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Eidgenössische Technische Hochschule Zürich
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Extreme Events in a Changing Climate

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Thanks to: Peter Brockhaus, Christoph Buser, Cathy Hohenegger,
Sven Kotlarski, Hans-Ruedi Künsch, Dani Lüthi, Elias Zubler

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Extreme events in the IPCC

Early IPCC-statements (SAR 1996):

"... it can be expected that changes in *hydrological extremes* will be more significant than changes in hydrologic mean conditions."

"In evaluating the societal ramifications of water resource changes, attention must be focused on changes in the *frequency and magnitude of floods and droughts*."

Early IPCC WG1 coverage of extreme events did not match these claims!

IPCC 1990: 7 pages (of 364)

IPCC 1996 SAR: 12 pages (of 572)

"This apparent neglect is not due to a failure to appreciate the importance of extreme events, but rather a result of *well-founded scientific caution*."

(Fowler and Hennessy, 1995)

More recent IPCC reports included rapidly growing coverage of extremes:

IPCC 1990: 7 pages (of 364)

IPCC 1996 SAR: 12 pages (of 572)

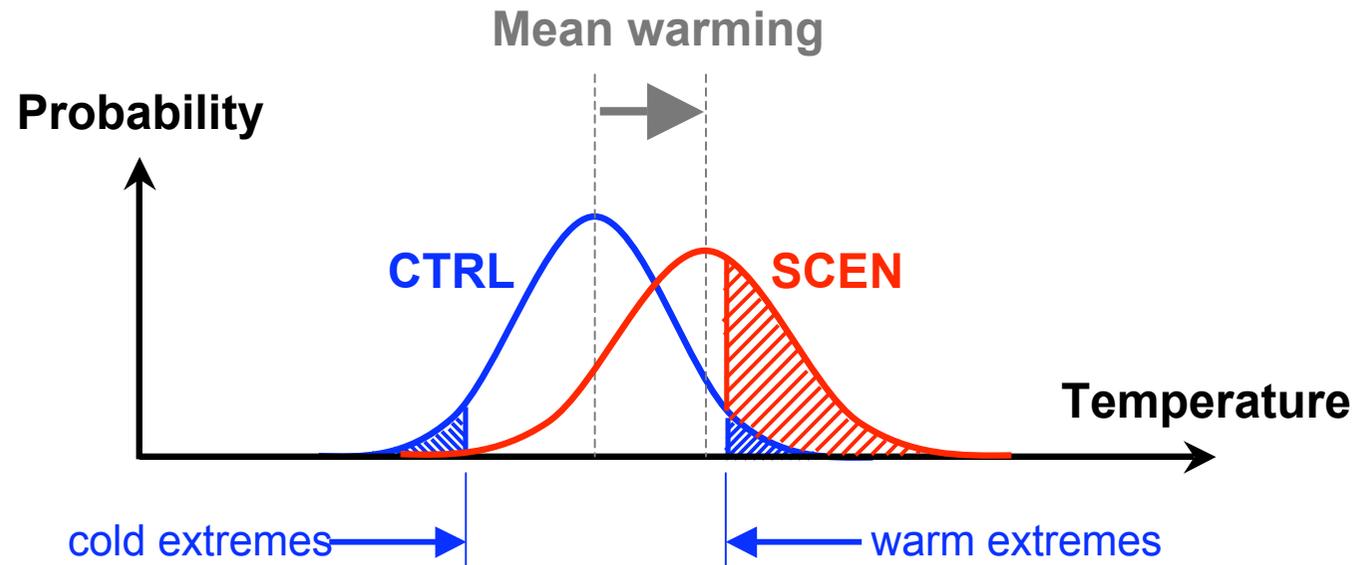
IPCC 2001 TAR: 25 pages (of 881)

IPCC 2007 AR4: 48 pages (of 994)

Note:

Doubling time = 1 assessment report

Extreme events defined



Extreme events are defined in statistical terms, as events that deviate strikingly from the statistical mean.

Climate change implies changes in frequency of extremes.

Generally needs to account for changes of the whole statistical distribution (i.e. mean, variability, skewness, etc)

Statistical versus socio-economic definitions

4

Extreme events

are defined in statistical terms,
as events that deviate strikingly
from the statistical mean.

Natural hazards

are defined in terms of impacts,
losses, damages, casualties, etc.

Extreme event \neq natural hazard

**Assessing natural hazards in a changing
climate requires an impact and/or
damage model, or the consideration of
some impact indices.**

Example 1: flood => hydrological model

Example 2: heat waves => health indices

Extreme events



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- **theory: precipitation intensity**
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- **observations: heat waves**

Role of impact models / indices? Example of heat waves

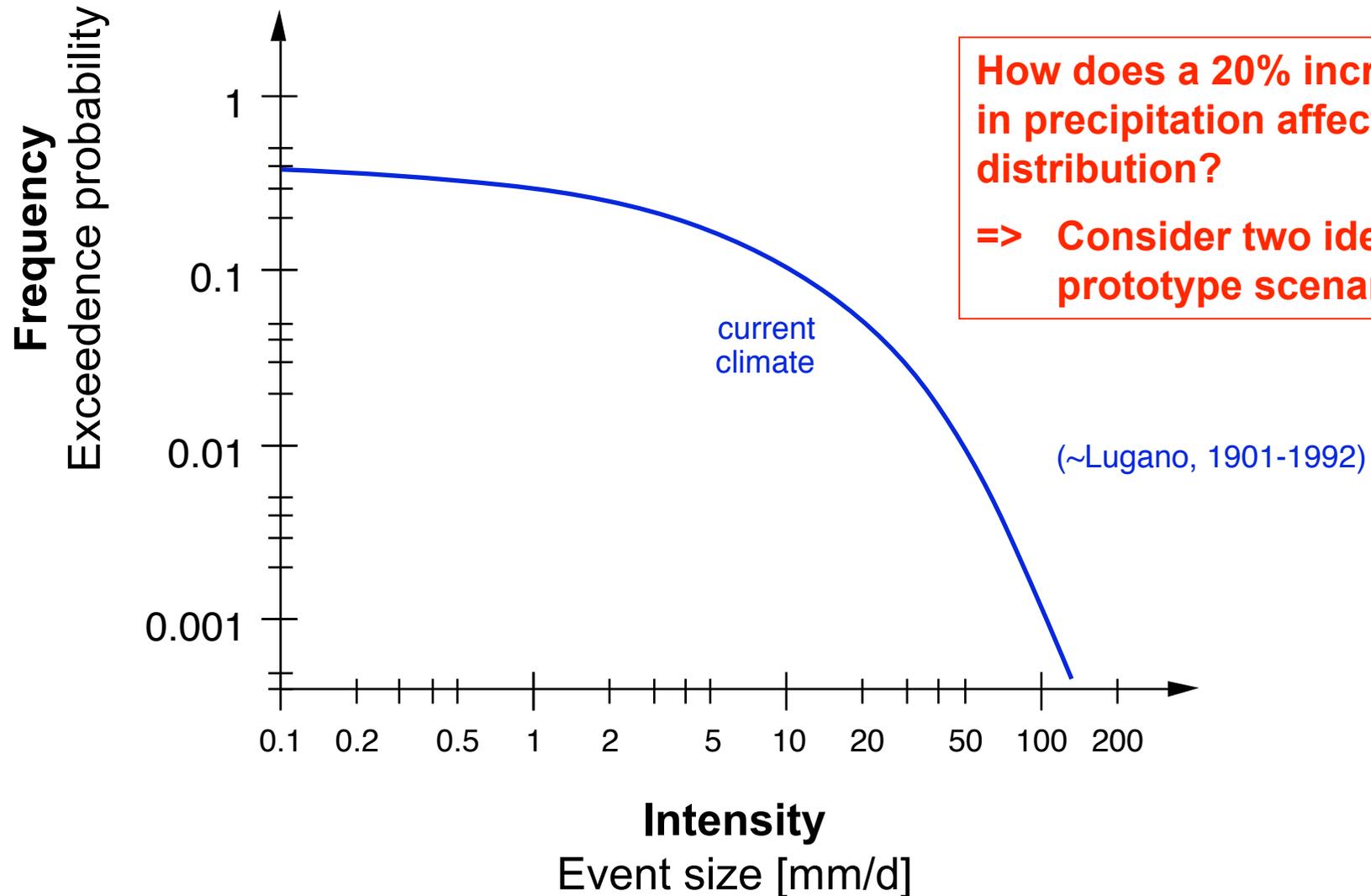
Role of model biases in assessing extremes

Role of computational resolution

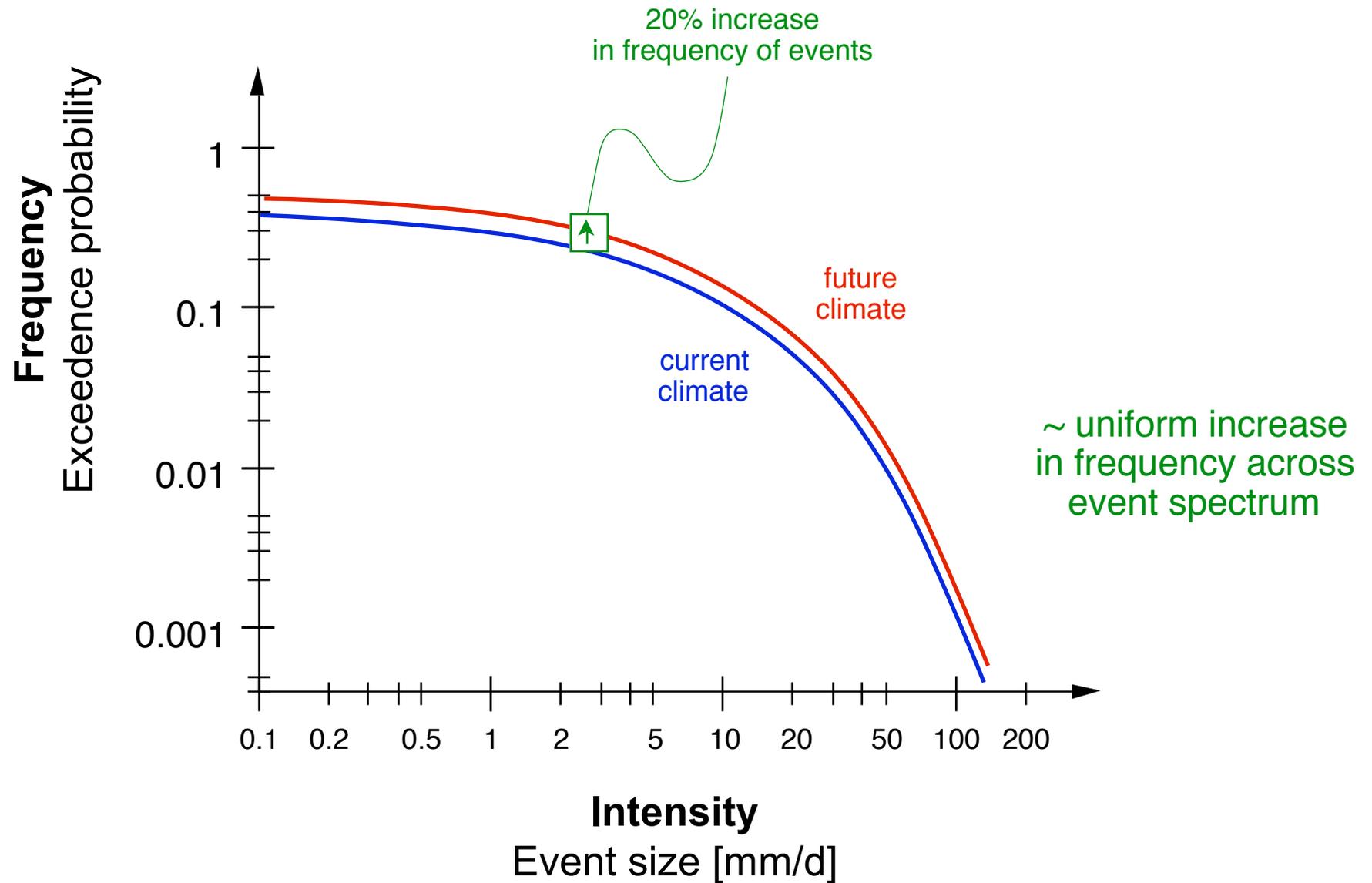
Sensitivity to model physics (parameterizations)

