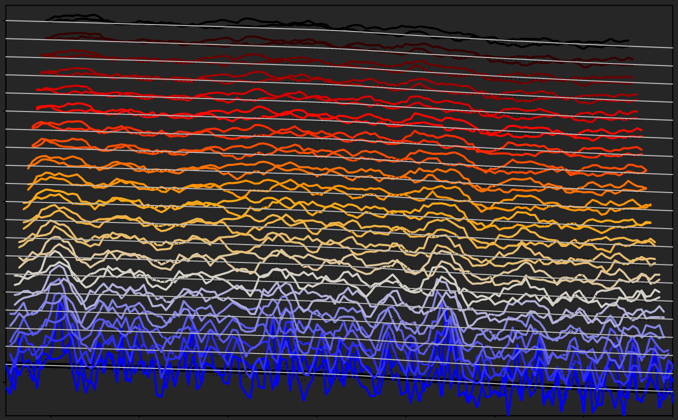

Internal variability in regional climate simulations

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EUCP
European Climate Prediction system

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EGU 2020-10990 / EUCP session - POSTER

Introduction (1)

- CP-RCMs are state of the art, but they have one drawback. They are quite expensive! Typical simulations are only O(10) years

- Therefore internal variability (INT) plays a role in these ‘short’ simulations and influences the derived climate-change signal. The question is, to what extent? E.g. what is INT at e.g. 10-year time scale when you have only one 10-year simulation?

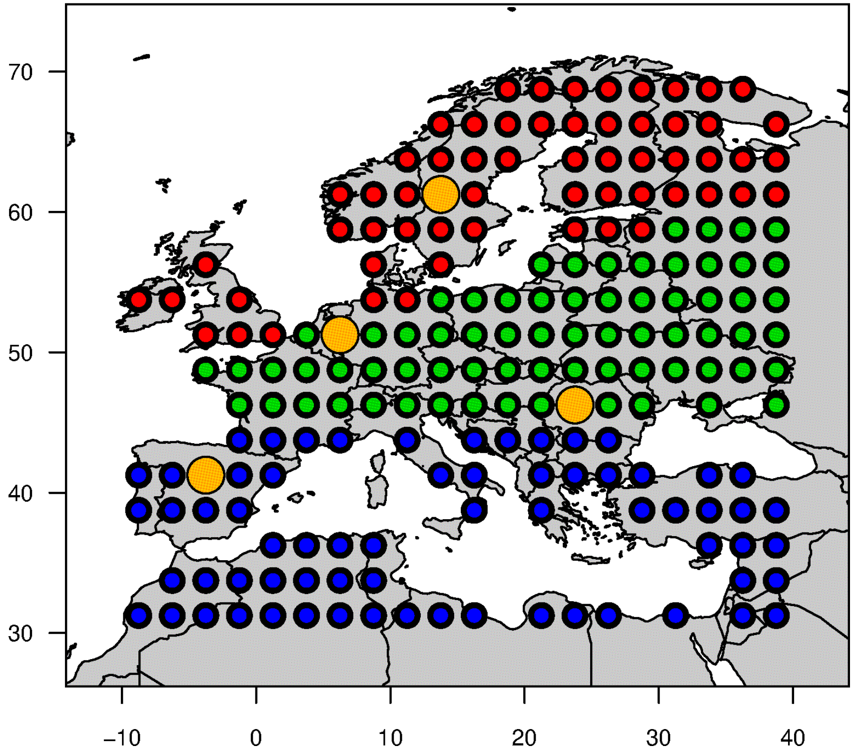
- Reducing effect of internal variability in cc signal. Options:
  - Long separation between REF & FUT periods & scaling
  - Aggregation and/or spatial pooling
  - Try to compute amplitude of INT <= The aim of today’s presentation

Introduction (2)

- Estimate the amplitude of internal variability (INT) at various time scales
- Ideally, the approach can be used with a single member, and converges to the ‘truth’ as more and more members are added
- Ideally, the method is compatible with the time-slice approach of the CP-RCM

Introduction (3)

- Data: 16-member ensemble of 1950-2100 GCM/RCM simulations obtained with EC-Earth/RACMO (certain decades of certain members have been downscaled with the CP-RCM HCLIM-AROME)
- Domains. EUCP WP2 domains (Brunner et al 2020)
  - SREX: MED, CEU, NEU
  - Individual 2.5deg grids



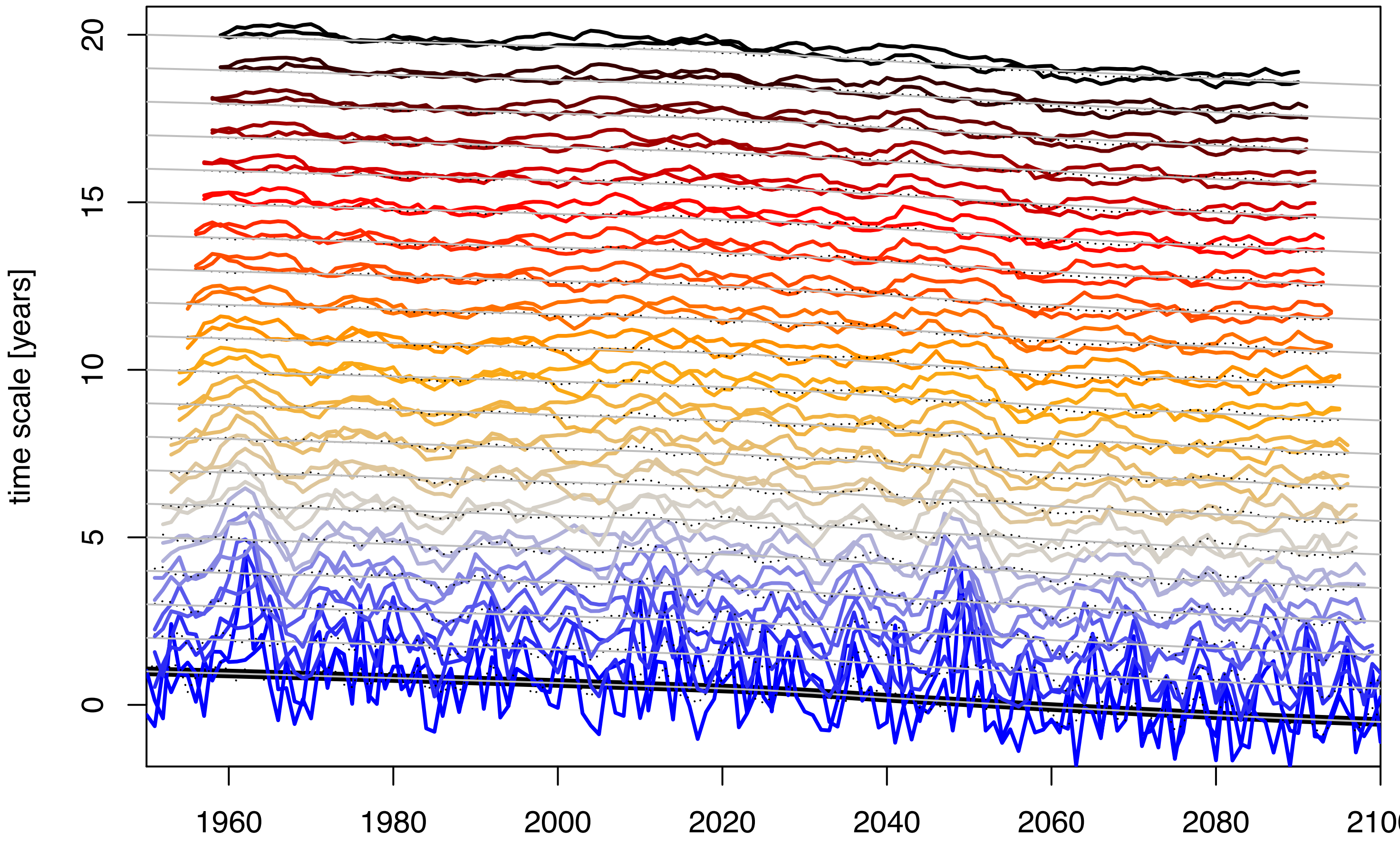
Approach to compute INT

- INT = ensemble spread at different time scales
- For time scale *n* in (1,2,..,50):
  - Compute sliding *n*-season averages of <u>precipitation</u> for all members and also for the ensemble mean
  - Take relative differences w.r.t the forced signal
    <u>Assumption</u>: forced signal = loess(ensmean)
  - Compute sd of anoms over all steps (p95-p05 ~ 3.3sd)

=> The result is a measure of the amplitude of the internal variability at that time scale (Q: or would one call this twice the internal variability?)

