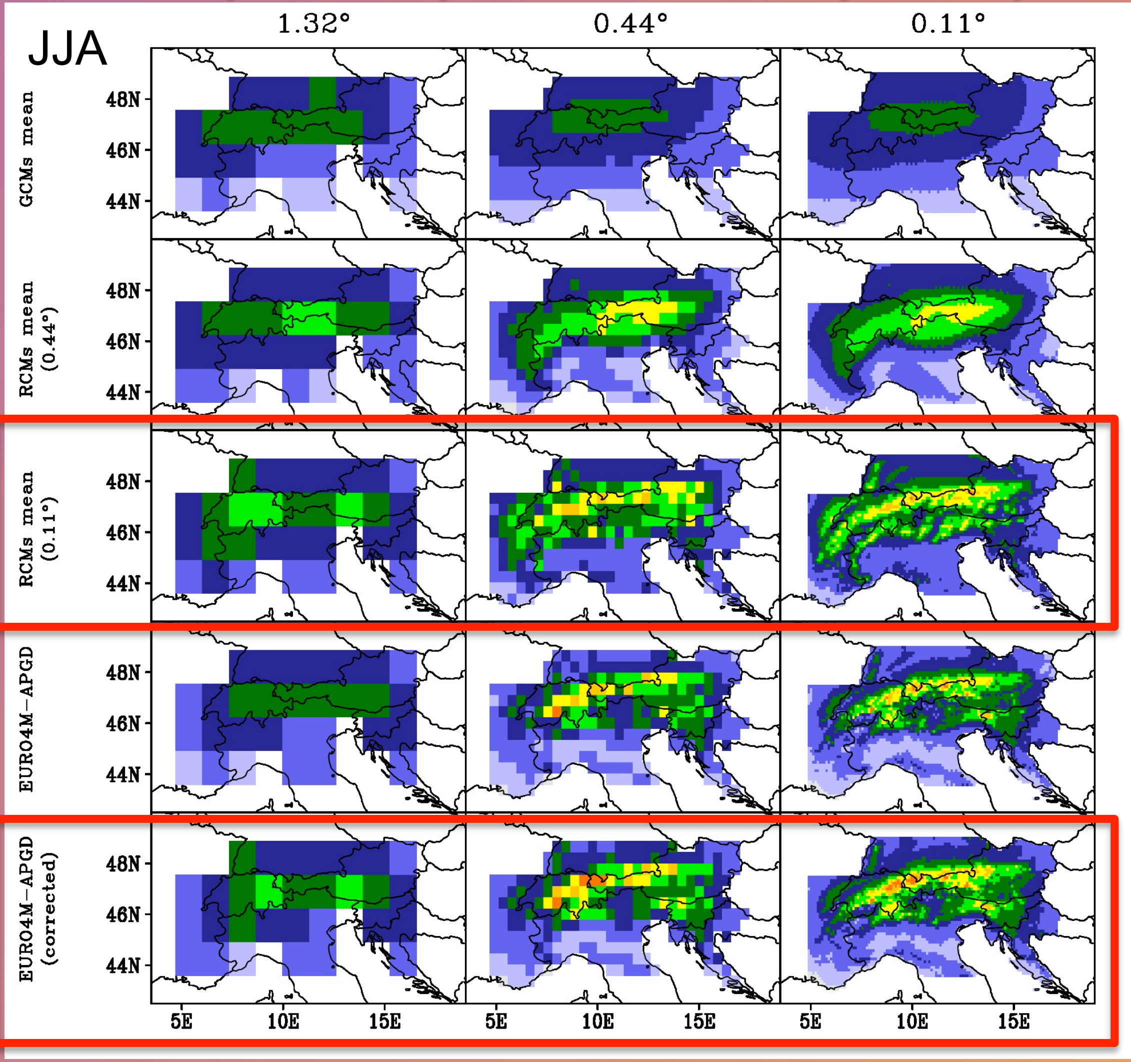


Due to the well known problem of precipitation under-catch, especially under cold season snow-blowing conditions (Adam and Lettenmaier 2003; Adam et al. 2006) , when wind can affect what really is detected by the device.
We added a gauge correction for the datasets that do not include it, i.e. the Alps, Spain, Germany, Italy, UK and the Carpathians.
For the other regional datasets, a similar correction was already included or was implicit in the use of a reanalysis, as reported in the literature.

The Regional Added Value: where can I find it?

NOT in the BIAS..but

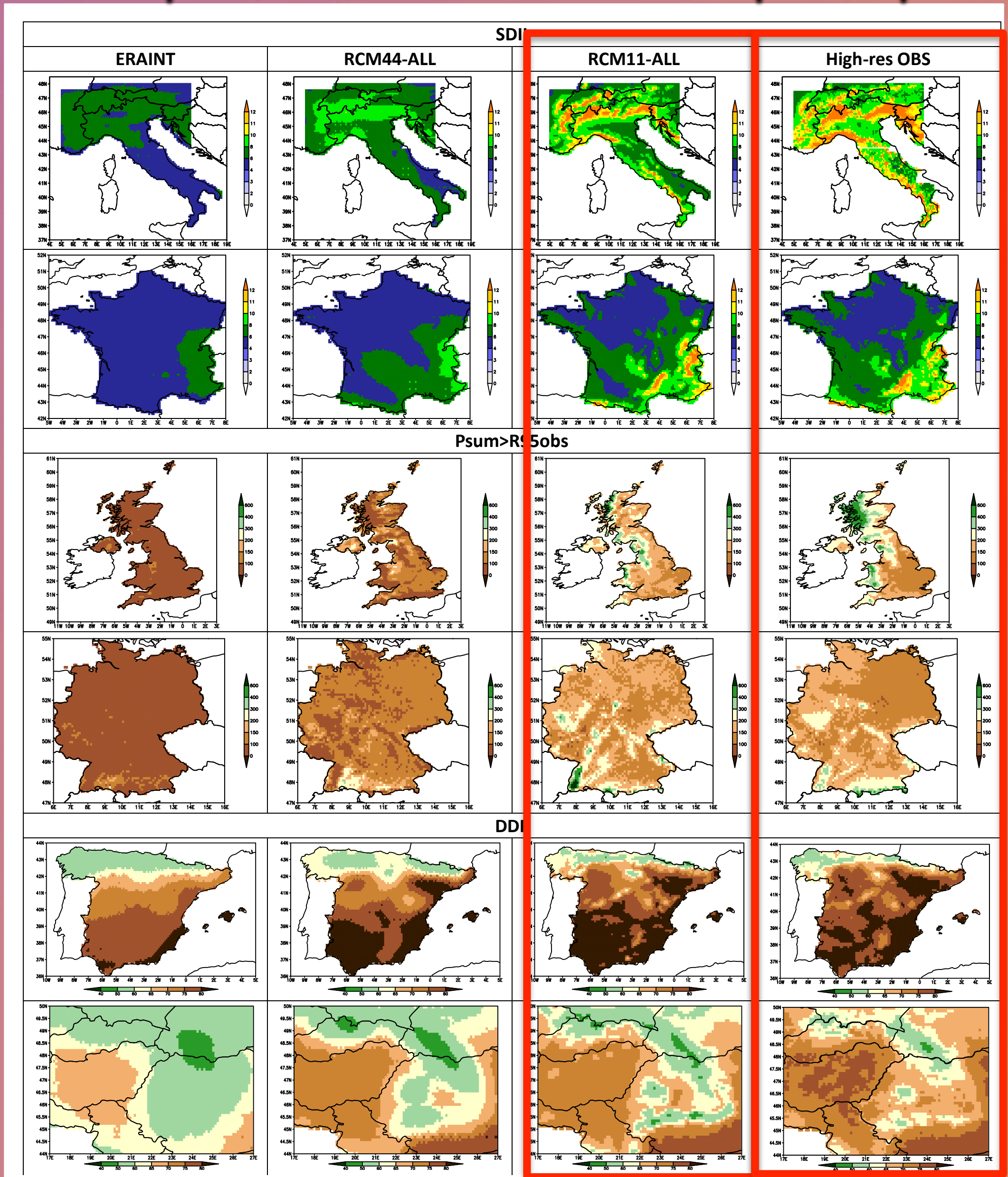
1. in the spatial patterns of precipitation



Torma et al., JGR, (2015)