Frequency / intensity effects

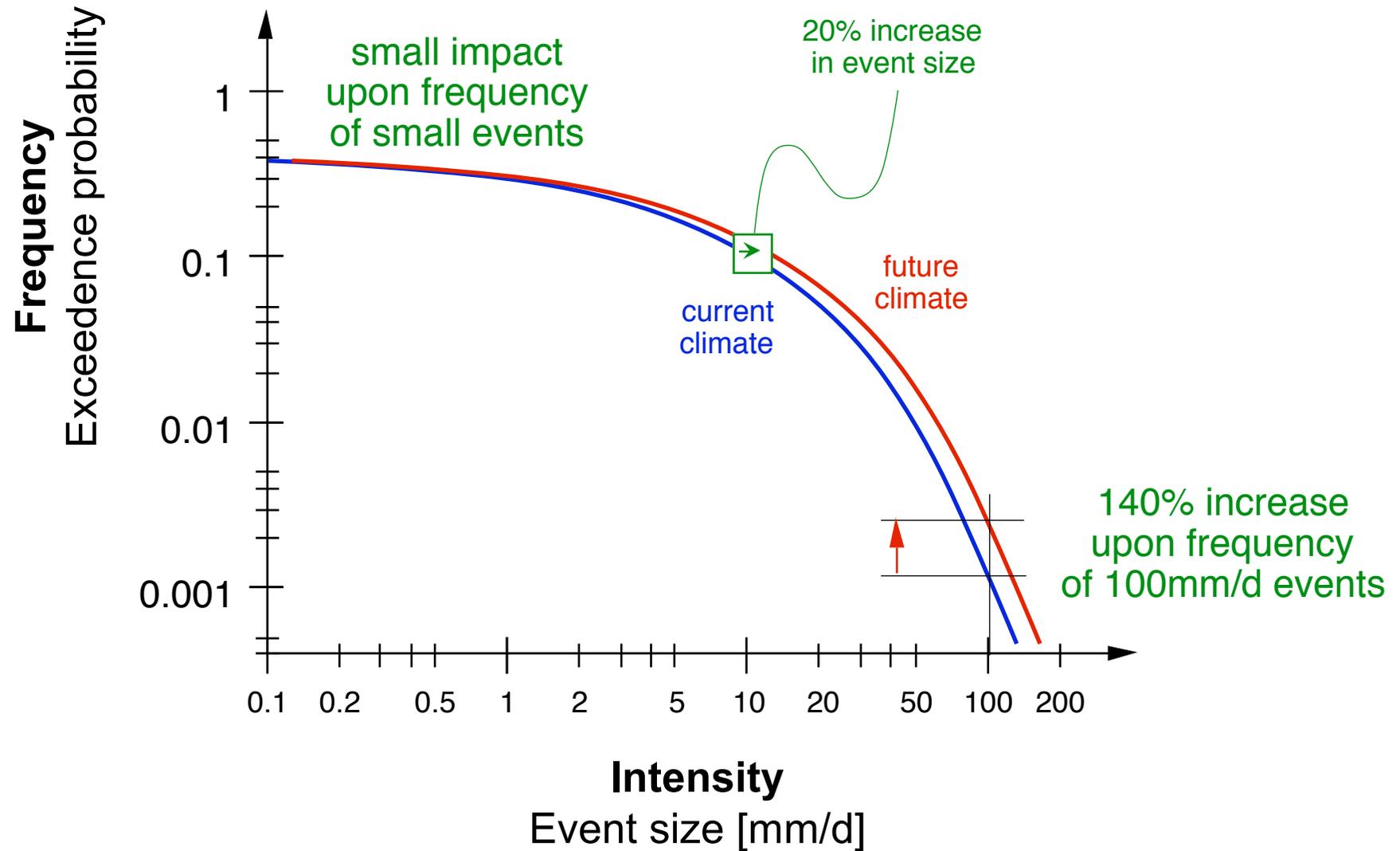
Frequency Distribution of Daylong Precipitation Events



Change in **frequency** of events

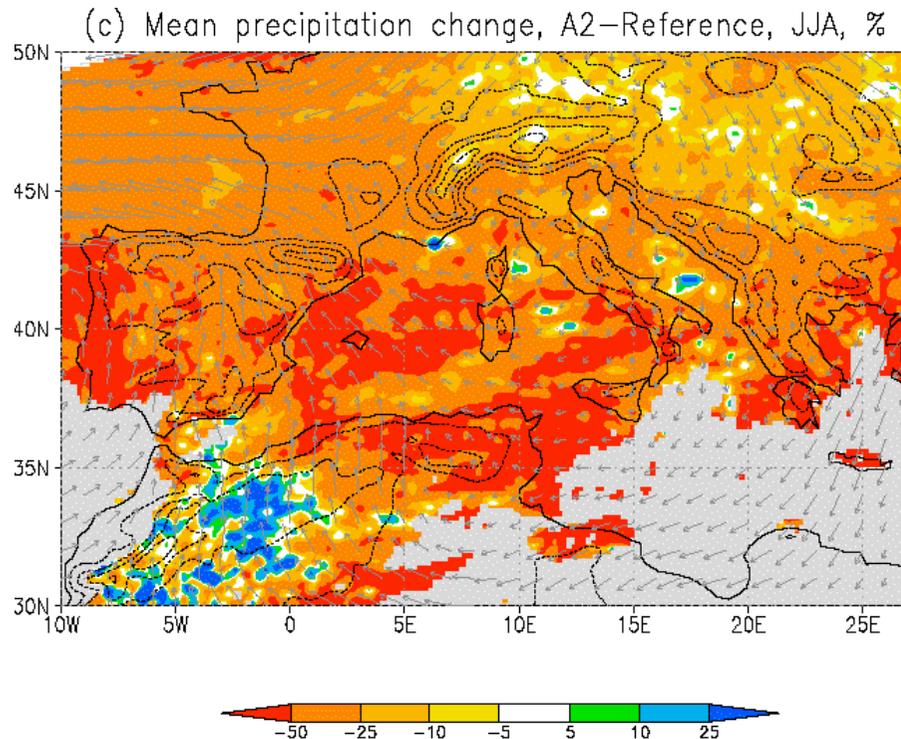


Change in **intensity** of events

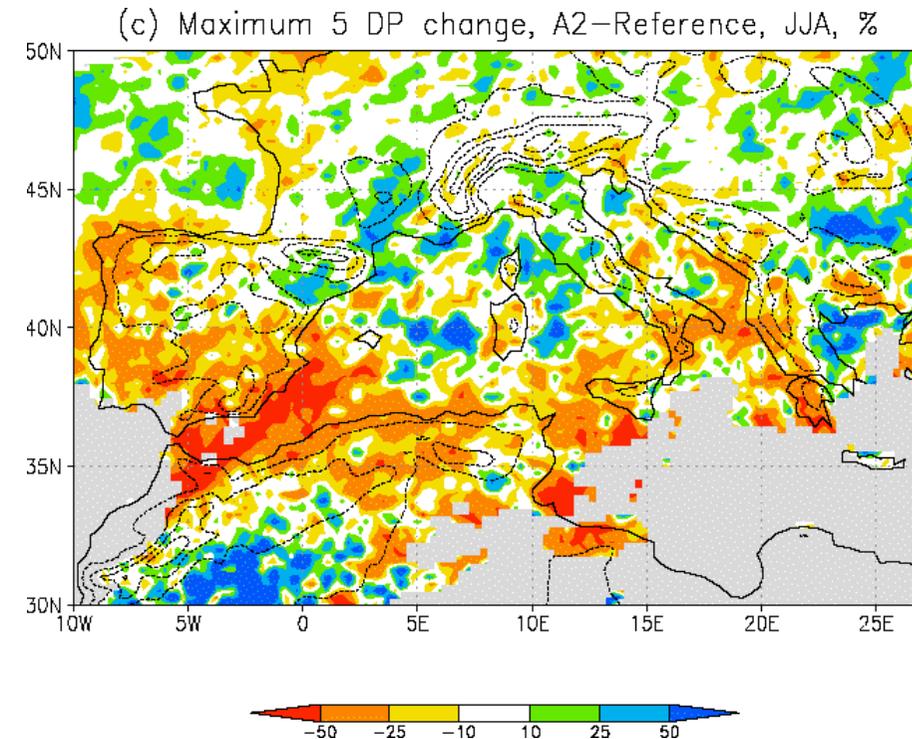


Summer precipitation changes in Europe

Mean changes [%]



Maximum 5-day precipitation [%]