Example: JJA precip (srex MED)

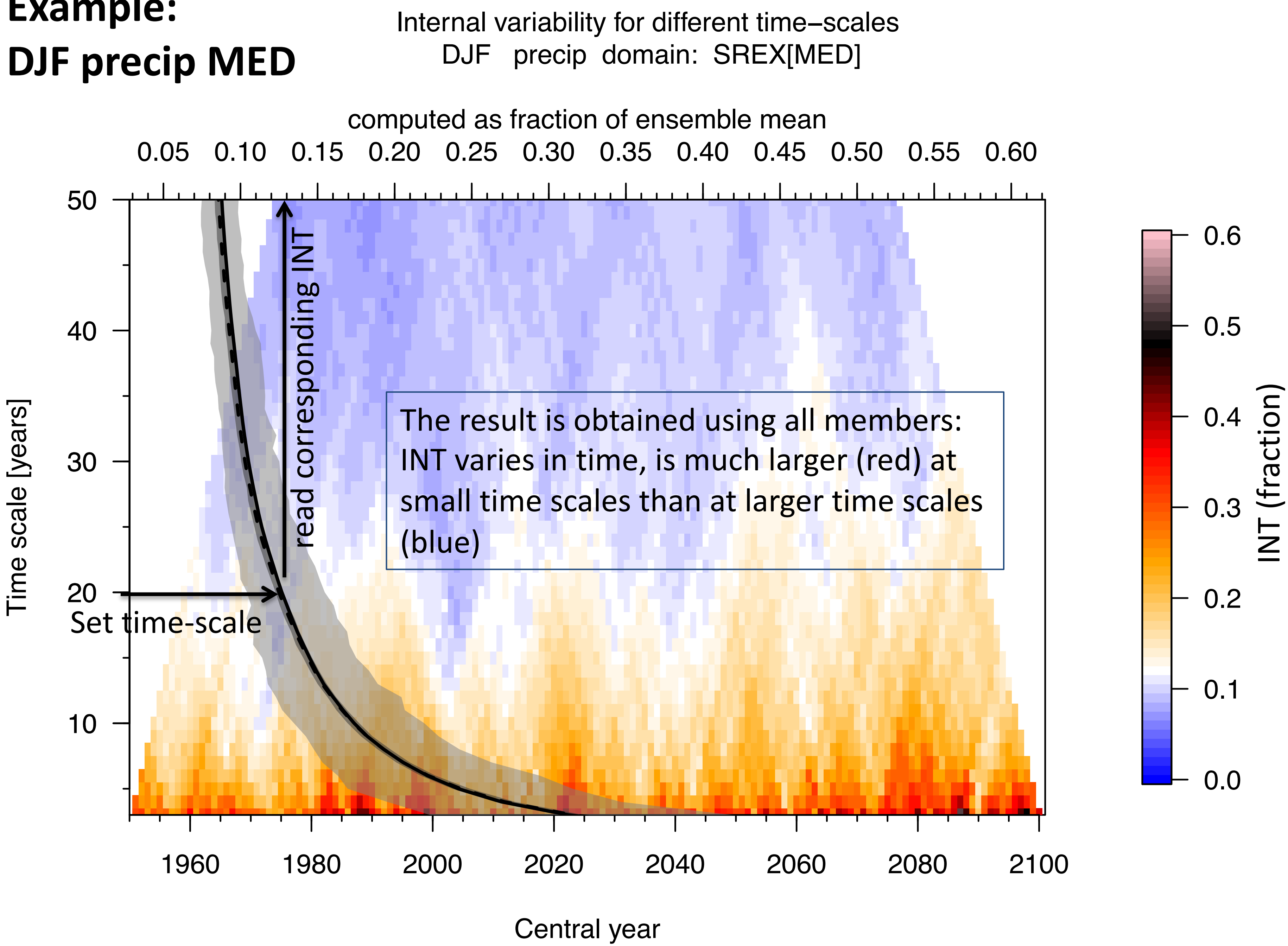
MED = SREX Mediterranean



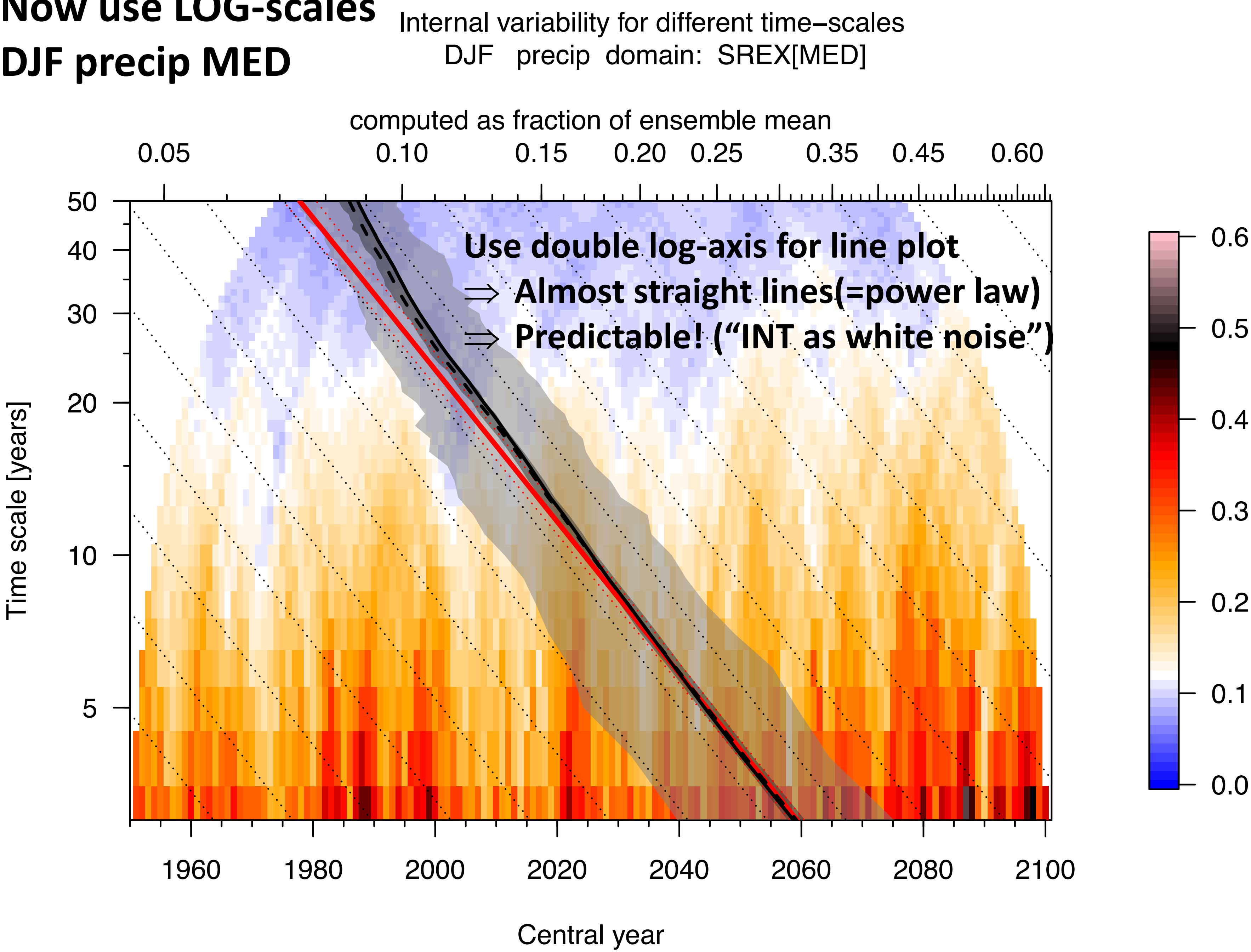
Loess regression

For plotting: JJA season data is first scaled (units of JJA sd).
Here computed for only two members (#1 en 2)
Now we can display INT (range of deviations) in a contour plot