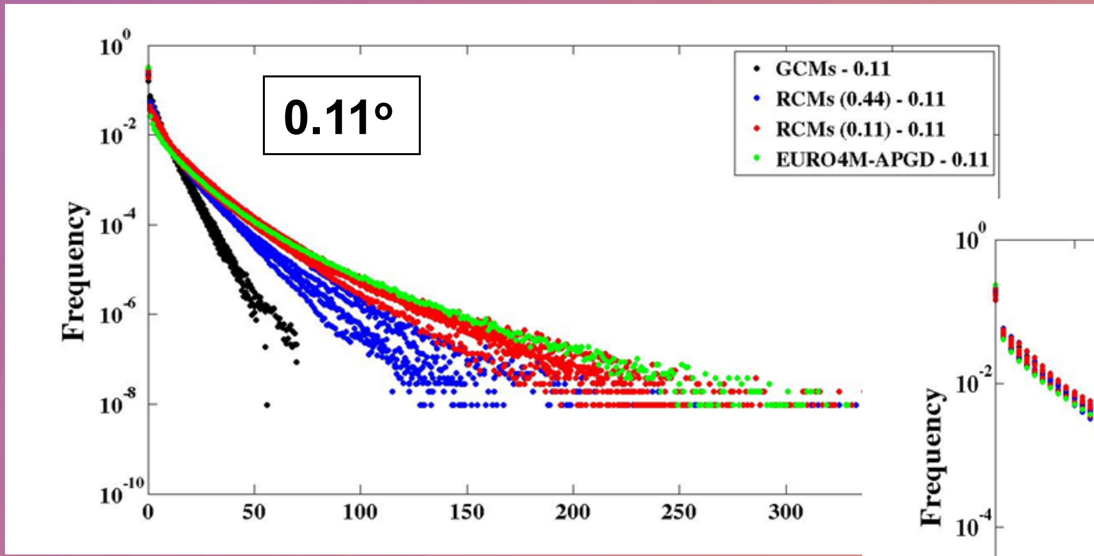
The Regional Added Value: where can I find it?

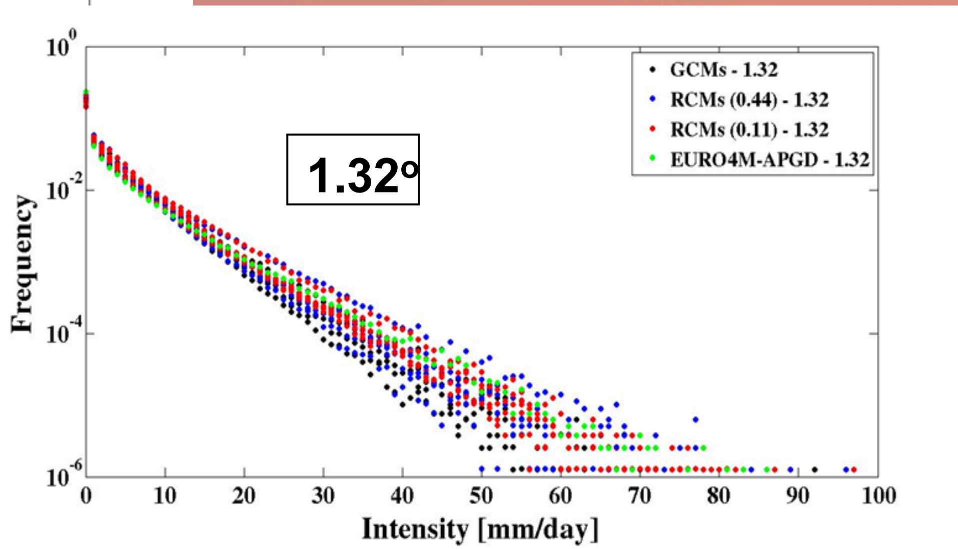
2. in the spatial patterns of extreme precipitation indices

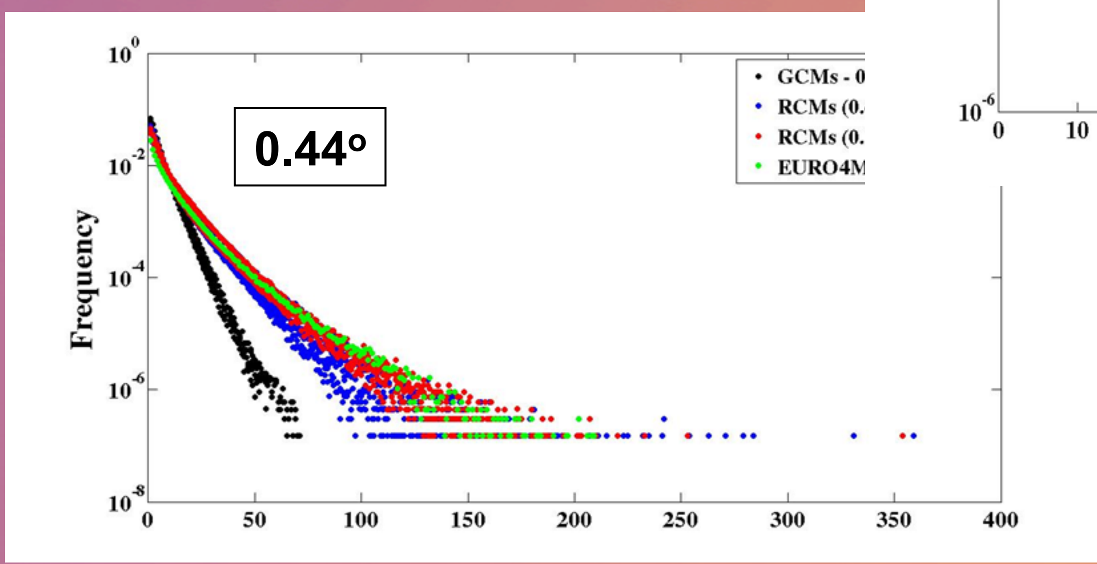


Fantini et al. (2016)

The Regional Added Value: where can I find it?
3. in the daily precipitation intensity PDF







RCMs are always closer
to OBS (also when upscaled)

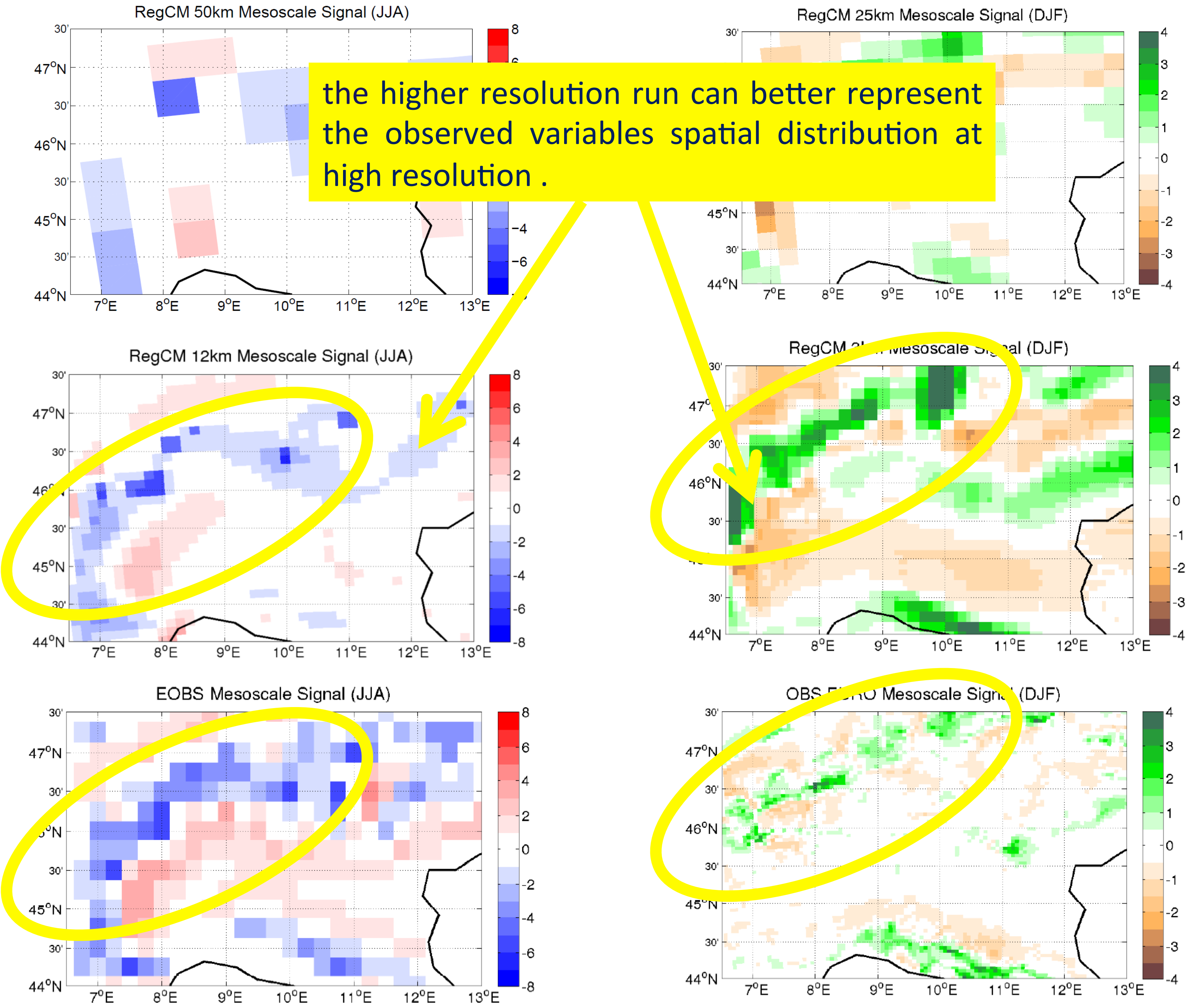
The Regional Added Value: where can I find it?
4. in the Mesoscale Signal