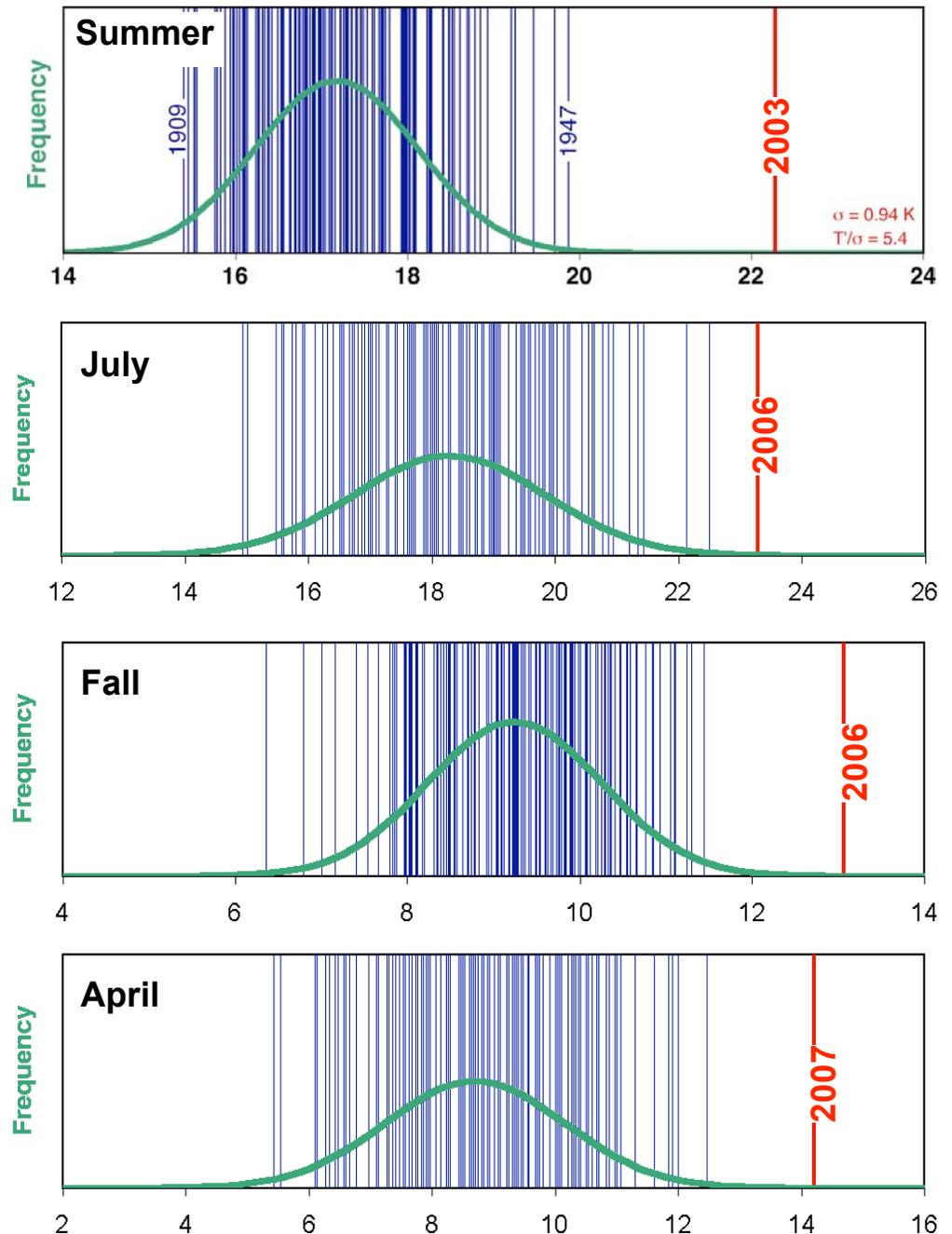


=> Increase in peak precipitation despite reduction in mean amounts <=

Recent European temperature extremes

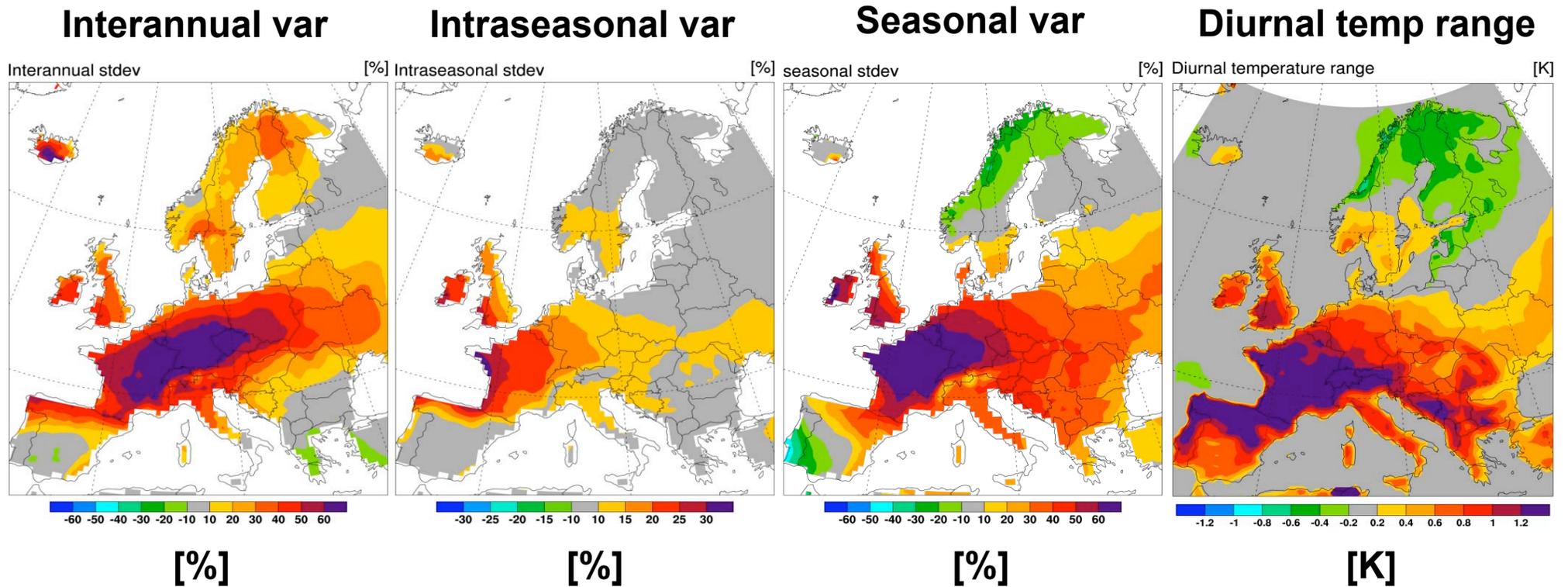
Can variability changes help to explain these **outliers**?

Data since 1864;
Average of 4 Swiss stations:
Zürich, Basel, Berne, Geneva



Variability changes in a changing climate

2070-2099 versus 1961-1990 (A2 scenario)



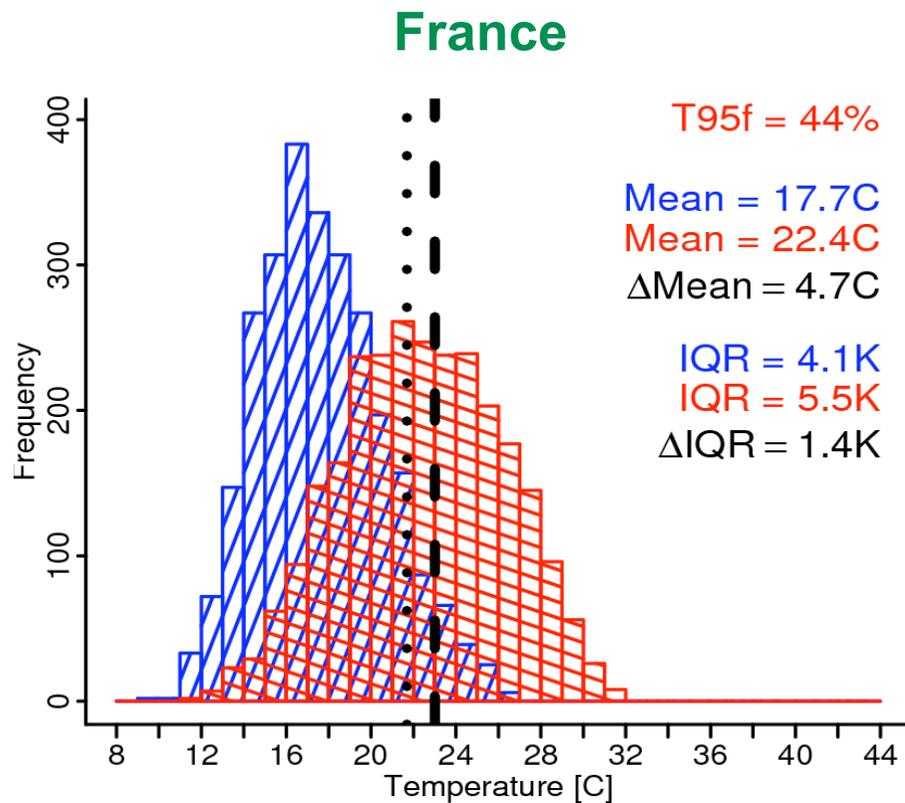
=> Pronounced variability increases on all time-scales <=

Regional response to climate change

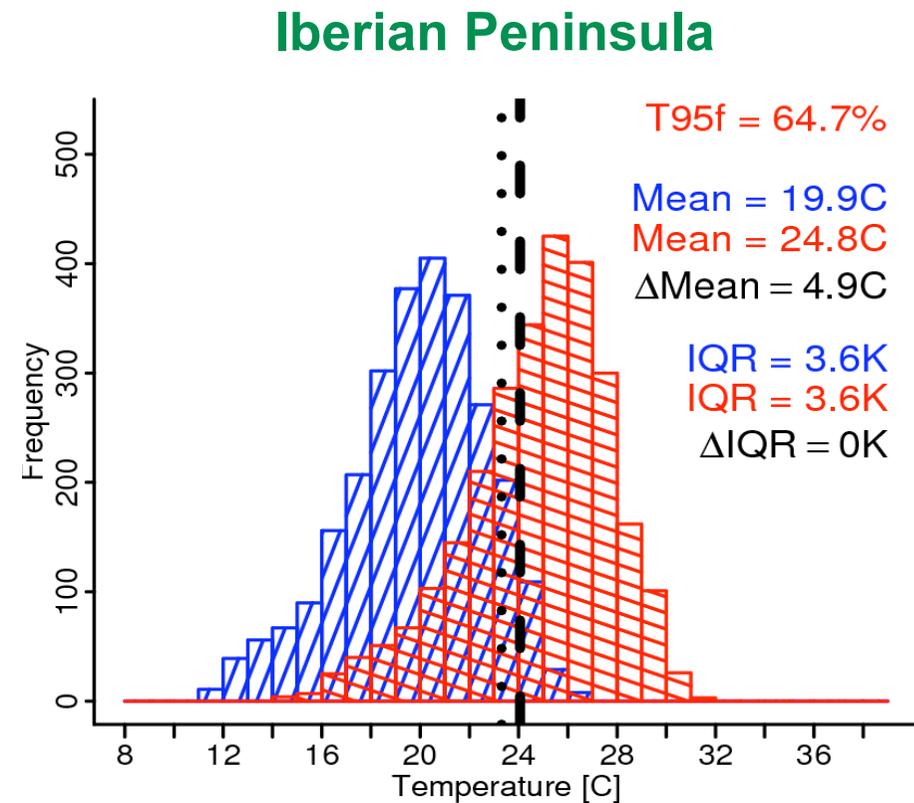
ETH model (CHRM) driven by HadAM3

CTL: 1961-1990

SCN: 2071-2100



Variability increase



Increase in skewness

PRUDENCE, CHRM model

Fischer and Schär 2009; Clim. Dynam, Observations from Haylock et al. 2008

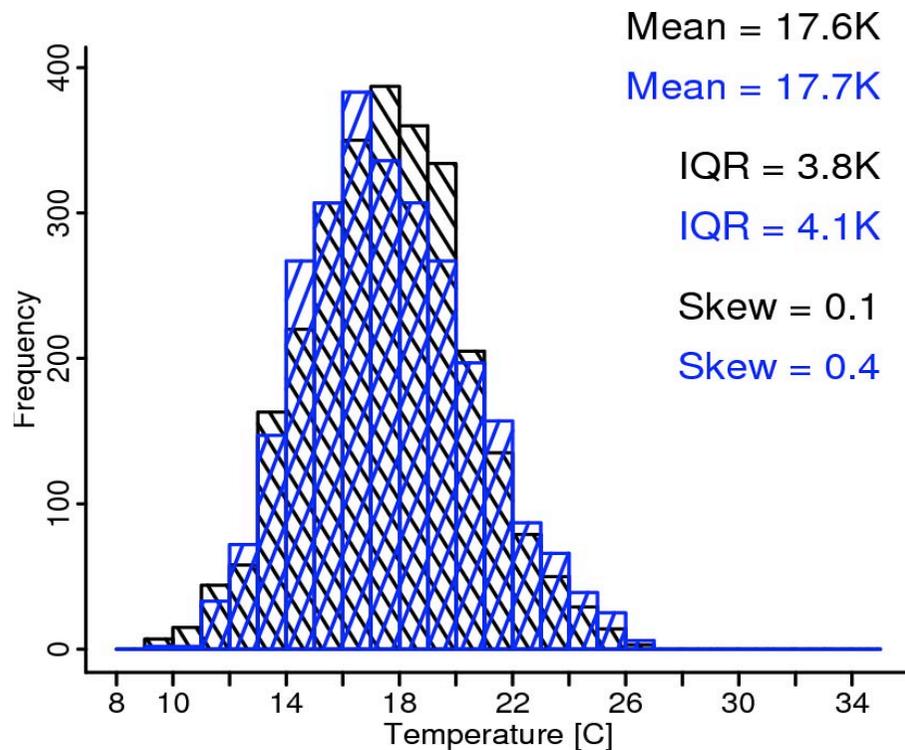
Validation of daily summer temperatures

ETH model (CHRM) driven by HadAM3 (1961-1990)