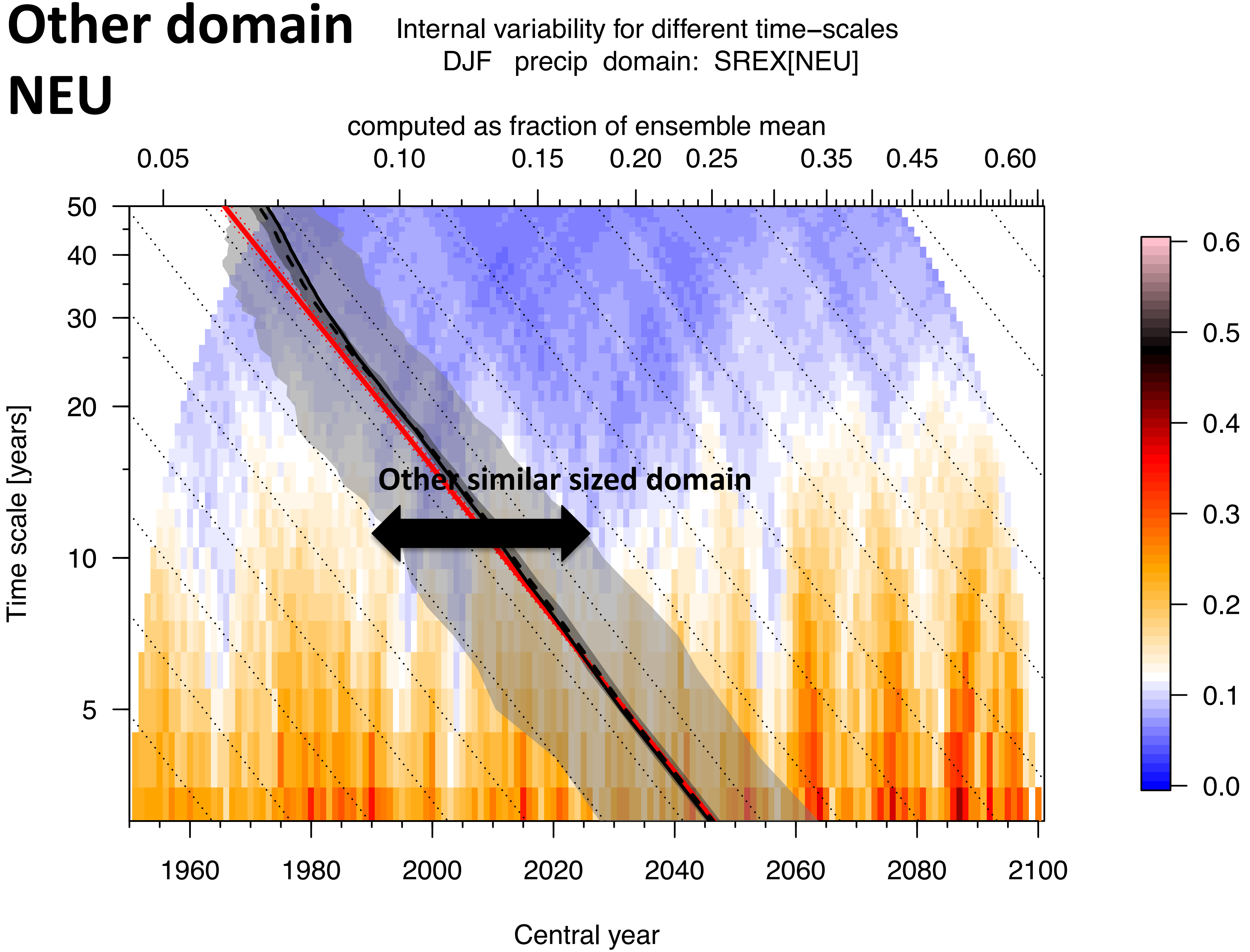
Example:
DJF precip MED



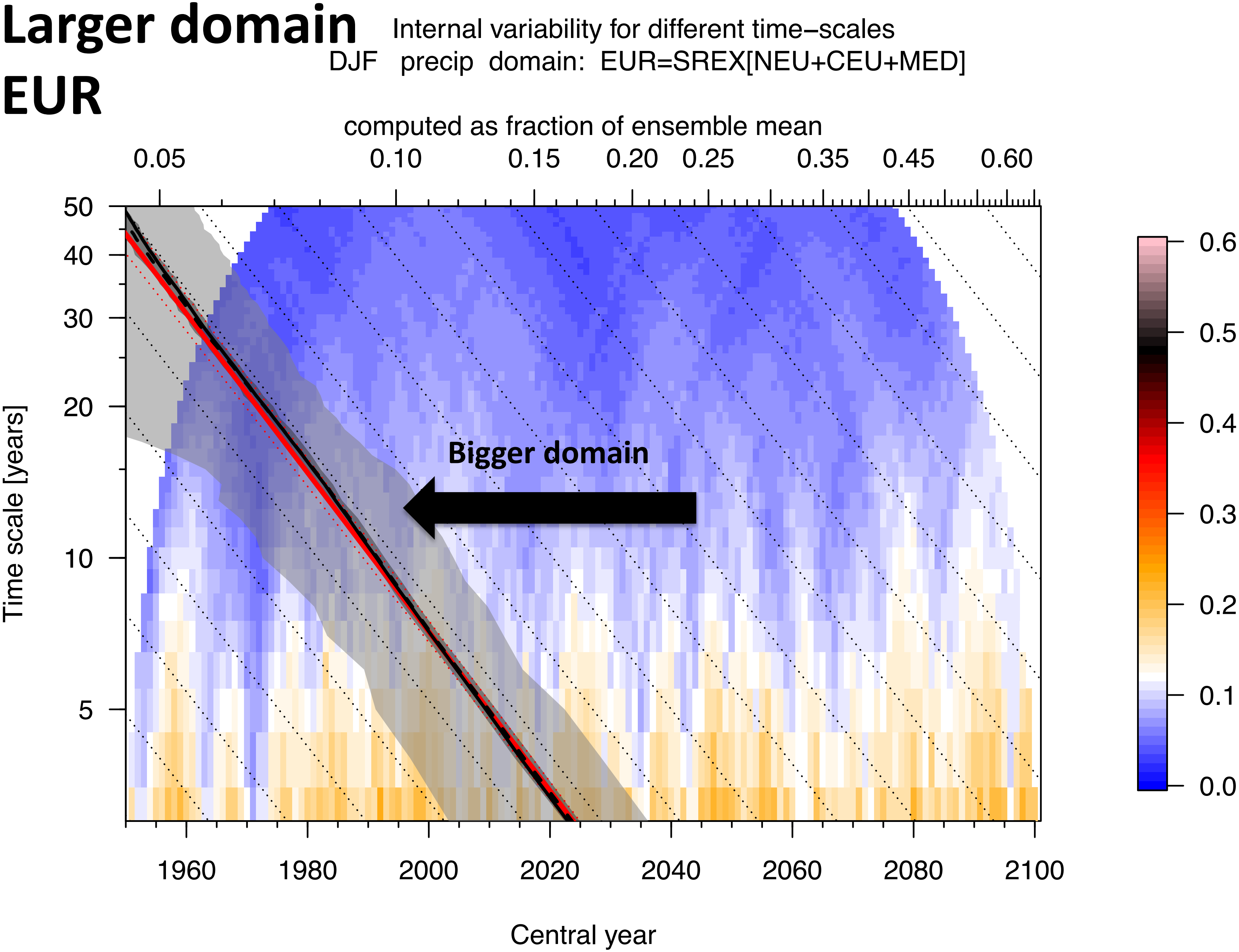
Now use LOG-scales
DJF precip MED



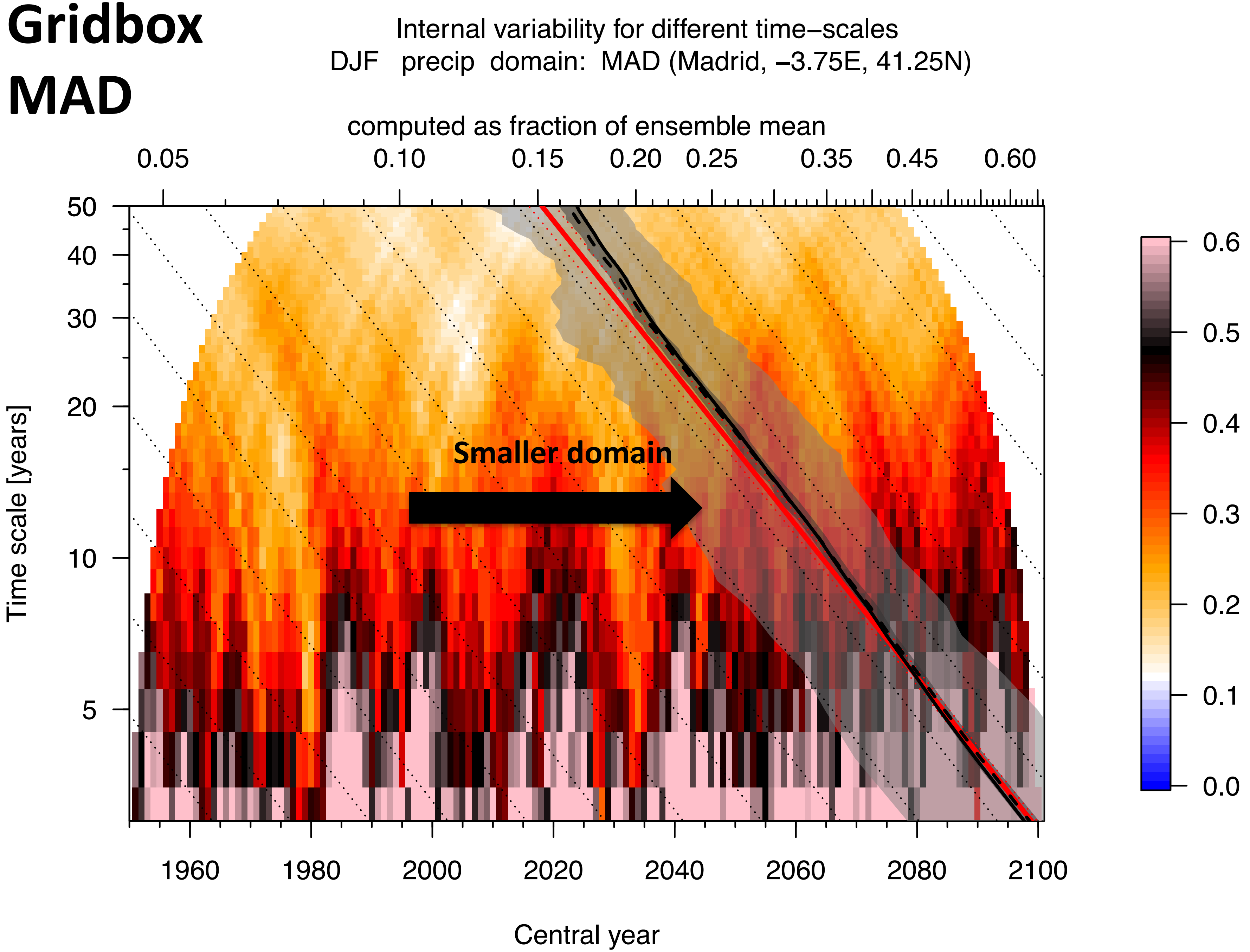
Other domain NEU



Larger domain EUR

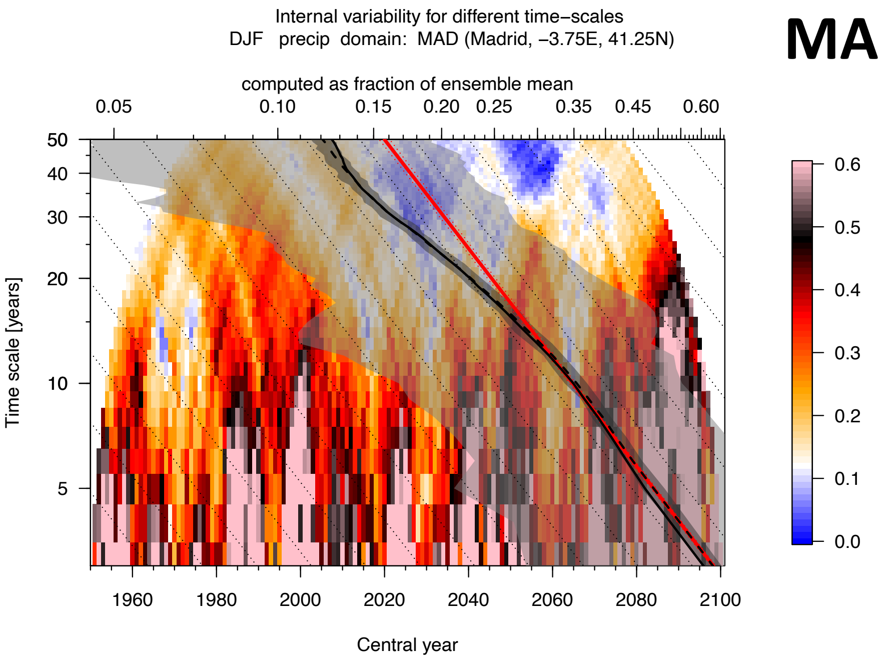


Gridbox MAD

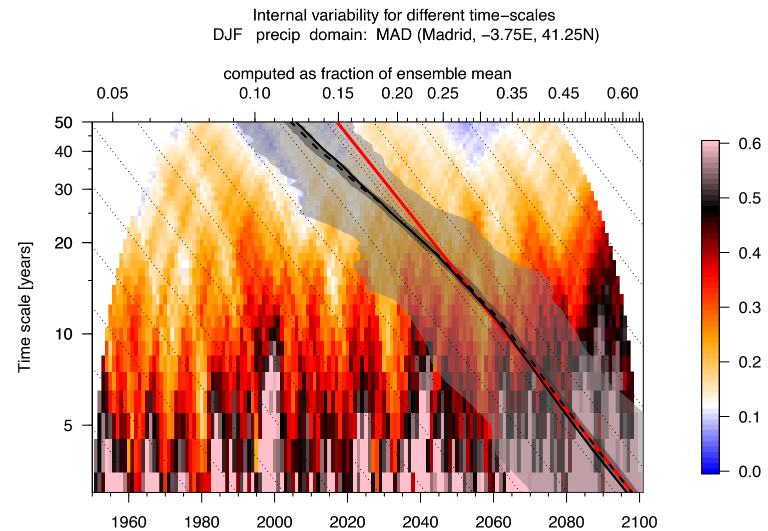

Internal variability for different time−scales
DJF precip domain: MAD (Madrid, −3.75E, 41.25N)
computed as fraction of ensemble mean
0.05
0.10
0.15
0.20
0.25
0.35
0.45
0.60
Time scale [years]
50
40
30
20
10
5
Smaller domain
1960
1980
2000
2020
2040
2060
2080
2100
Central year
0.6
0.5
0.4
0.3
0.2
0.1
0.0