It can be obtain by decomponing the RegCM signal into a large-scale component and a mesoscale signal (Coppola et al., 2010):

- The large-scale component, for example, can be identified by carrying out a spatial average of the RCM fields to reach a resolution of ~ 100 km.

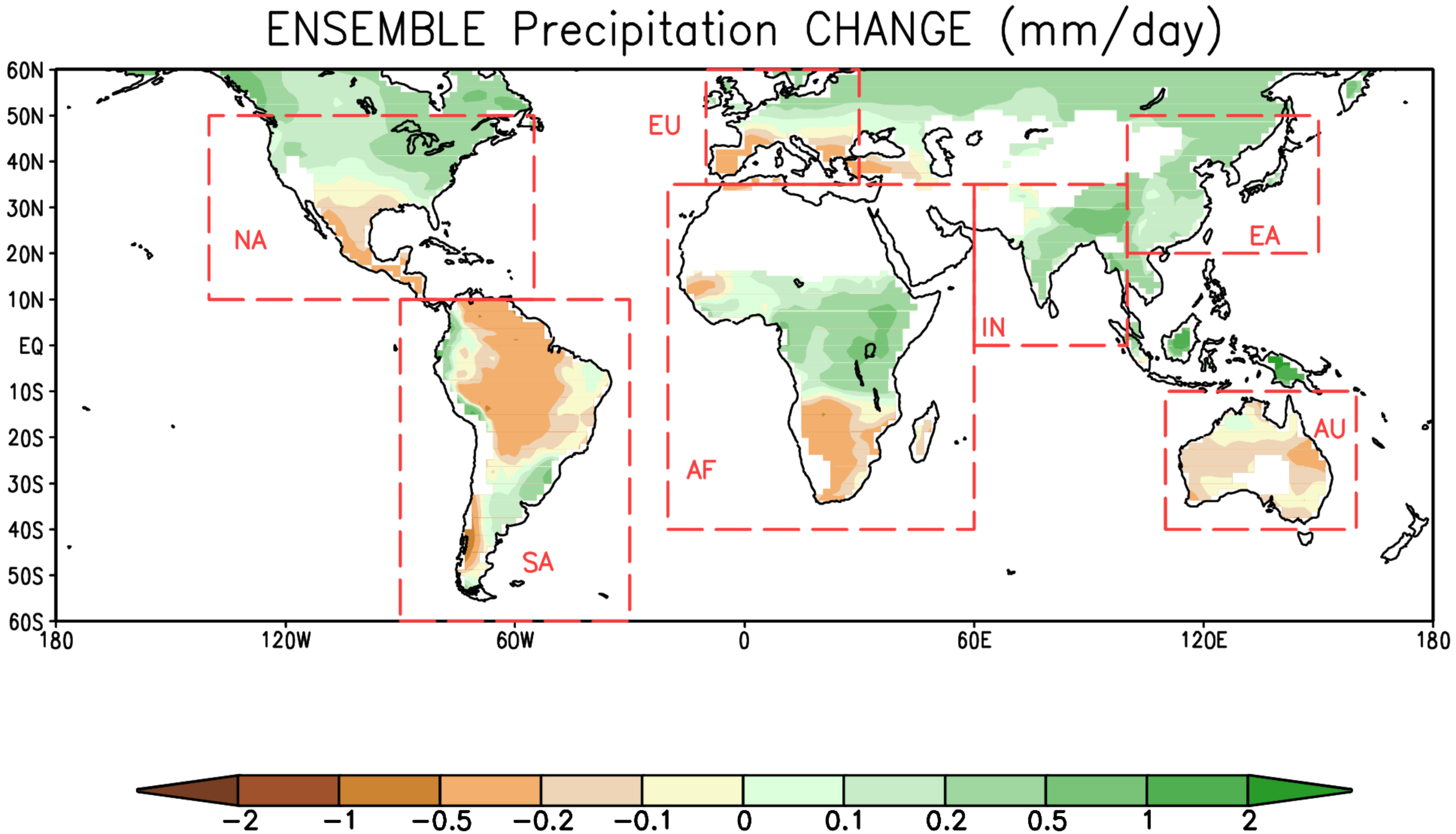
- The mesoscale signal is then obtained by simply subtracting the calculated large-scale component from the full RCM fields.

- This generates an anomaly field in which the large-scale component is filtered out.



RegCM 50km Mesoscale Signal (JJA)
RegCM 25km Mesoscale Signal (DJF)
the higher resolution run can better represent the observed variables spatial distribution at high resolution .
RegCM 12km Mesoscale Signal (JJA)
EOBS Mesoscale Signal (JJA)

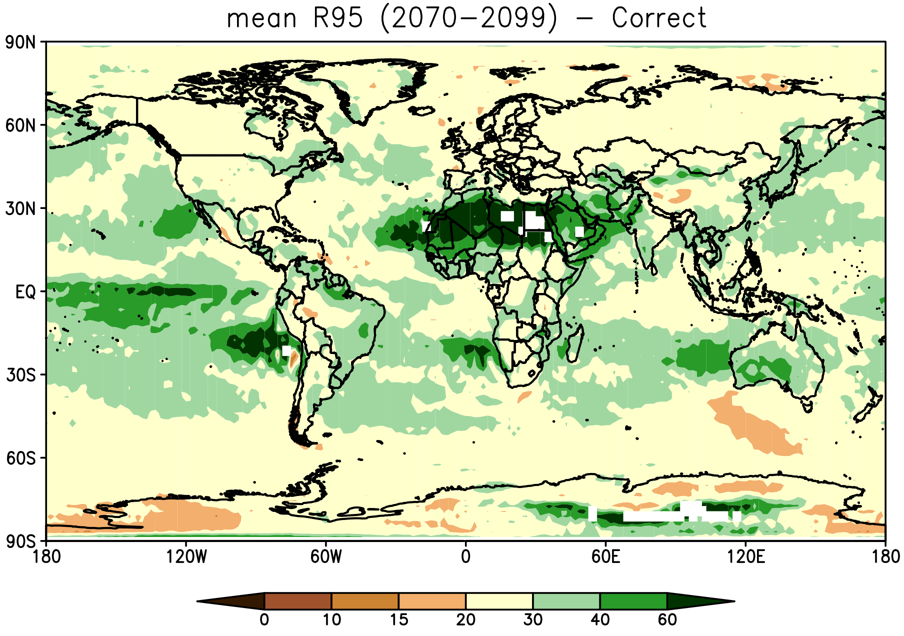
Climate Change Signal (ensemble of models): 1. the mean change