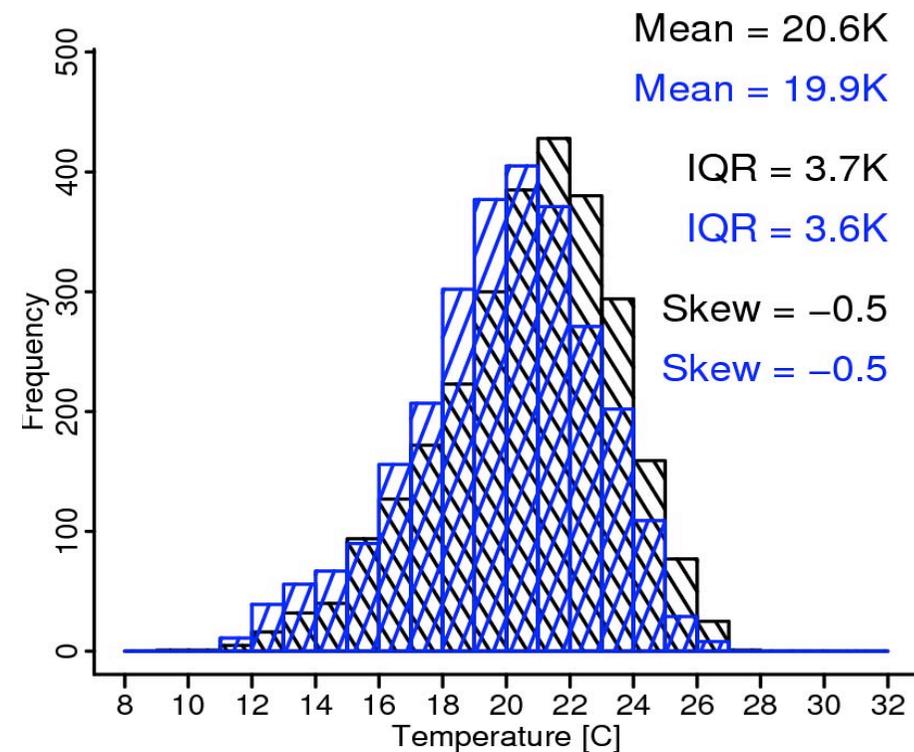
OBS: 1961-1990

CTL: 1961-1990

France



Iberian Peninsula



Regional variations captured!

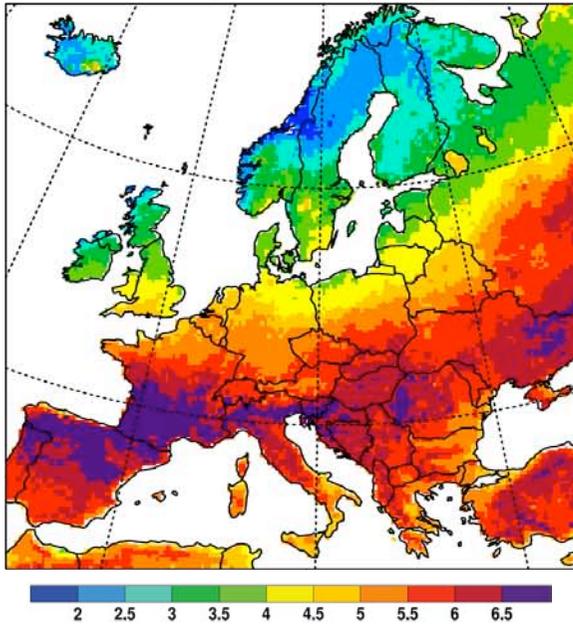
PRUDENCE, CHRM model

Fischer and Schär 2009; Clim. Dynam, Observations from Haylock et al. 2008

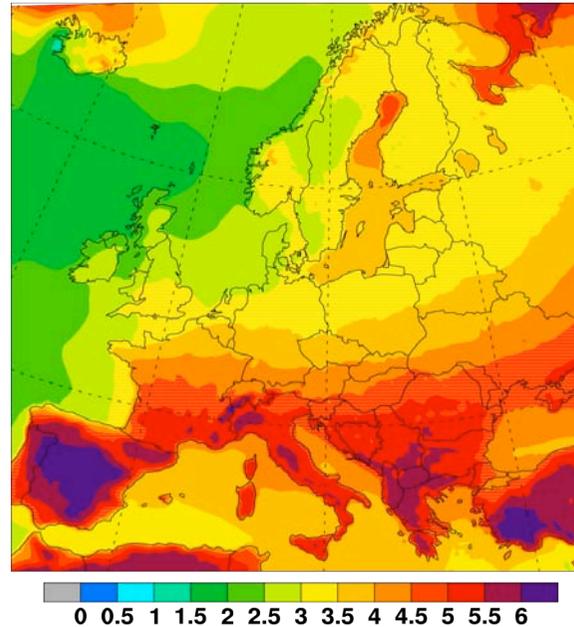
How will the warming proceed?

2071-2100 versus 1961-1990

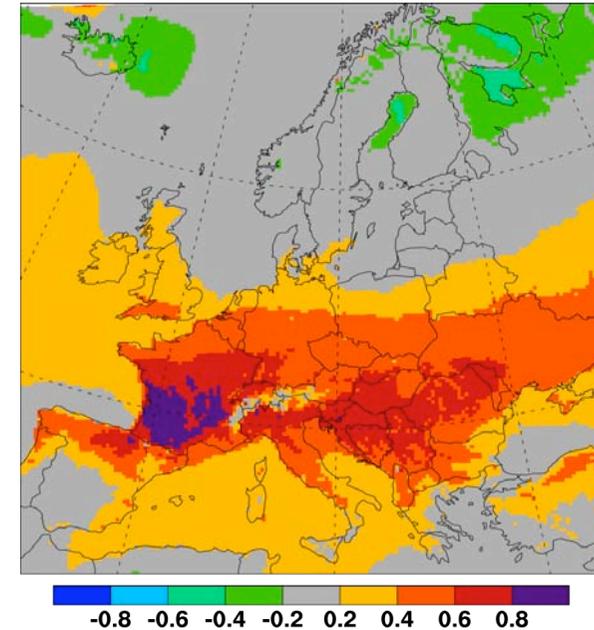
JJA T2m change
99th percentile [K]



JJA mean warming [K]



Change in JJA daily
variability [K]

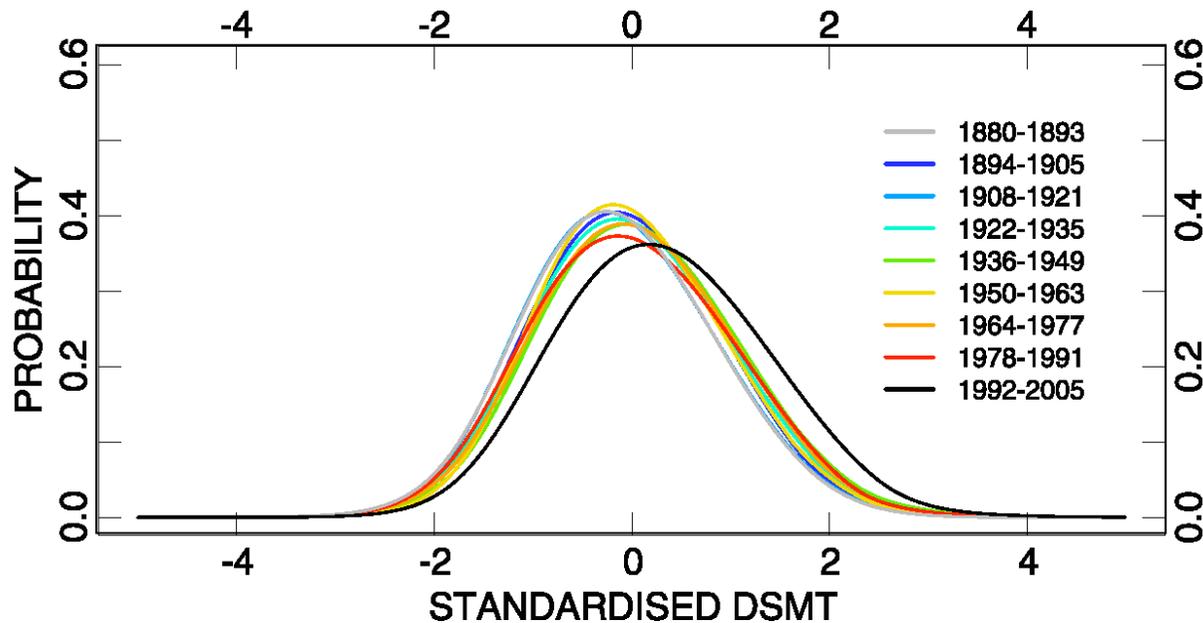


Strongest 99th percentile increase to the north of strongest mean warming

Good agreement with PRUDENCE results (Kjellström et al. 2007, Fischer and Schär 2009)

Differences between mean and 99th percentile is due to variability changes

Observed increases in temperature variability?¹⁶



Analysis of 54 high-quality homogenized temperature records from 1880-2005.

Finds a statistically significant signal.

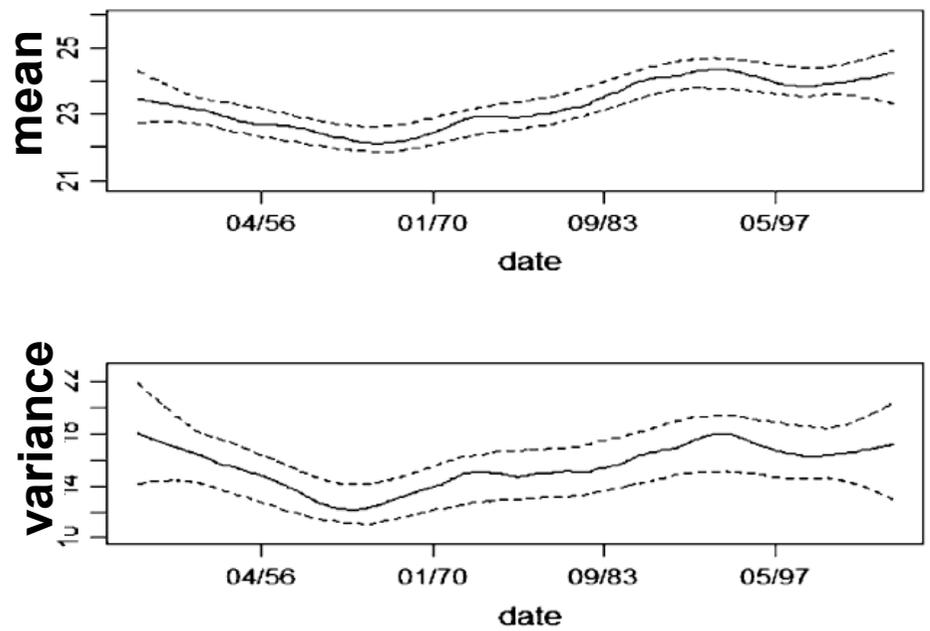
Region, R (n_s)	$\Delta\mu_R$ ($^{\circ}C$)	$\Delta\sigma_R$ (%)	$\Delta\gamma_R$ (%)
Western Europe (54)	$+1.6 \pm 0.4$	$+6 \pm 2$	$+0 \pm 7$
Central Western Europe (36)	$+1.3 \pm 0.5$	$+11 \pm 2$	$+0 \pm 6$
Iberian Peninsula (12)	$+2.6 \pm 0.6$	-7 ± 3	-1 ± 12
Scandinavia (6)	$+1.7 \pm 0.7$	$+4 \pm 6$	$+9 \pm 6$

Geographical pattern of trends is consistent with climate change scenarios:

- variability increases has maximum in Central Europe
- warming has maximum in Iberian Peninsula

Observed relationship between mean and variance?