Can we get away with fewer members? (LOCAL)

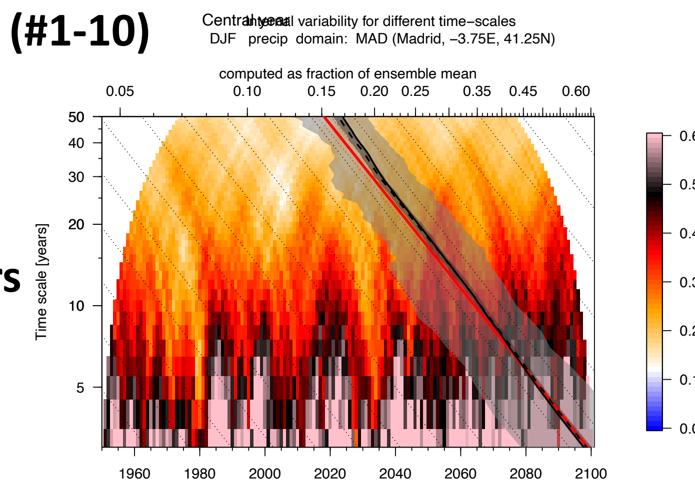
MADRID



5 members (#1-5)



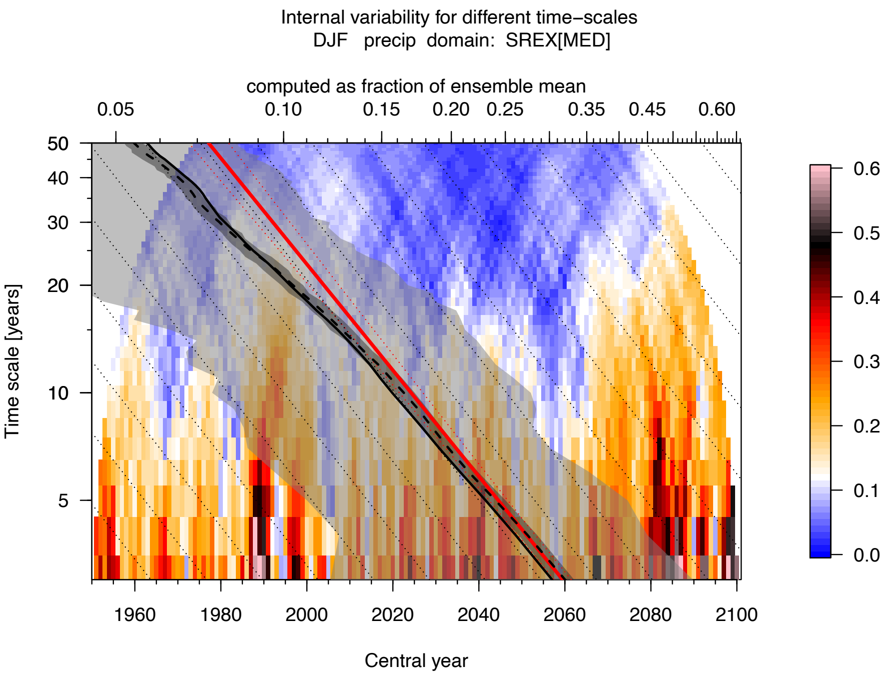
10 members (#1-10)



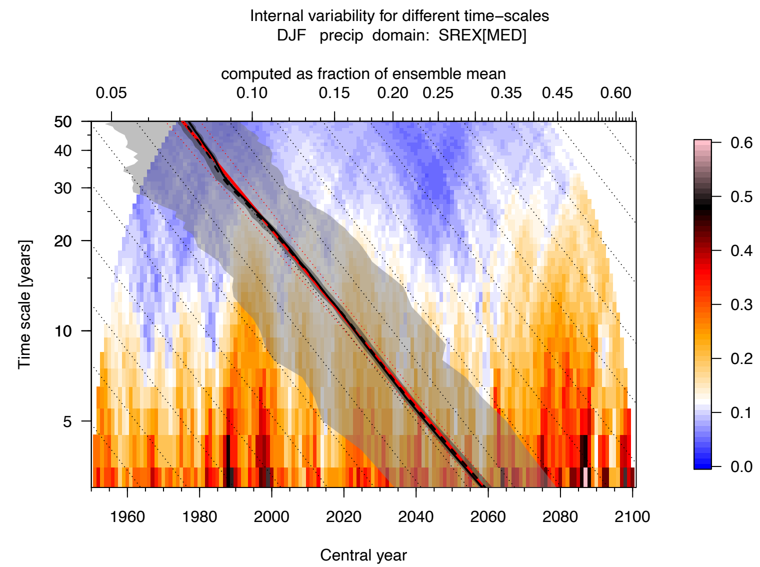
All 16 members

Short answer: Yes

Can we get away with fewer members? (REGIONAL)

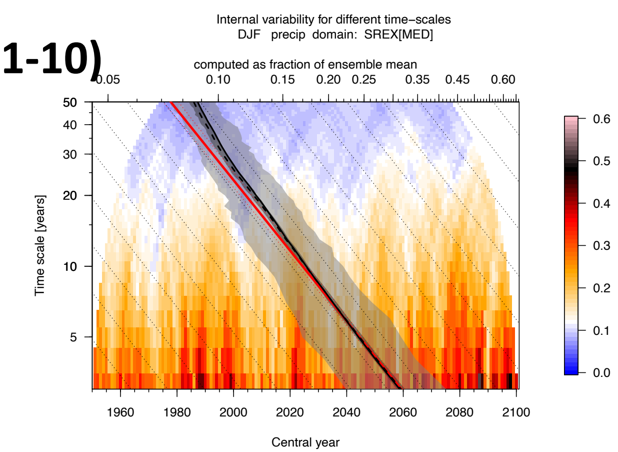


MED



5 members (#1-5)

10 members (#1-10)