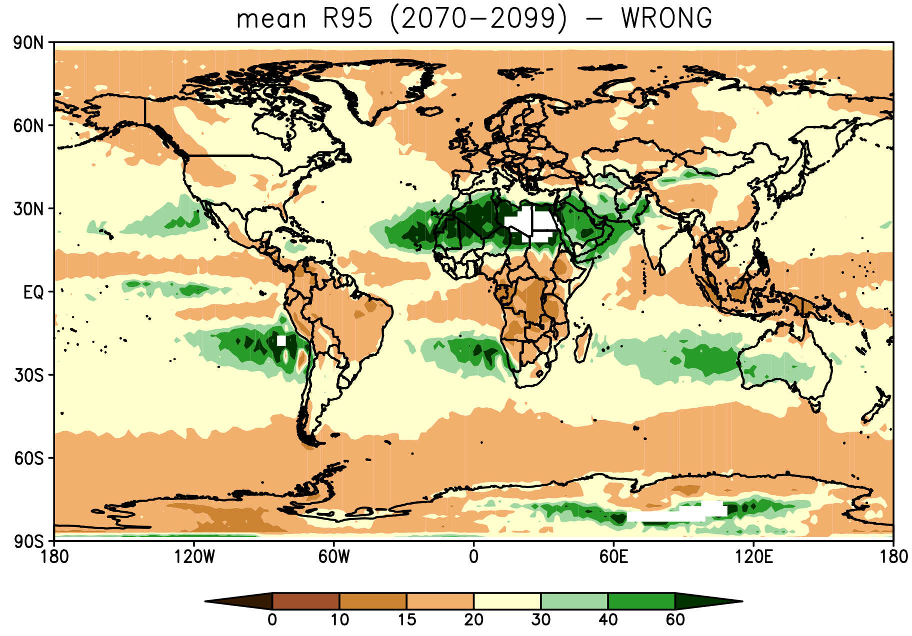


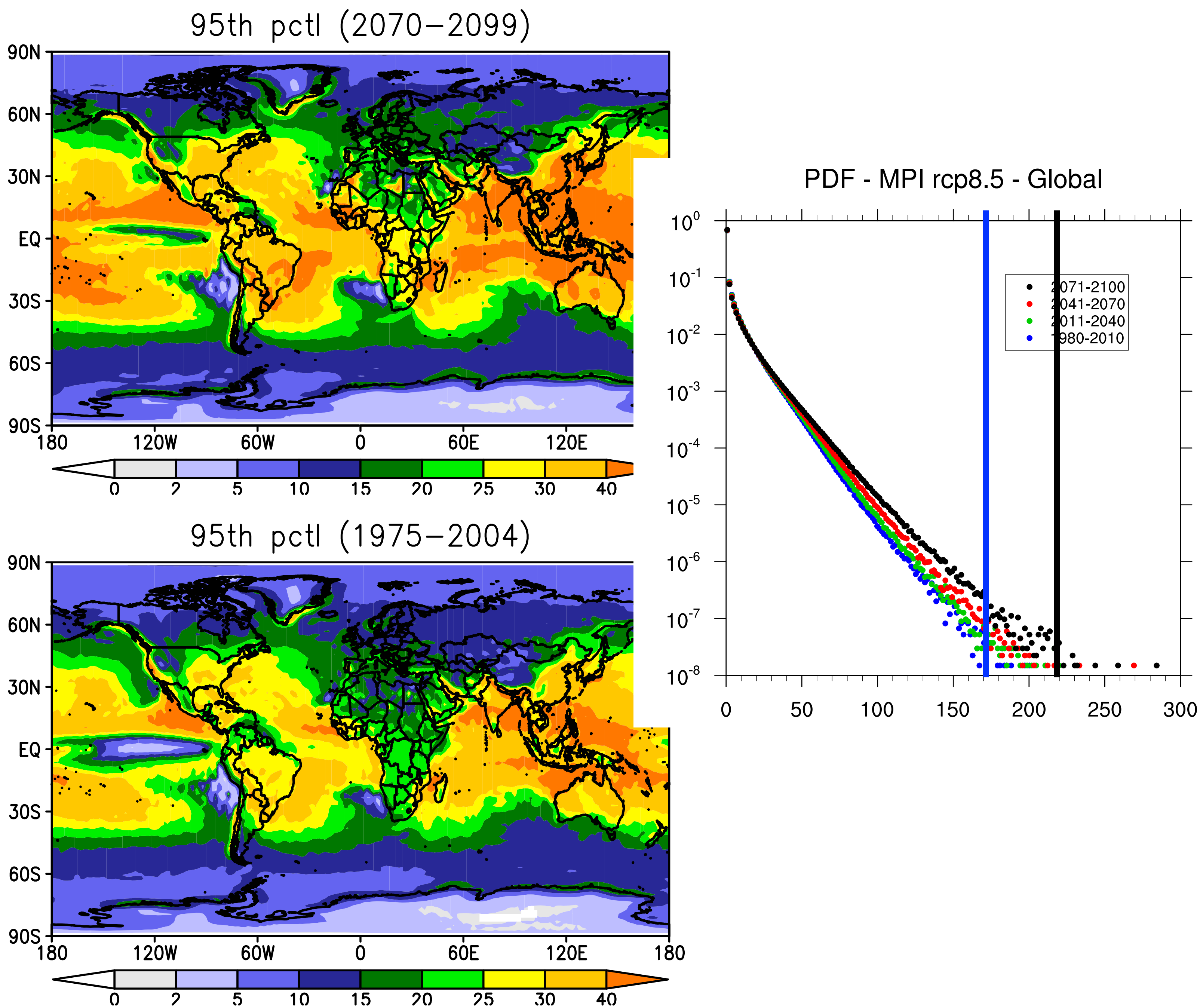
1. the individual change for each member of the ensemble is computed
2. the ensemble CHANGE is the ensemble mean of all the changes

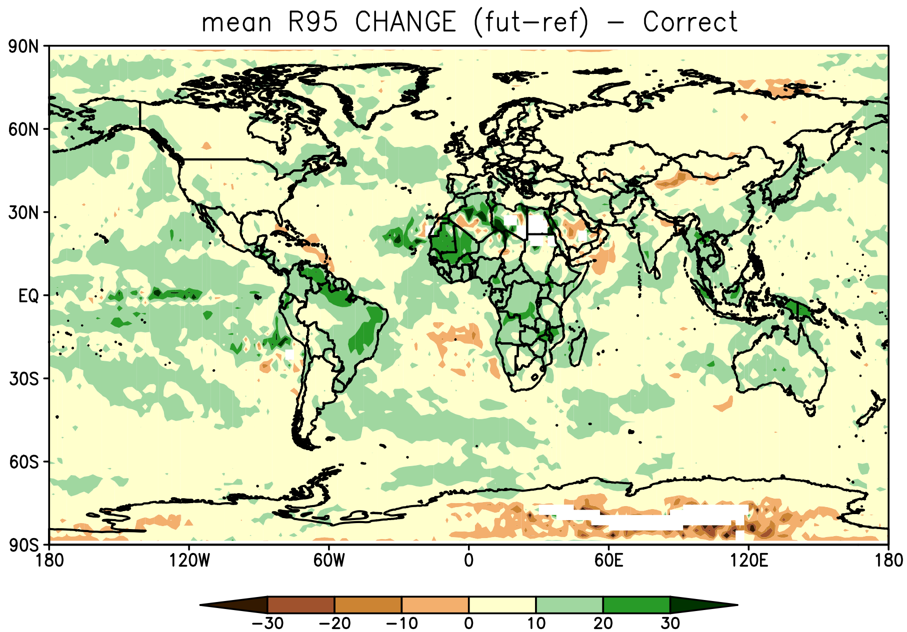
Climate Change Signal (ensemble of models): 2. the change in the extreme indices

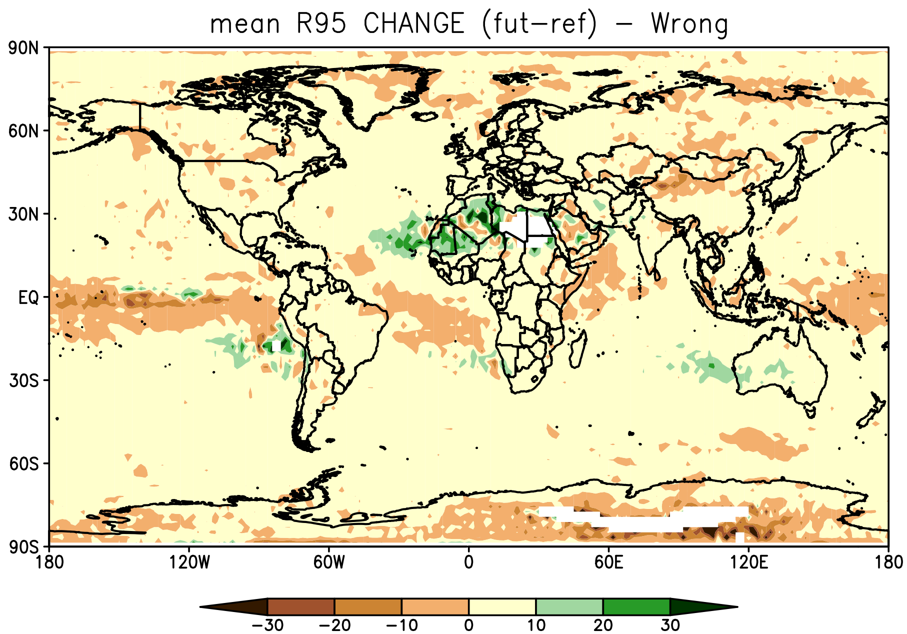
Example: the R95 DEFINITION is
“Precipitation percent due to the sum of those days > 95th (or 99th) percentile of the daily precipitation amount at WET days (precip >= 1 mm) for any period used as reference”