Temporal evolution of mean and variance, Summer daily maximum temperature (La Rochelle, France)

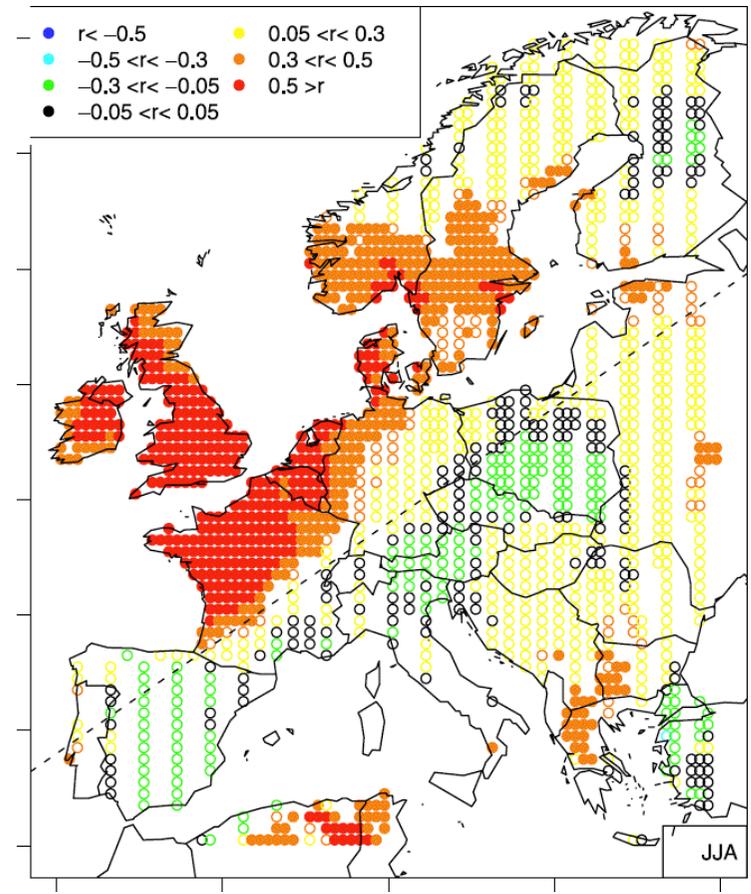


Evolution of mean and variance correlate!

Warm periods have higher variability

(Parey et al., 2010)

Correlation between mean and variance over Europe, summer (ECA&D data set)



(Yiou et al., 2009)

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Role of model biases in assessing extremes

Role of computational resolution

Sensitivity to model physics (parameterizations)

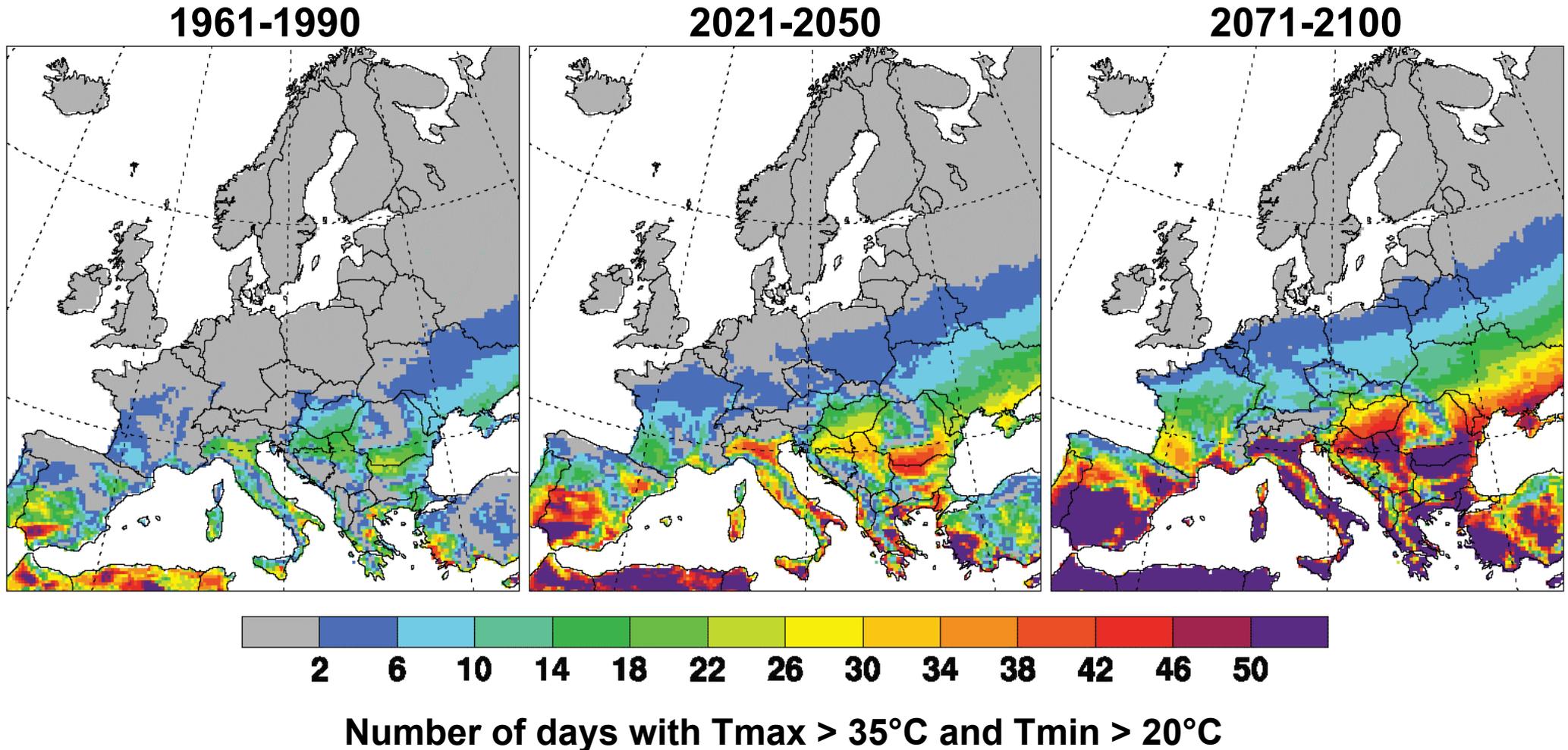
Key health impact factors

Health impacts of heatwaves are not only affected by peak temperatures. Studies of previous heat waves have isolated 3 key factors:

- (1) Extended length of heat wave (accumulation effect)
=> study heat wave duration**
- (2) High daytime AND nighttime temperatures (sleep deprivation)
=> study number of hot days / tropical nights**
- (3) High relative humidity (reduces evaporative cooling)
=> study “apparent temperature” or “heat index”**



Hot days and tropical nights



Dramatic increases in low-altitude Mediterranean (river basins and coasts)

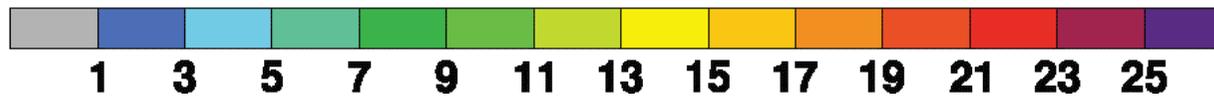
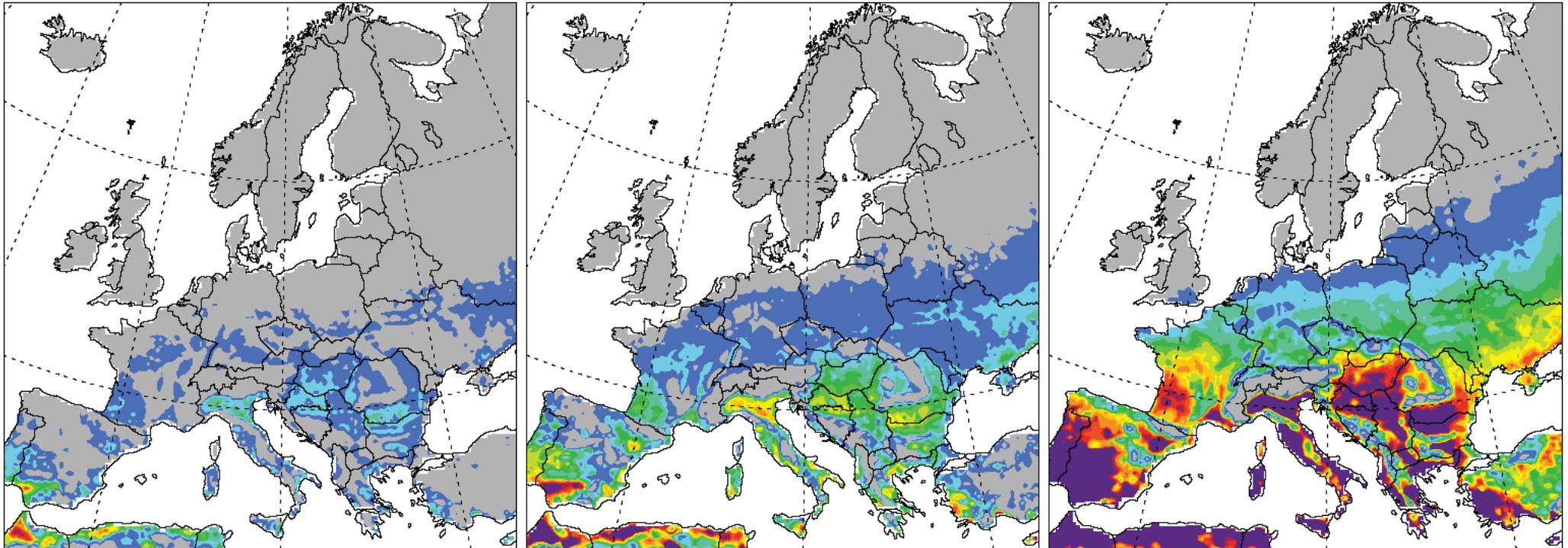
ENSEMBLES, mean of 6 models, scenario A1B
Fischer and Schär 2010, *Nature Geoscience*

Apparent temperature

1961-1990

2021-2050

2071-2100



Number of days with apparent temperature $\geq 40.6^{\circ}\text{C}$
(large heat stroke risk with extended exposure)

Dramatic increases in low-altitude Mediterranean (river basins and coasts)

ENSEMBLES, mean of 6 models, scenario A1B
Fischer and Schär 2010, *Nature Geoscience*