Short answer: Yes

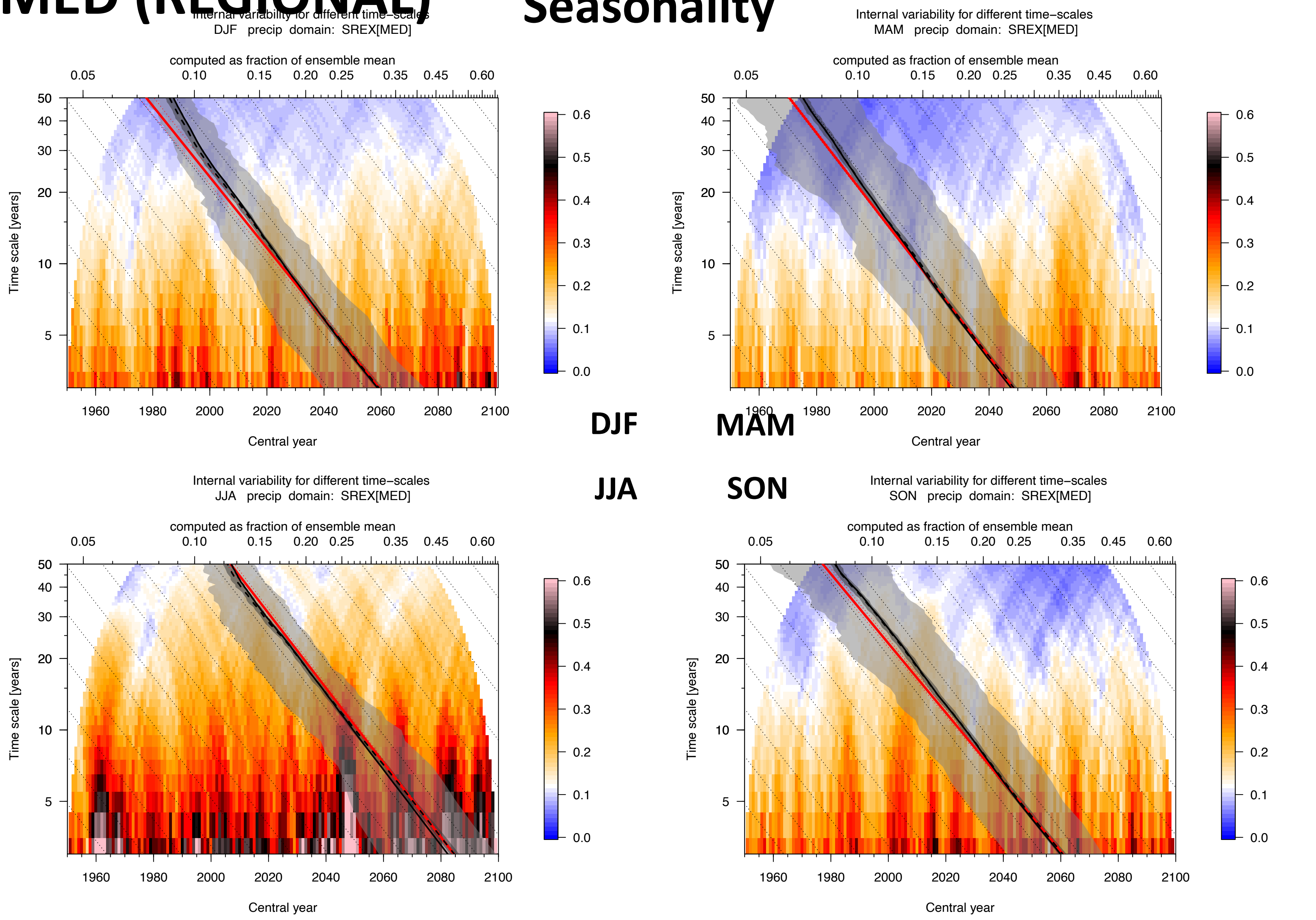
All 16 members

Summary / Pros and cons

- Pros
  - Simple method using INT defined from ensemble spread.
  - The amplitude of INT can be predicted from an exponential fit using the fastest time scales (These you can estimate also in shorter simulations).
  - Makes clear how INT basically scales as random noise (see additional slides).

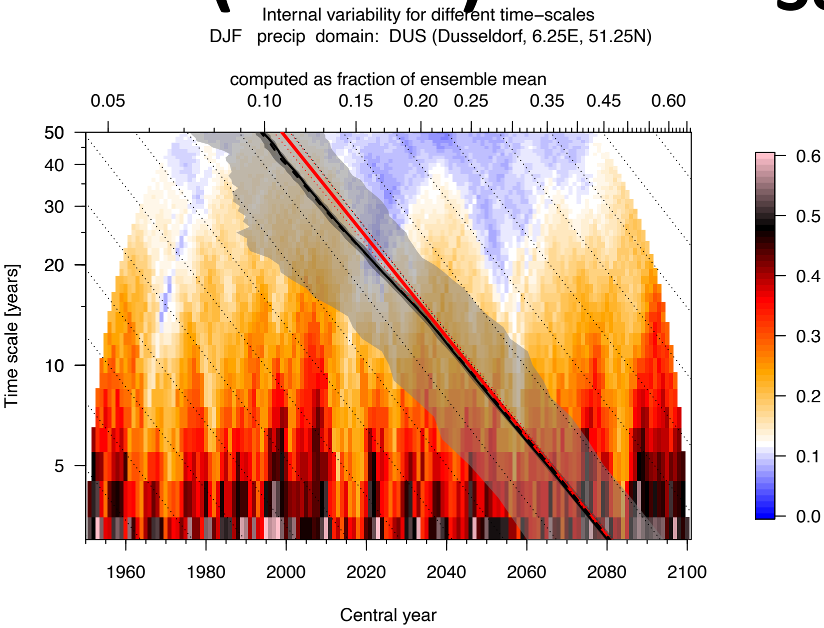
- Cons
  - Shown here are values <u>relative</u> to ensmean. Need to adjust when applying to e.g. temperature
  - The last step (aggregating over time) removes possible changes of INT over time. Only the (contour)-maps can show these
  - Assumes that we can determine the "forced signal" in another way (i.e. by loess regression). Usually it is the main aim to determine the forced signal, and here we assume we have it already.... => Ideally, you would compute the internal variability from a pre-industrial control simulation, but then we have no clue as to whether variability changes or not..

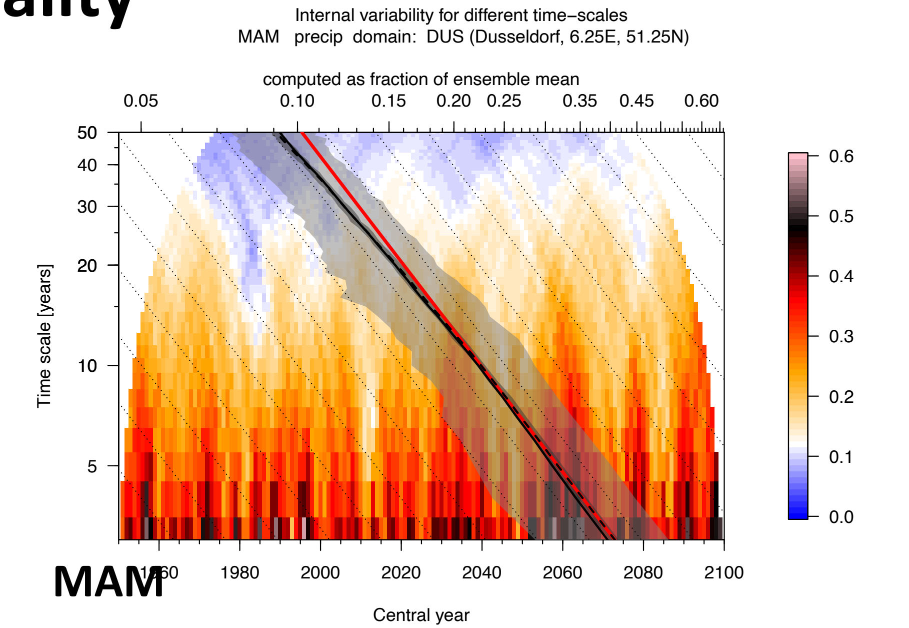
MED (REGIONAL) Seasonality



DUS (LOCAL)