95th pctl (2070–2099)
90N
60N
30N
EQ
30S
60S
90S
180
120W
60W
0
60E
120E
0 2 5 10 15 20 25 30 40
95th pctl (1975–2004)
90N
60N
30N
EQ
30S
60S
90S
180
120W
60W
0
60E
120E
180
0 2 5 10 15 20 25 30 40
PDF - MPI rcp8.5 - Global
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
0 50 100 150 200 250 300
2071-2100
2041-2070
2011-2040
1980-2010


mean R95 CHANGE (fut−ref) − Correct
90N
60N
30N
EQ
30S
60S
90S
180
120W
60W
0
60E
120E
180
−30
−20
−10
0
10
20
30


mean R95 CHANGE (fut−ref) − Wrong
90N
60N
30N
EQ
30S
60S
90S
180
120W
60W
0
60E
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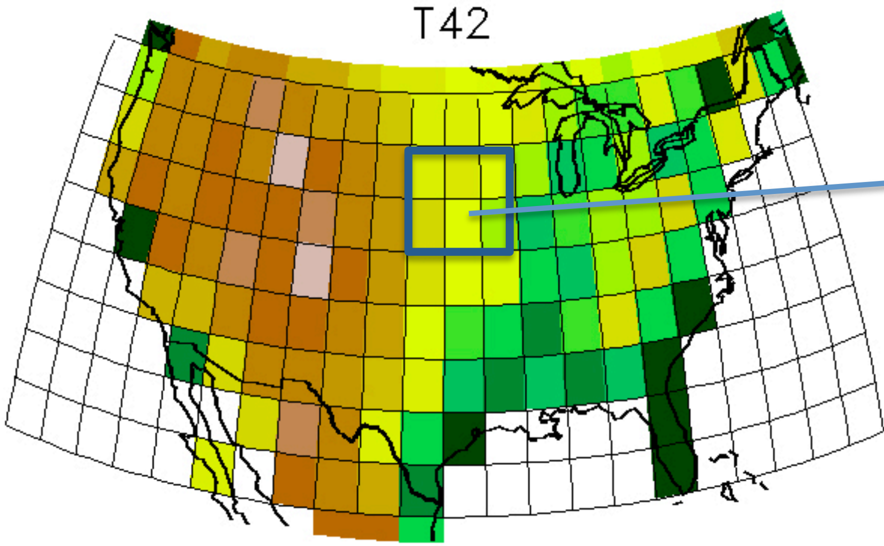
180
−30
−20
−10
0
10
20
30



year 1

2	3	4
2	2	3

year 2

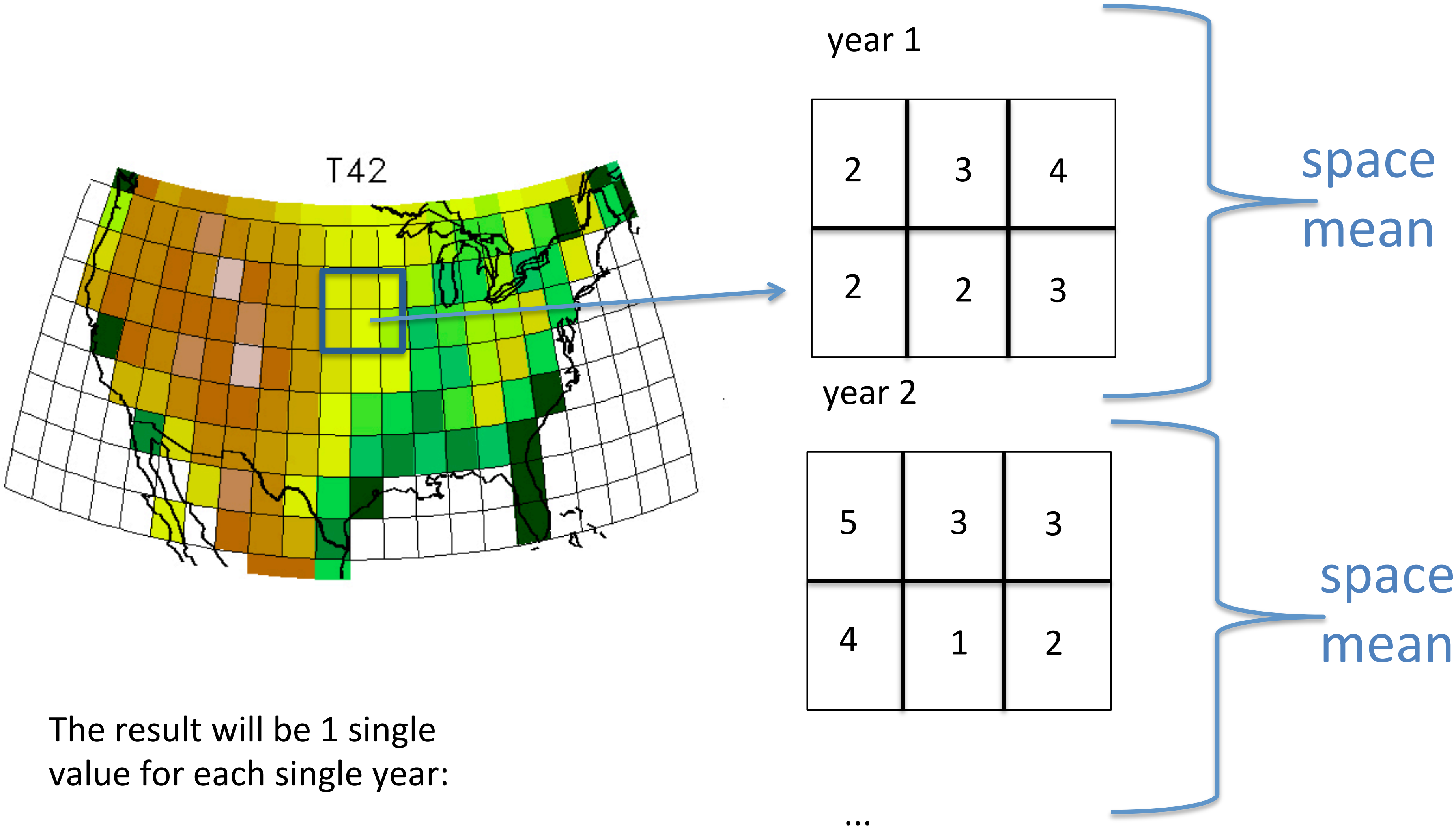
5	3	3
4	1	2

...

Time mean

The result will be a MAP of mean values with only 1 timestep:

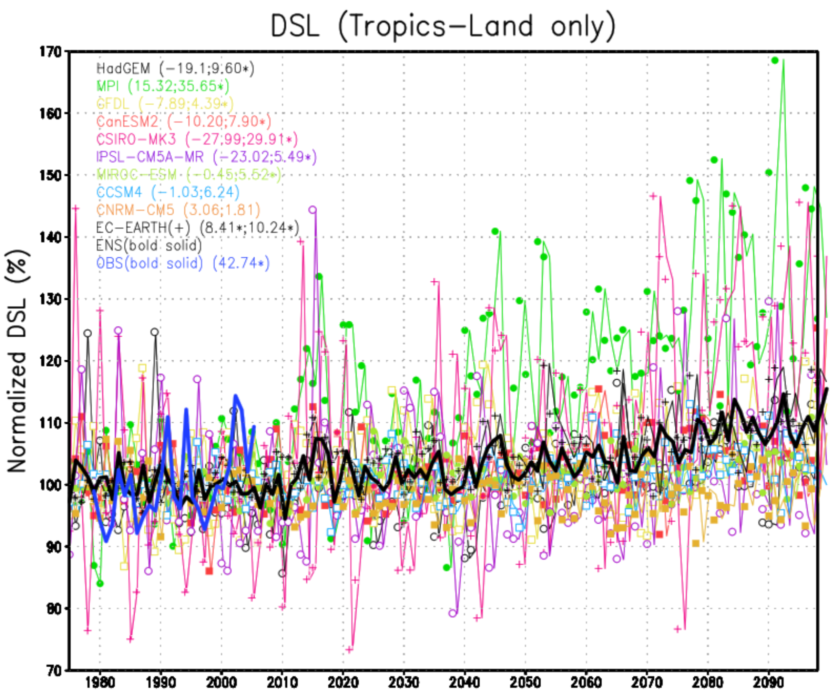
3.5	3	3.5
3	1.5	2.5

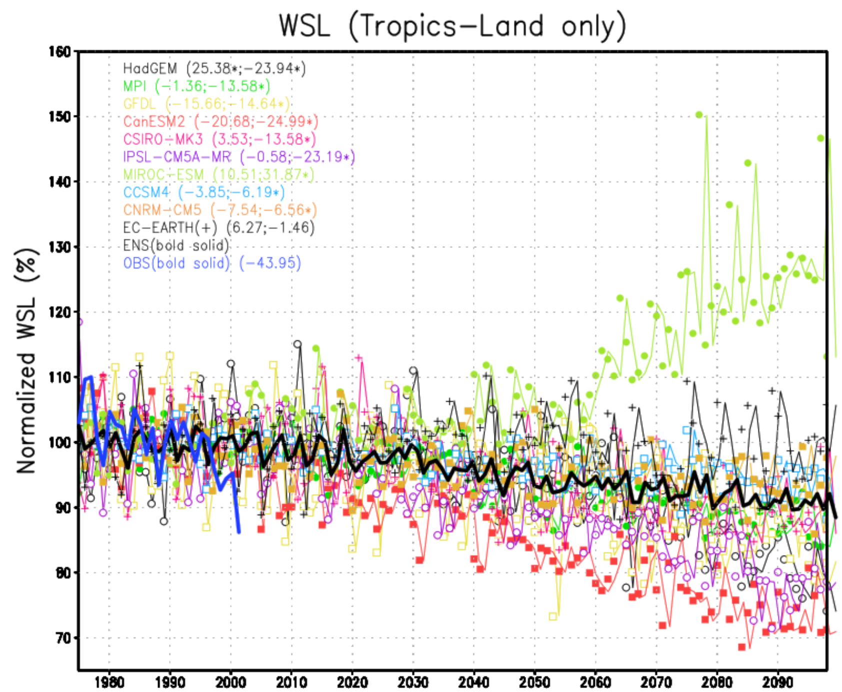


The result will be 1 single value for each single year:

year 1: 2,7; year2: 3 ...

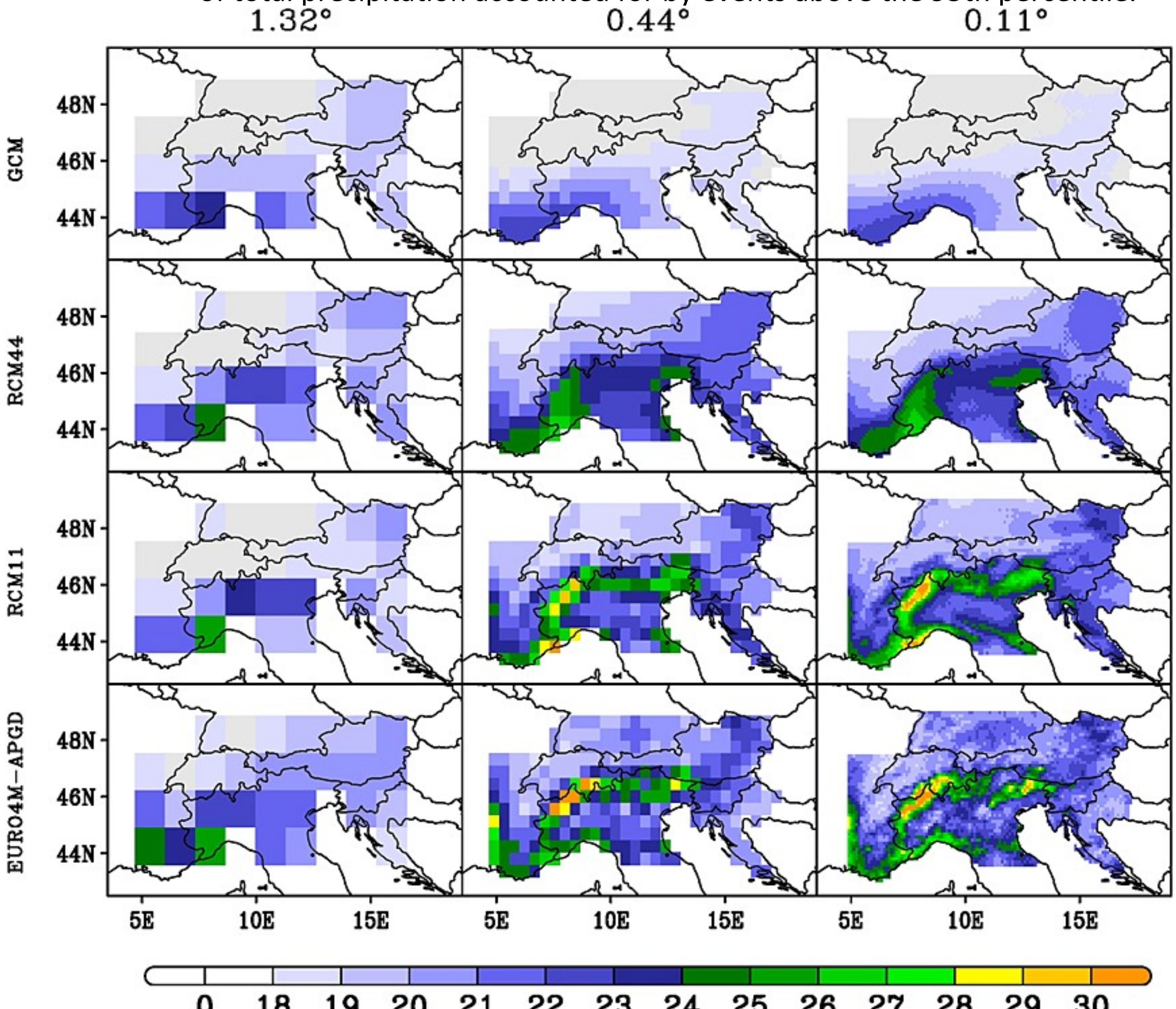
Climate Change Signal (ensemble of models): 3. Spaghetti plots