Affected regions

2071-2100

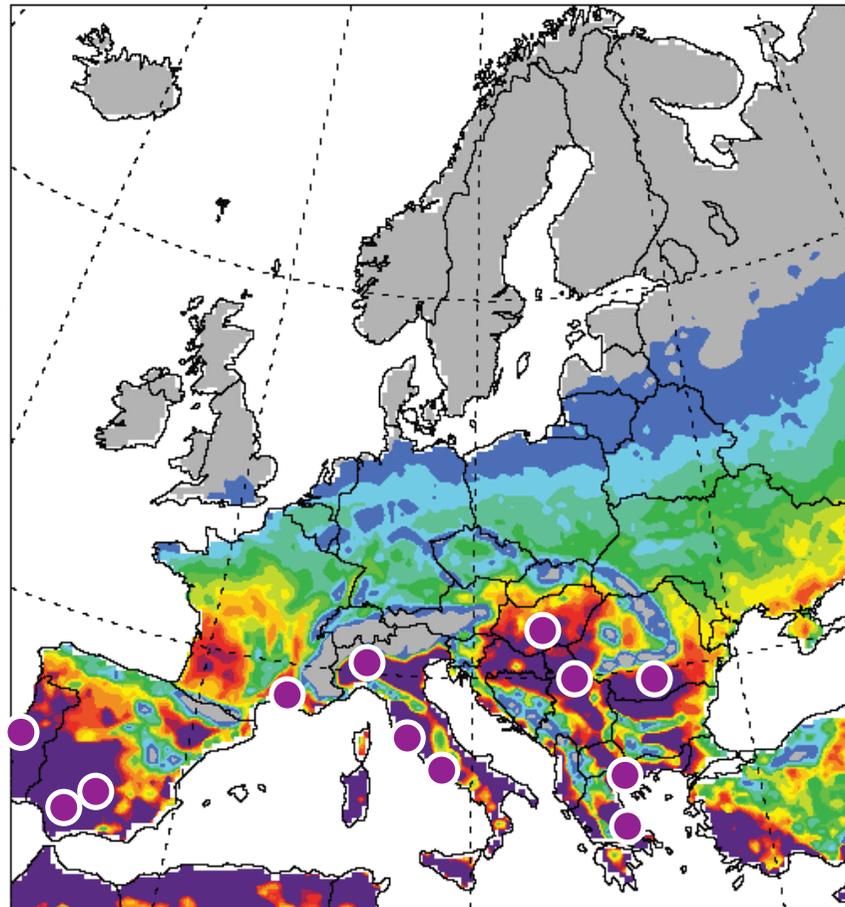
Affected river basins

Tejo
Ebro
Rhone
Po
Tiber
Danube

Affected towns

Lisbon
Seville
Cordoba
Marseille
Milan
Roma
Napels
Budapest
Belgrade
Bucharest
Thessalonica
Athens

Geographical pattern is consistent across all model chains and health indices considered, but amplitude strongly depends upon model



1 3 5 7 9 11 13 15 17 19 21 23 25
Number of days with apparent temperature $\geq 40.6^{\circ}\text{C}$

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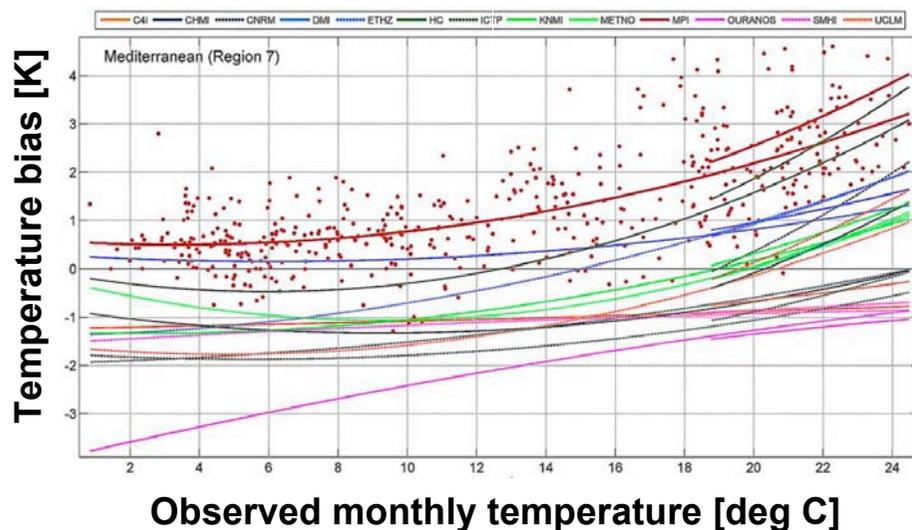
Role of model biases

Special role of biases for analysis of extremes:

- **biases in statistical distribution beyond biases in means (i.e. in variability)!**
- **impacts often depend on absolute thresholds => biases particularly crucial!**

Model biases are state dependent!

Analysis of ERA-40 driven RCM simulations (ENSEMBLES)

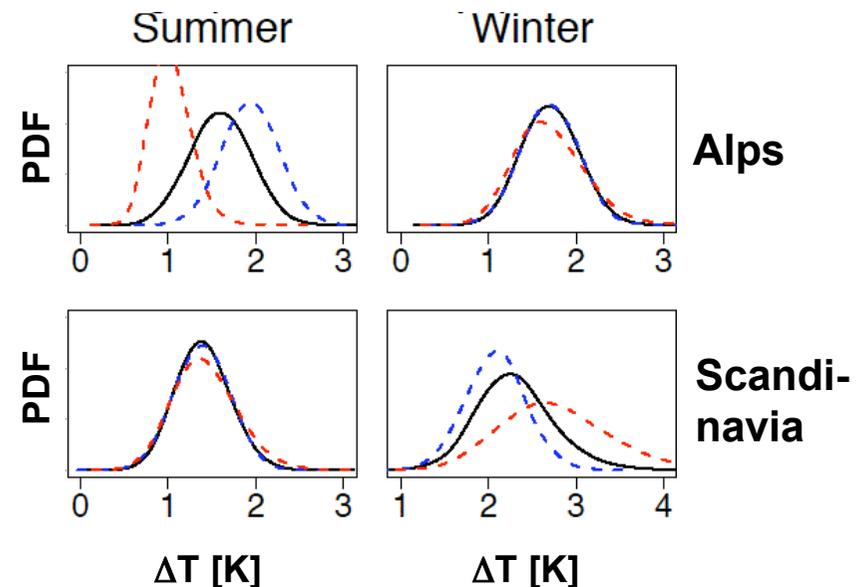


(Christensen et al. 2008)

Assumptions about bias changes matter!

Bayesian methodology using ENSEMBLES results (2021-2050) with TWO bias assumptions:

constant bias | **constant relation** | joint estimate



(Buser et al. 2009, Buser et al., sub)

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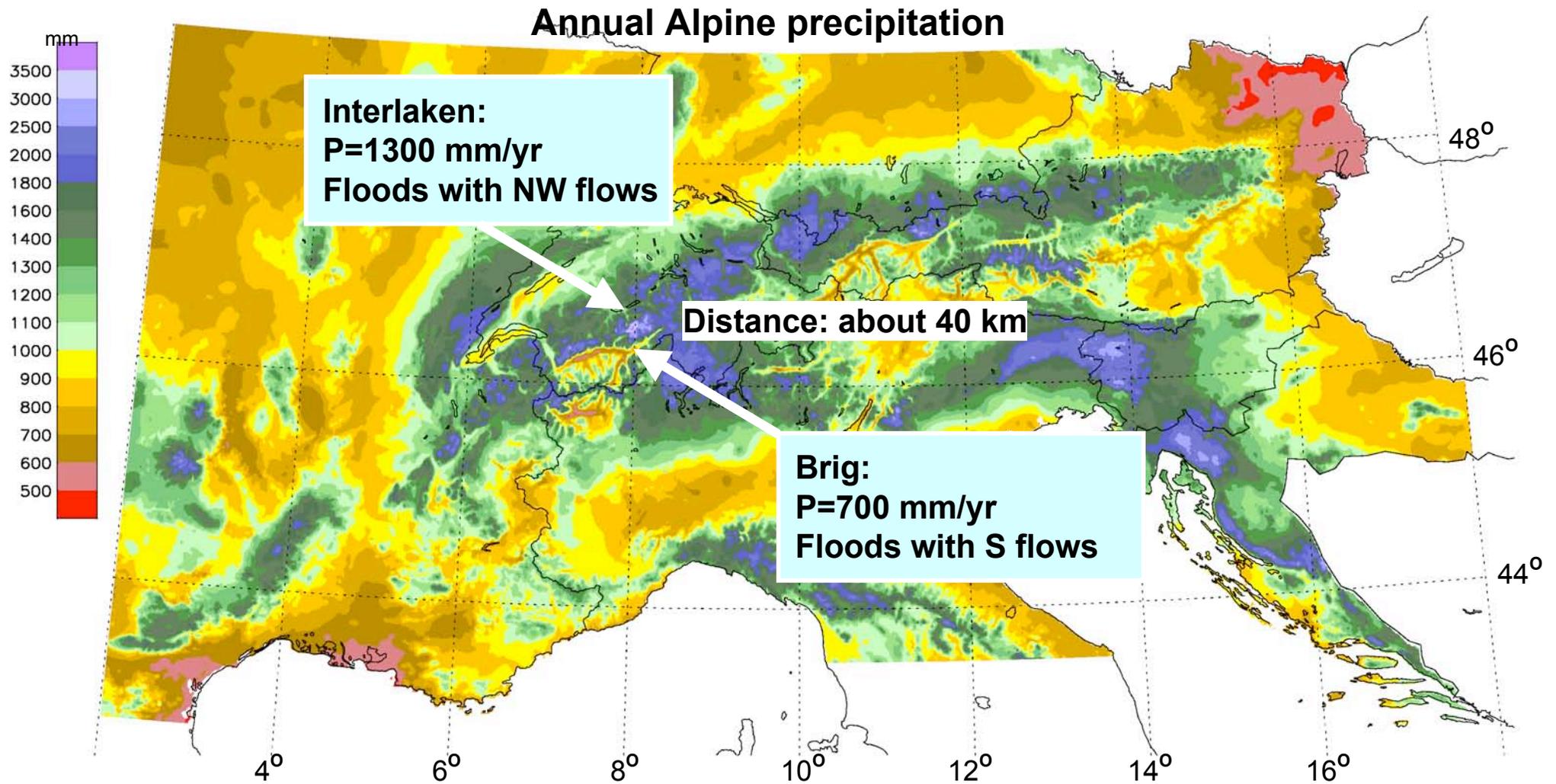
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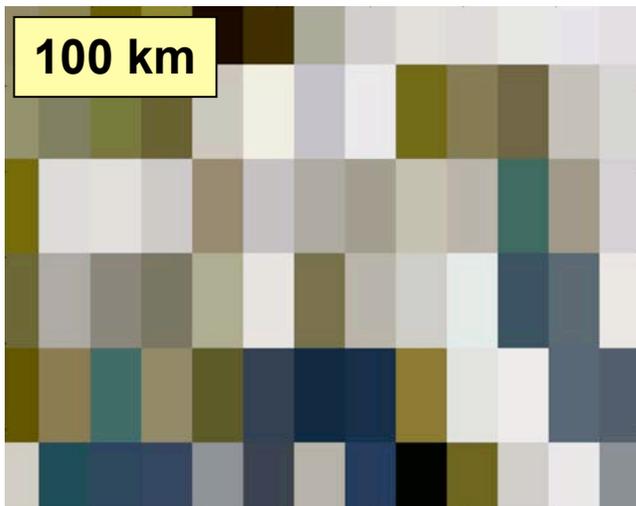
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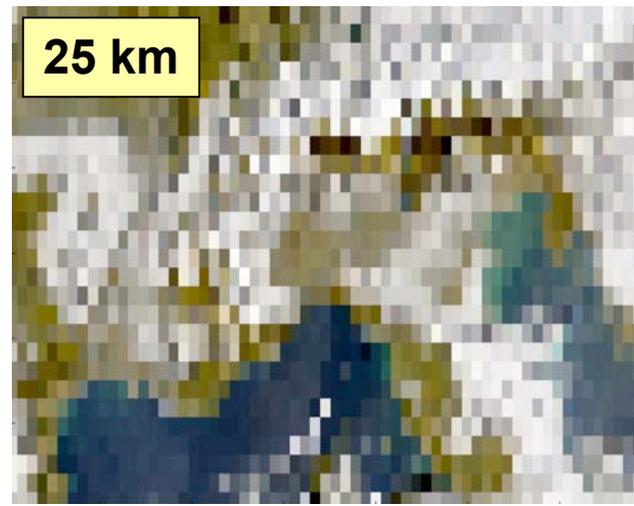
Spatial variations in extremes