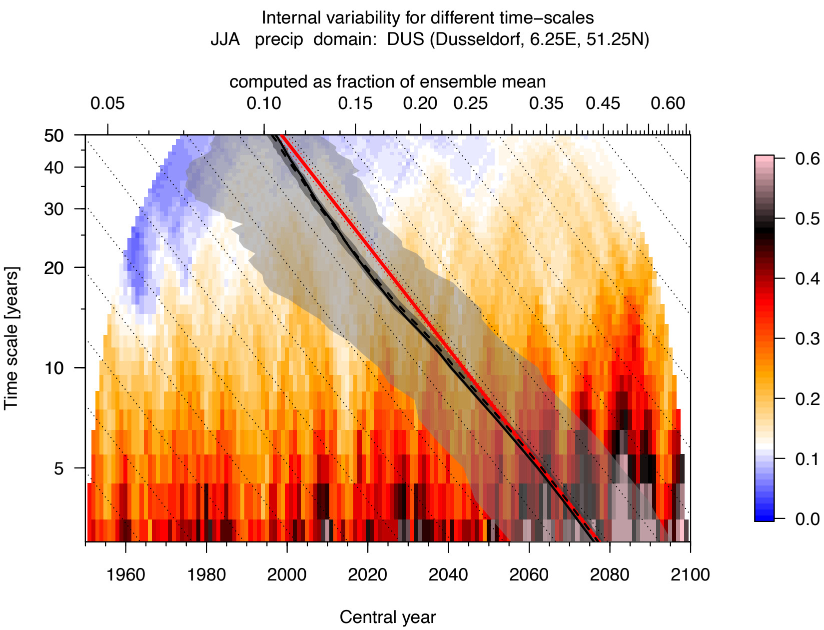
Seasonality

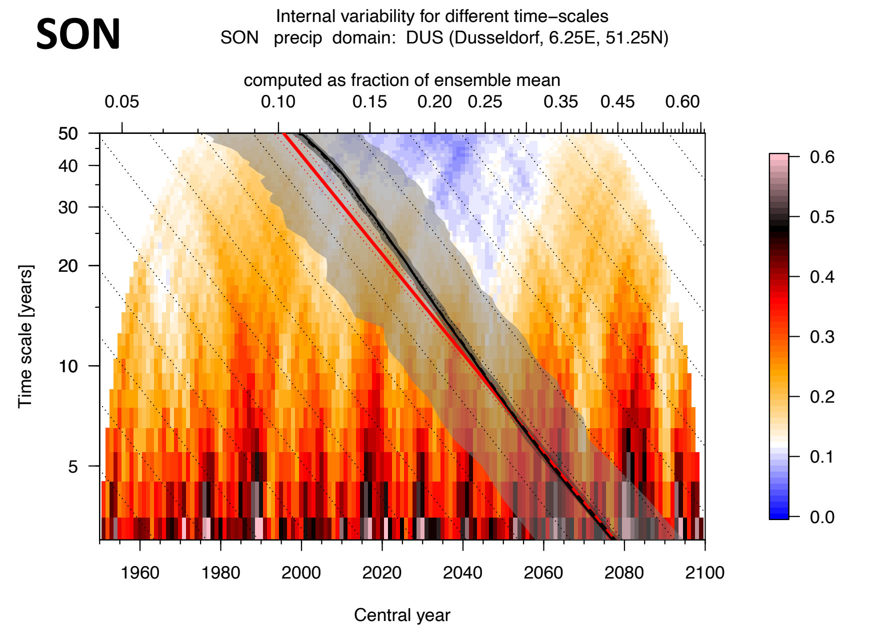




DJF MAM

JJA SON

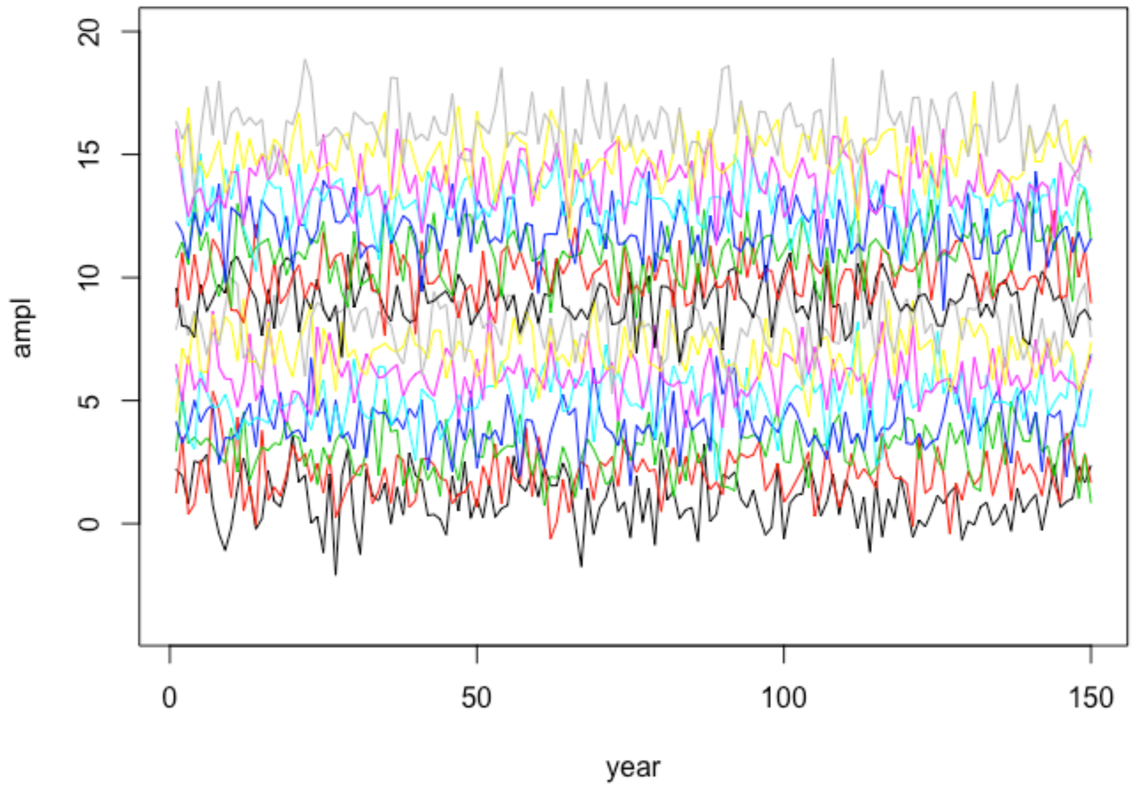




Additional slides

But hey isn't this all familiar from white noise theory?

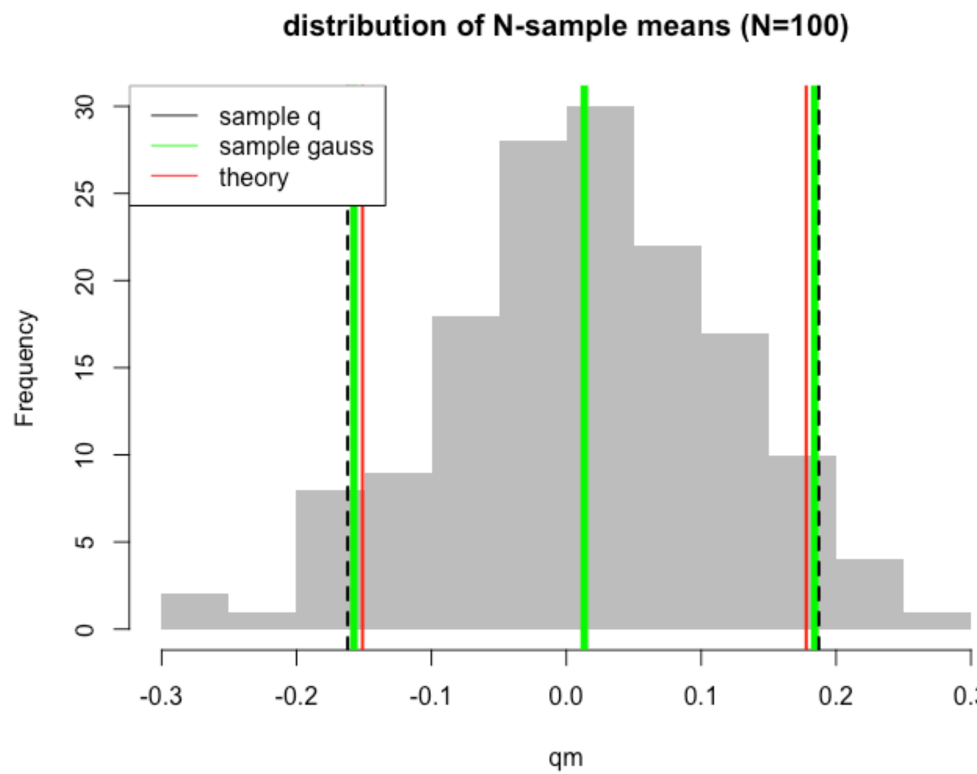
Example: white noise



16 time series of white noise (surrogate for JJA precip for example) – offset for display only

Example: white noise

- N-sample mean from normal distribution N(0,1)
- The N-sample mean is distributed again normally, as N(0,sd)
- where sd=1/sqrt(N)