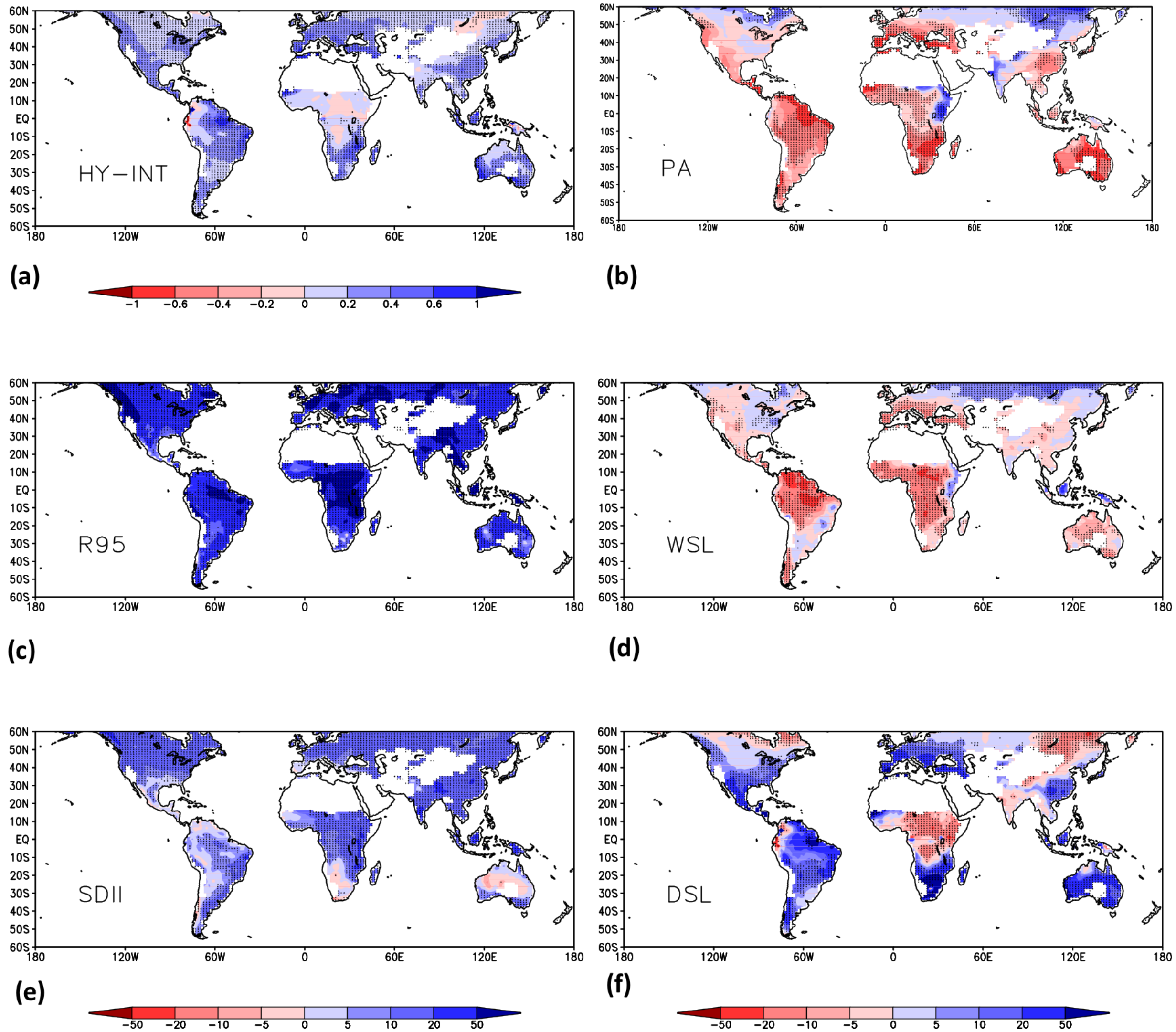


Time evolution of annual values of the 2 hydroclimatic indices considered averaged over tropical land areas for 10 GCM and their ensemble mean. Also shown for the historical period are the corresponding values for the CPC_GLOBAL observations. The two values in parentheses are the linear trends for the 1976-2005 and 2006-2100 periods, respectively and an asterisk indicates that the trend in statistically significant at the 95% confidence level. Units are % / 100 yrs.

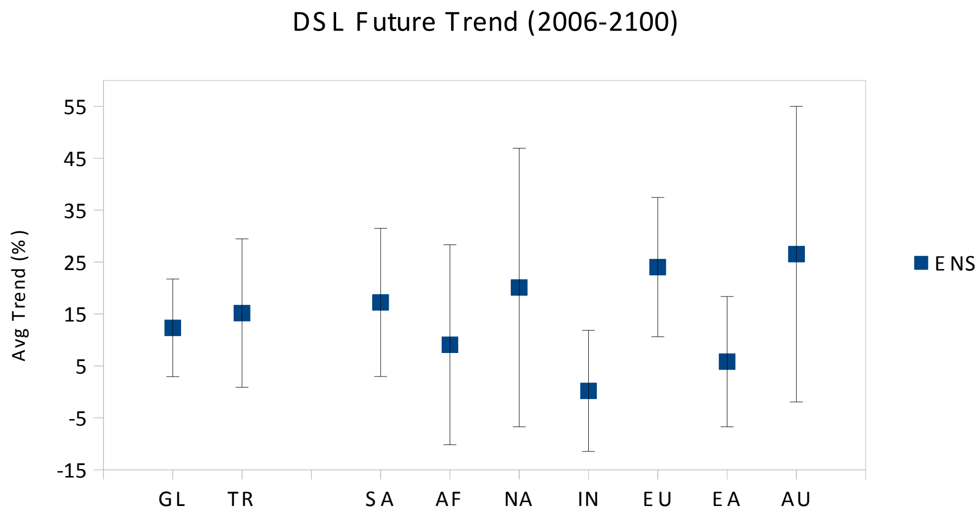
Added Value: R95 change for the historical period 1976–2005 and the three resolution grids. Units are in pe
of total precipitation accounted for by events above the 95th percentile.

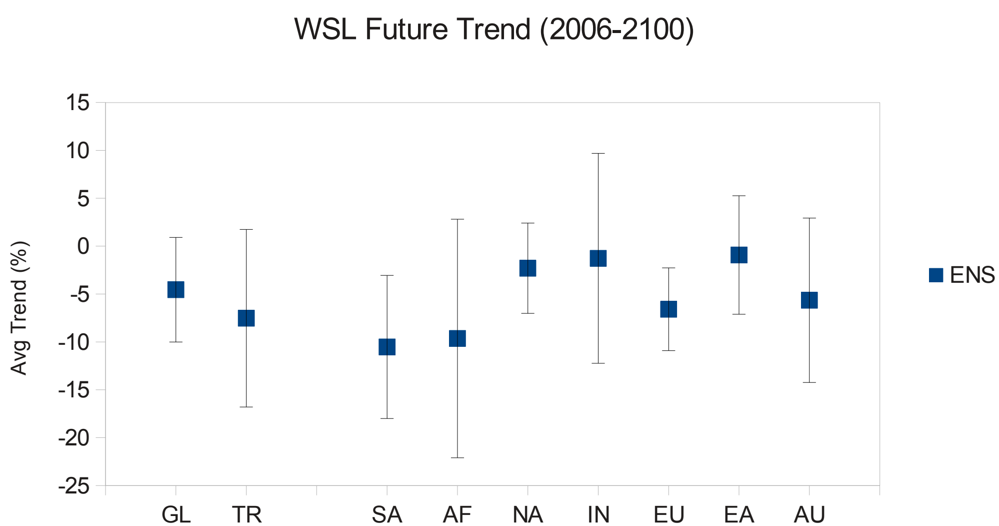


Ensemble mean linear trend values for the future period 2006-2100



Climate Change Signal (ensemble of models):
4. Model consensus





Ensemble mean and inter-model 90% significance range of the linear trend values for the period 2006-2100, averaged over global (60 S - 60 N) and tropical (30 S - 30 N) land areas and over 7 continental regions. Units are % / 100 yrs

Climate Change Signal (ensemble of models):
5. Change of Inter-annual variability

the value of a single year

mean value of temp (for example)
for the period considered

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{n}}$$

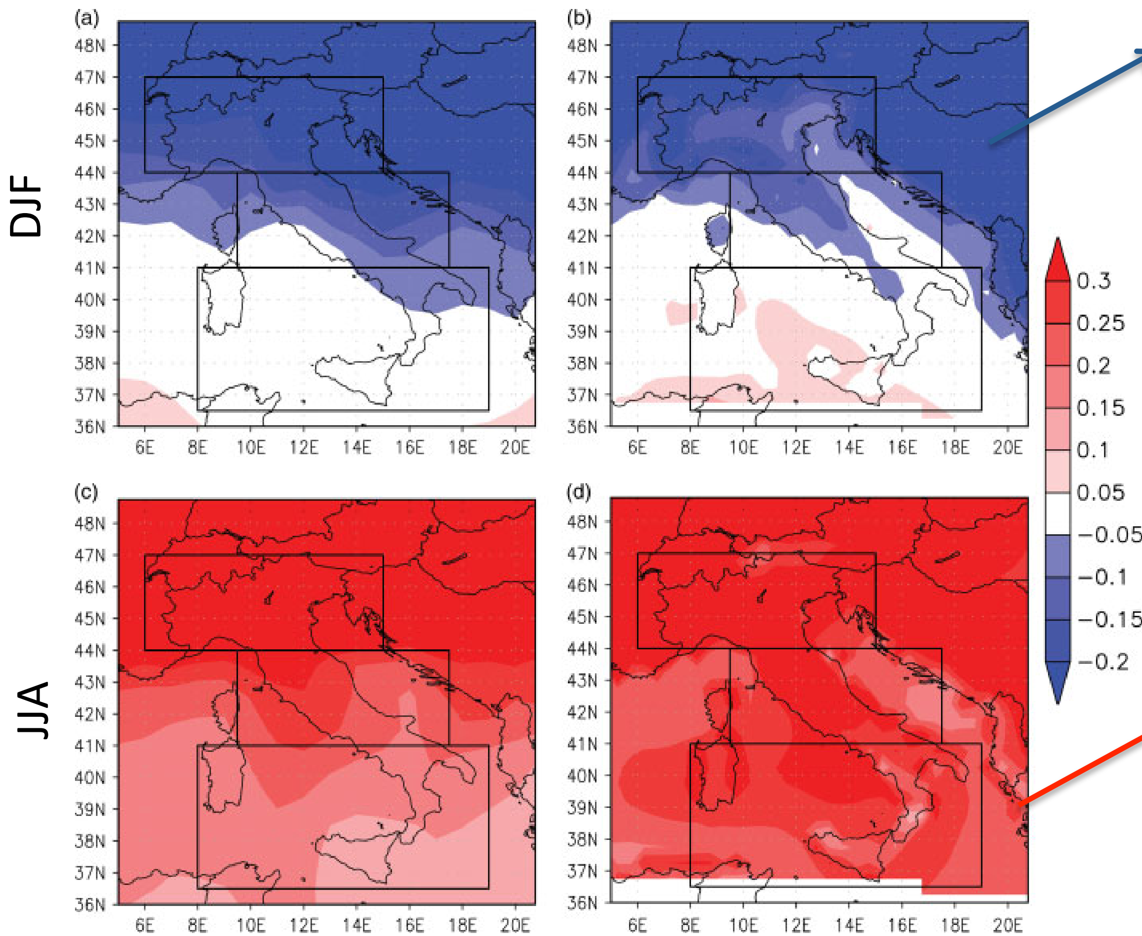
number of years

- to be calculated both for teh REFERENCE period and for the FUTURE
- the change will be:

$$\sigma_{fut} - \sigma_{ref}$$

Climate Change Signal (ensemble of models): 5. Inter-annual variability

Temperature

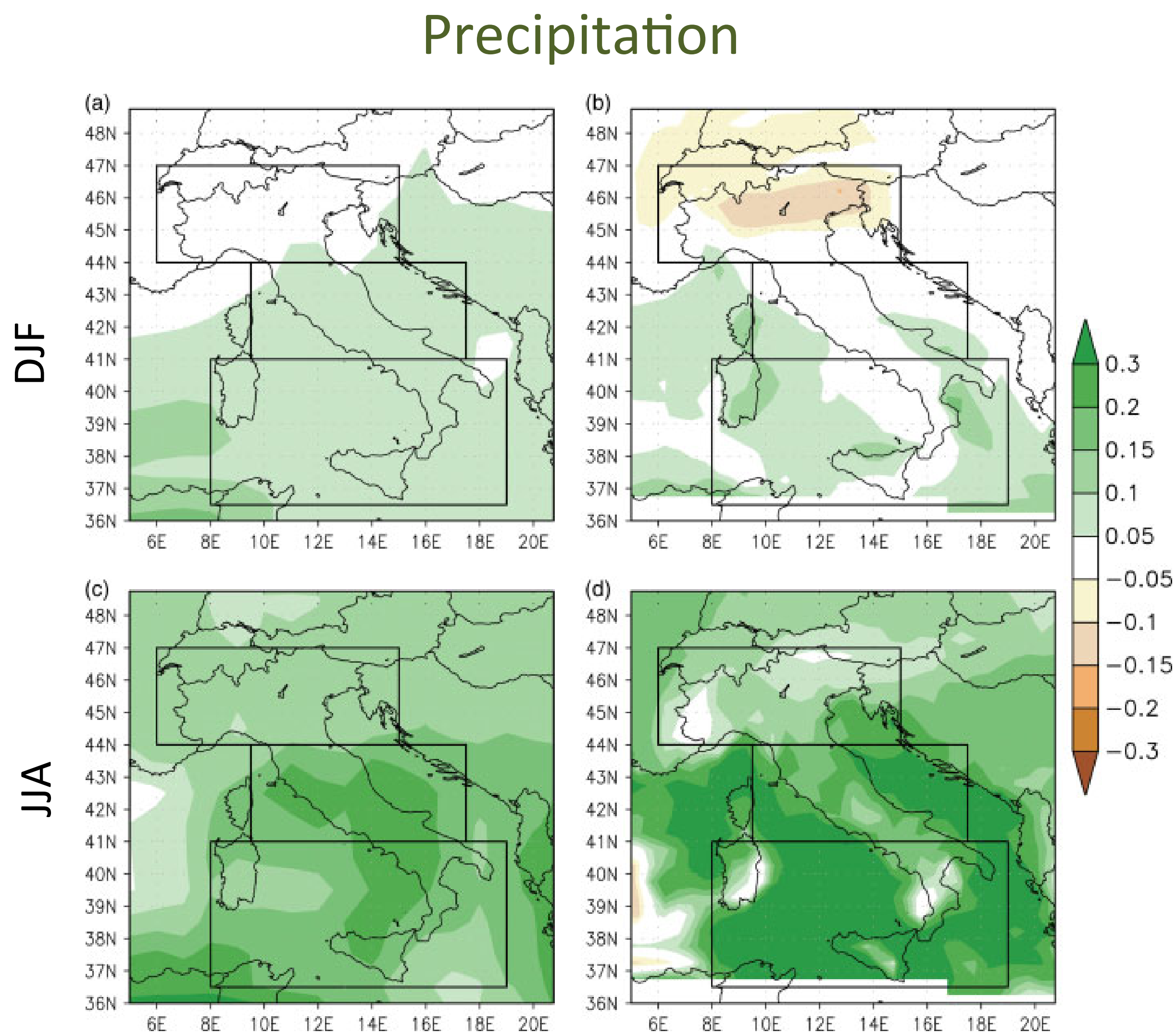


Coppola et al. (2009)

A decrease in variability is projected to extend from northern to central (and some areas of southern) Italy. This is consistent with the decrease in cold climate temperature variability found in previous analyses of climate change simulations (Ra¨ isa¨ nen, 2002; Giorgi and Bi, 2005b). It has been attributed primarily to the reduction of snow cover and associated weakening of the snow albedo feedback mechanism (which tends to increase variability)

By contrast, summer temperature variability increases over the whole Italian peninsula, especially the northern regions. This is also consistent with previous findings (Ra¨ isa¨ nen, 2002; Giorgi *et al.*, 2004b; Scha¨r *et al.*, 2004; Giorgi and Bi, 2005b) and has been attributed, at least partially, to an enhancement of the soil moisture–temperature feedbacks in the drier soil conditions of future warmer climates.

Climate Change Signal (ensemble of models): 5. Inter-annual variability



Coppola et al. (2009)

only small changes in the winter, but a marked increase throughout the peninsula in summer.
It is likely that in the summer the increase in temperature and pre-cipitation variability are coupled to each other, as clear (rainy) conditions are associated with higher (lower) insolation and higher (lower) temperatures.

The list of the variables created by pycordex postprocessor

variable	RegCM file	Description
tas	SRF,STS	Near-Surface Air Temperature
pr	SRF,STS	Precipitation
prc	SRF	Convective Precipitation
huss	SRF	Near-Surface Specific Humidity
hurs	SRF	Near-Surface Relative Humidity
evspsbl	SRF	Evaporation
mrros	SRF	Surface Runoff
ps	SRF	Surface Air Pressure
psl	ATM	Sea Level Pressure
tasmax	STS	Daily Maximum Near-Surface Air Temperature

tasmin	STS	Daily Minimum Near-Surface Air Temperature
sfcWindmax	STS	Daily Maximum Near-Surface Wind Speed
mrro	SRF	Total Runoff
sfcWind	SRF	Near-Surface Wind Speed
ua850	ATM,ATMp	Eastward Wind (at 850 hPa)
va850	ATM,ATMp	Northward Wind (at 850 hPa)
ta850	ATM,ATMp	Air Temperature (at 850 hPa)
hus850	ATM,ATMp	Specific Humidity (at 850 hPa)
ua500	ATM,ATMp	Eastward Wind (at 500 hPa)

va500	ATM,ATMp	Northward Wind (at 500 hPa)
ta500	ATM,ATMp	Air Temperature (at 500 hPa)
zg500	ATM,ATMp	Geopotential Height (at 500 hPa)
ua200	ATM,ATMp	Eastward Wind (at 200 hPa)
va200	ATM,ATMp	Northward Wind (at 200 hPa)
ta200	ATM,ATMp	Air Temperature (at 200 hPa)
zg200	ATM,ATMp	Geopotential Height (at 200 hPa)

...and other 2 levels will be extracted (700 and 925 hPa)...
...is there anything else to add??
Do you think that these variables are enough to capture the climatic processes of your domain?

...and finally.. here is the archive of the data to be analized:

- /home/clima-archive4/WORKSHOP/daily/ and monthly/ folders
- example: /home/clima-archive4/WORKSHOP/daily/South_America -->will contain daily pycordex generated precip and temperature for South America
- /home/clima-archive4/WORKSHOP/monthly/South_America -->will contain monthly pycordex generated precip and temperature for South America
- /home/clima-archive4/WORKSHOP/scripts/