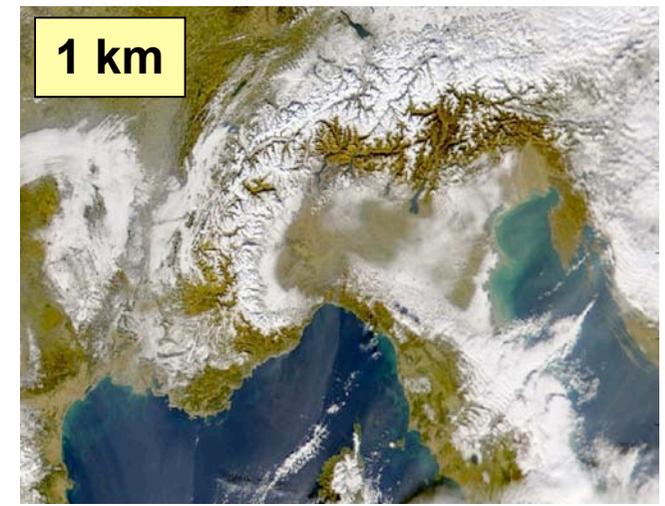
Role of resolution



GCM



RCM

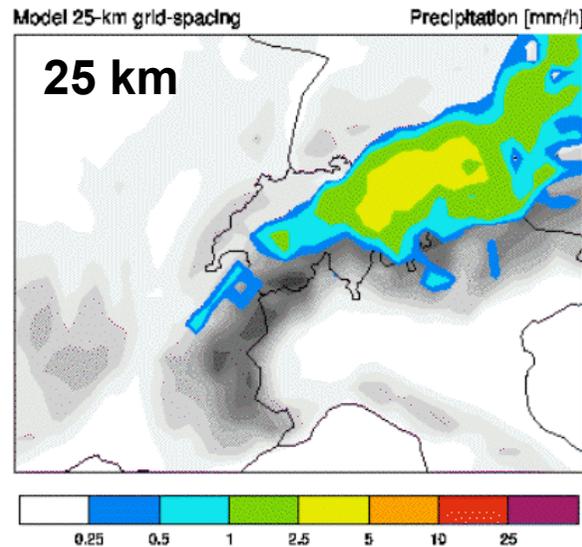
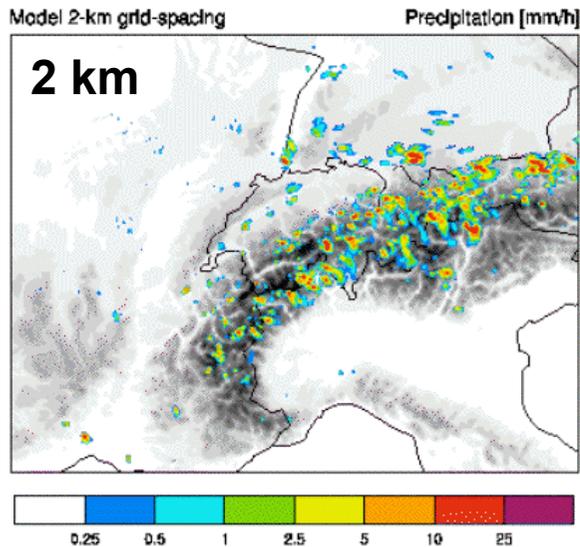


CR RCM

**Extreme events are often of small spatial extent
=> Computational resolution particularly important <=**

Precipitation at two resolutions

23 July 2006 18 UTC



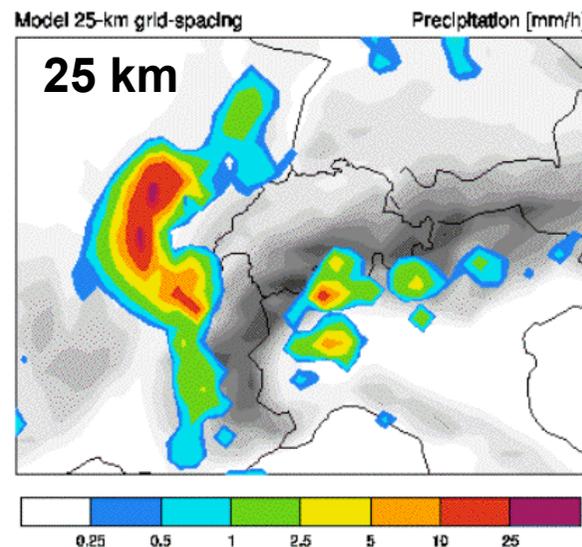
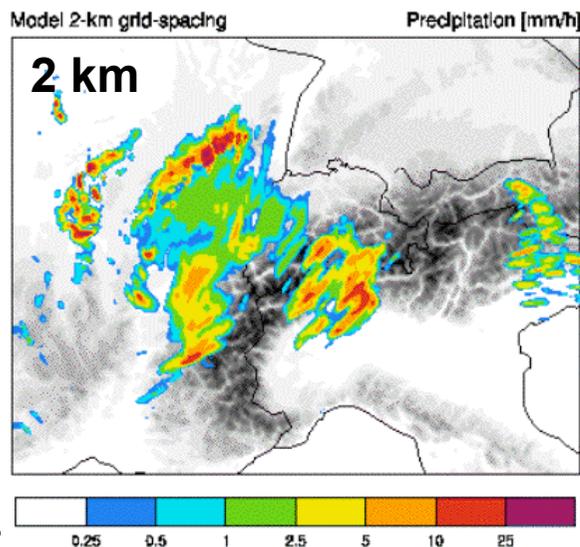
Precipitation snapshots [mm/h] in two month-long simulations using

- explicit (2 km) and
- parameterized (25 km) convection,

Simulations exhibit large differences in

- diurnal cycle,
- spatial structure and
- peak amounts.

28 July 2006 06 UTC



The high-resolution domain encompasses 501x301x45 grid points.

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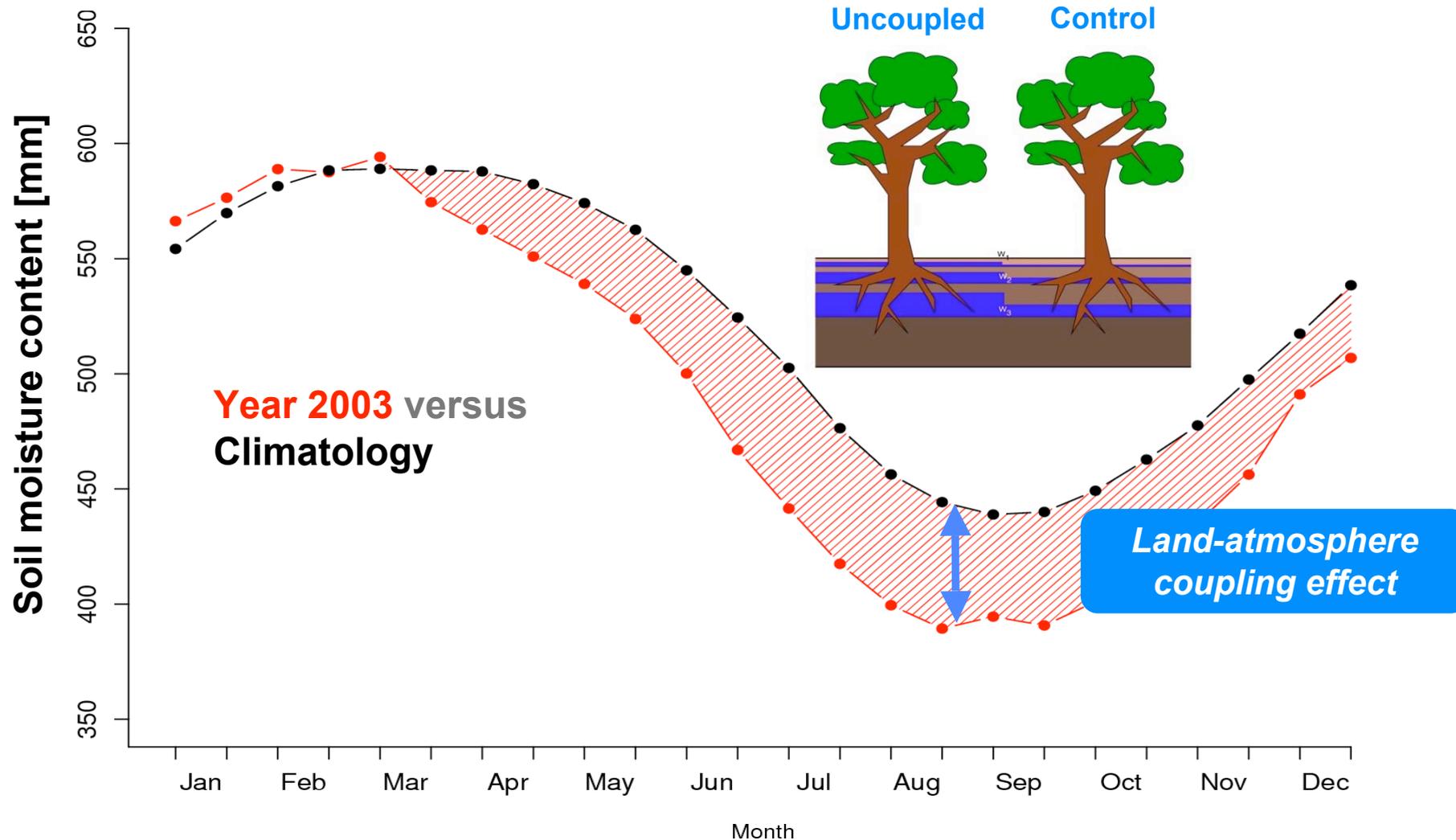
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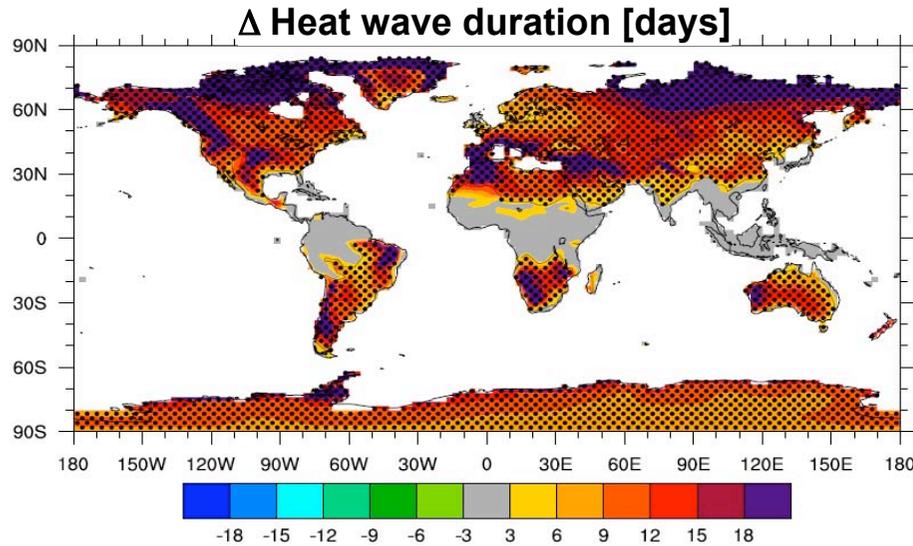
Role of computational resolution

Sensitivity to model physics (parameterizations)

Role of land-surface processes



Perturbed physics ensemble (land-srf proc.)