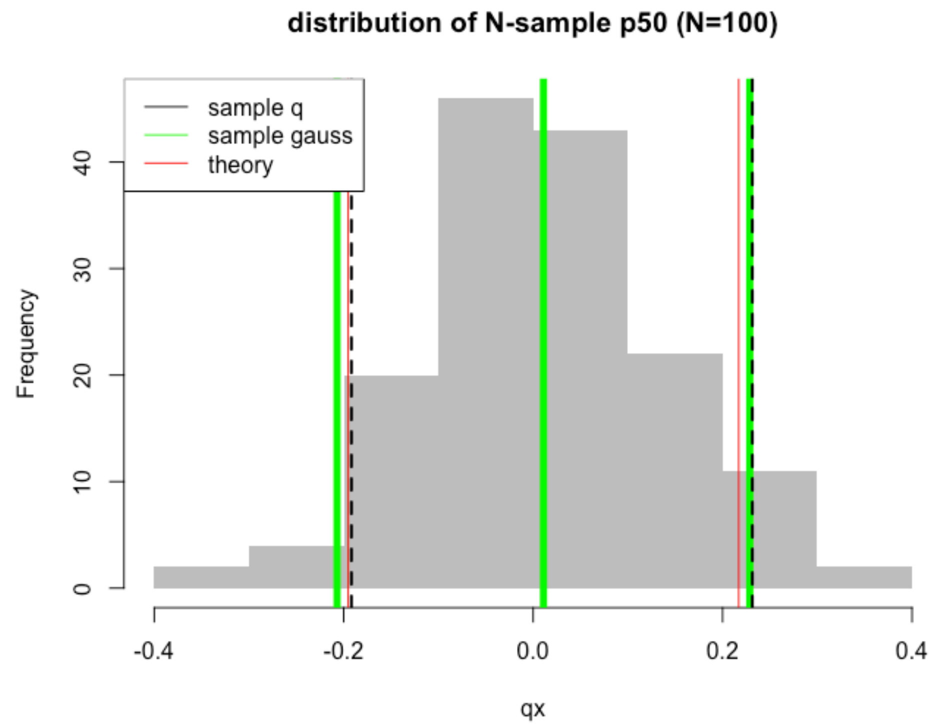
Example here, Nmem=100,Nyear=150

Example: white noise

- N-Sample quantiles from normal distribution N(0,1)
- The N-sample quantile is distributed again normally, as N(0,sd)
- But now sd is more complex... **But still proportional to 1/sqrt(N)**)

- If p is quantile (0...1) then sd^2=p(1-p)/f(p)^2, where f(p) is the density of that quantile given the distribution.

P50



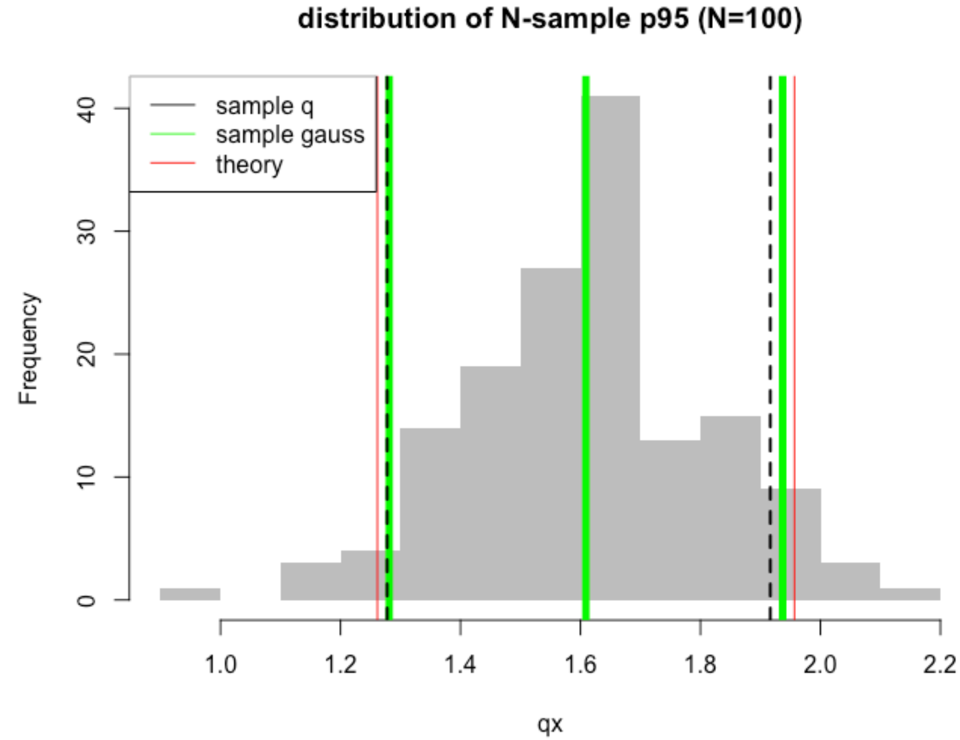
Example here, Nmem=100,Nyear=1000

Example: white noise

- N-Sample **quantiles** from normal distribution N(0,1)
- The N-sample quantile is distributed normally, as N(0,sd)
- Now sd is more complex... **But still proportional to 1/sqrt(N)**)

- If p is quantile (0...1) then sd^2=p(1-p)/f(p)^2, where f(p) is the density of that quantile given the distribution.

P95



Example here, Nmem=100,Nyear=1000

Typically sd of sample-q gets broader for higher quantiles

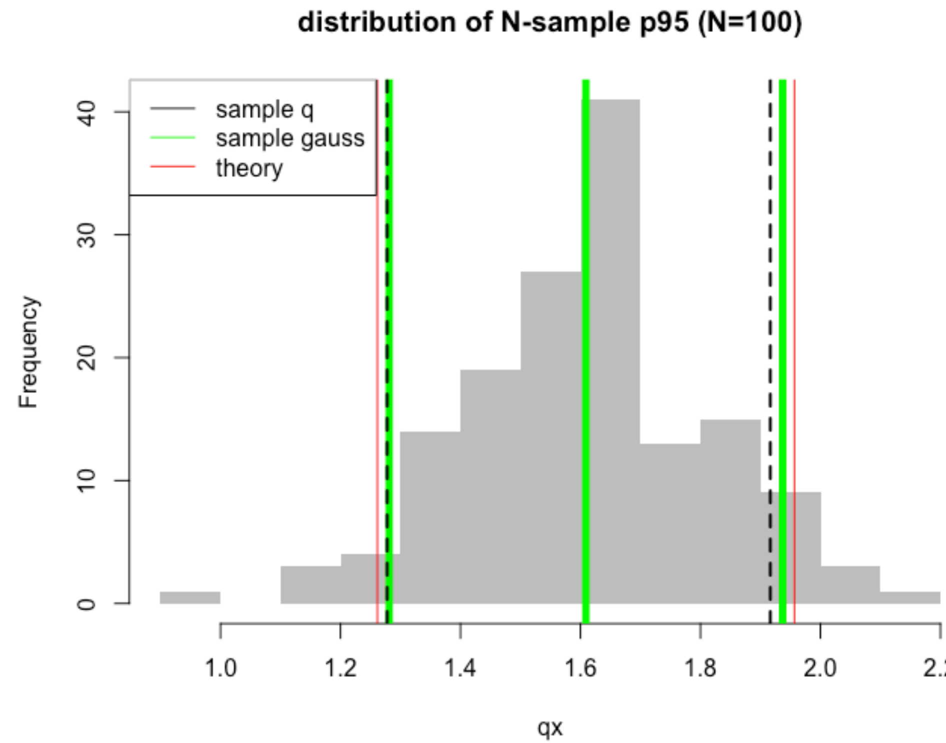
Example: white noise

- The **difference** of two normal distributions is again normally distributed, with
- Z = Y – X ~

  N(my-mx,sx^2+sy^2)

- This implies that our n-sample measure of internal variability (P95-P05) is also distributed normally!

P95



Example here, Nmem=100,Nyear=1000