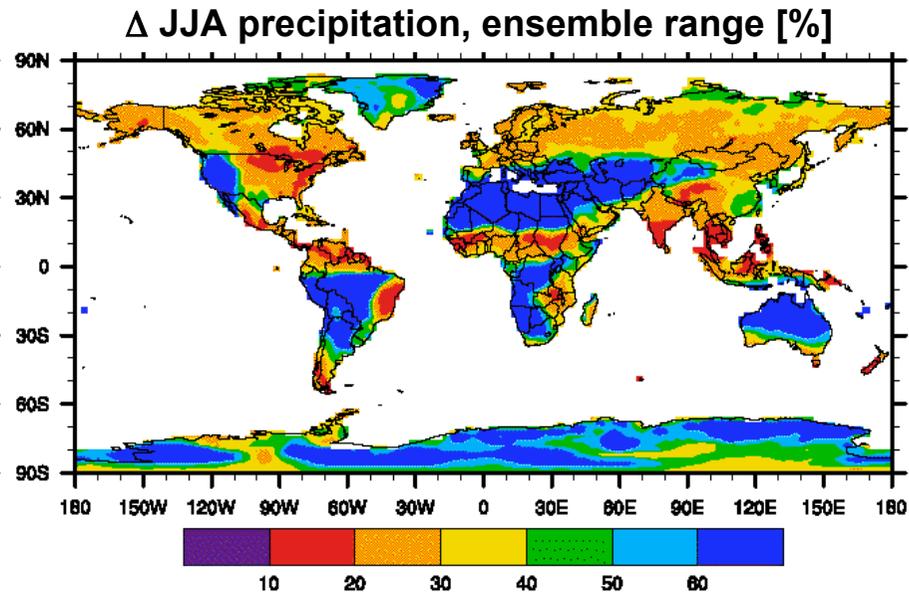
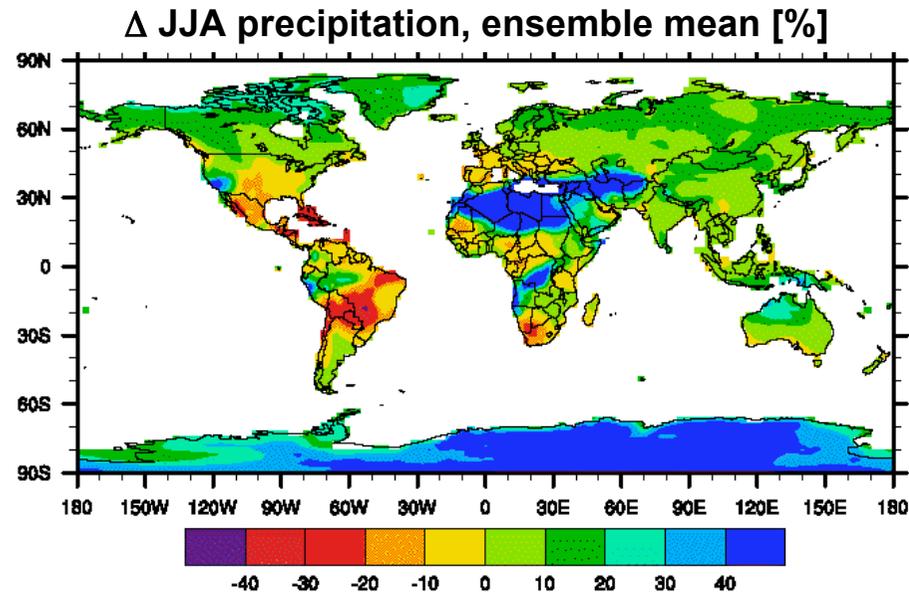
Perturbed physics ensemble testing the role of land-surface physics parameters at 2xCO₂ (108 simulations, 2x2.5 deg).

Δ heat wave duration (left):

- robust signal, uncertainty in amplitude

Δ JJA precipitation (bottom):

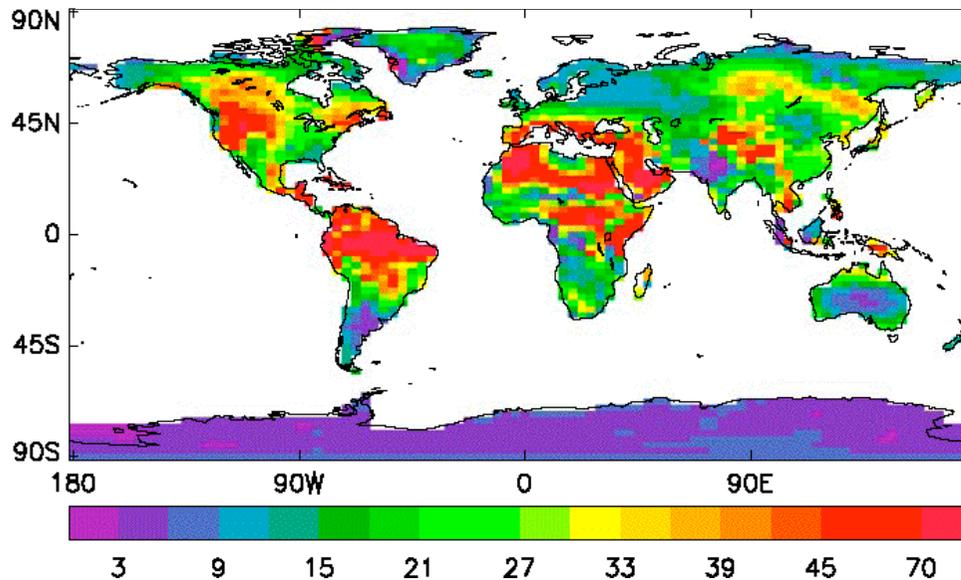
- global land: min=+14, max=+22%
- Mediterranean: min=-9%, max=+20%



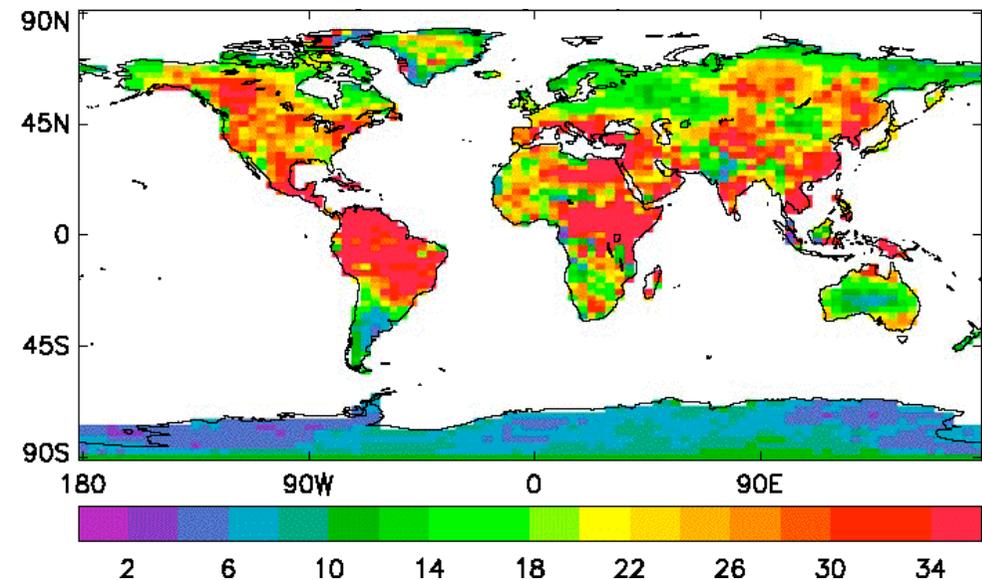
Perturbed physics ensemble (full physics)

**Perturbed physics ensemble testing the key physics parameters at 2xCO₂
(53 simulations, 2.5x3.75 deg).**

**Increase in July temperature extremes [factor]
(99th percentile of Tmax)**



**Ensemble range
(80% range)**

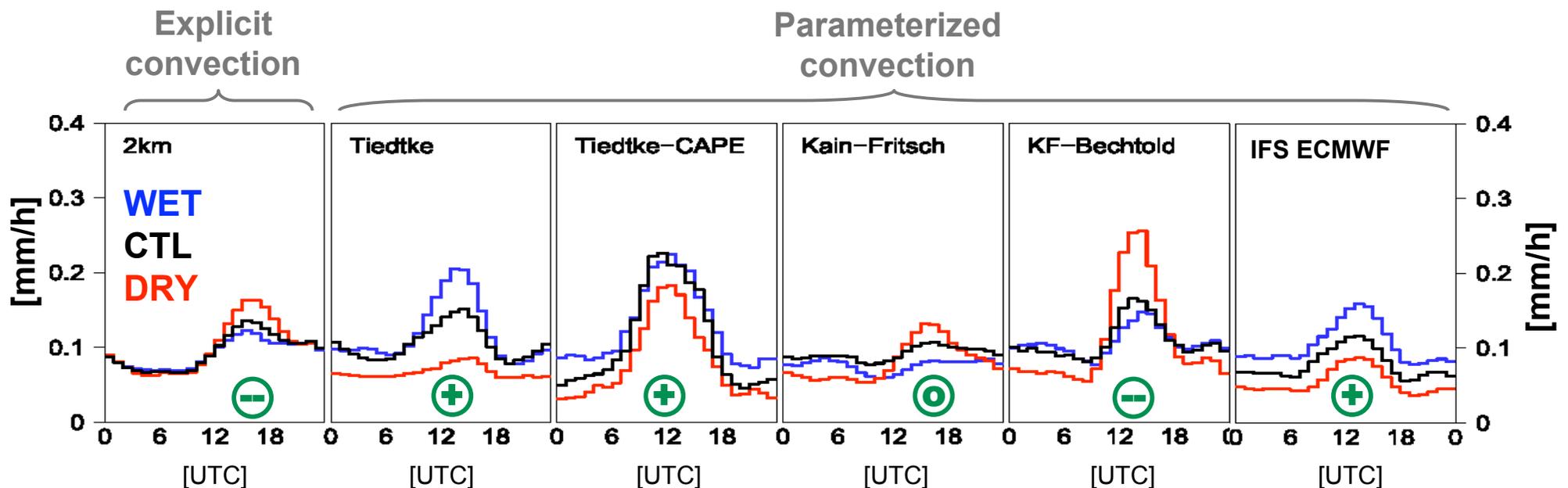


Role of convection



Convection => soil-moisture precip feedback ³⁴

Previous studies suggest EUROPE has \oplus positive soil-moisture precipitation feedback.
APPROACH: Test mean diurnal cycle of precipitation in July simulations with perturbed (**wet**, **dry**) initial soil moisture.



=> Dramatic differences between explicit and parameterized convection, and between different schemes!
=> Convection governs sign of feedback!

Summary

- **Consideration of extreme events implies the consideration of statistical distributions. Variability and shape changes do matter! Accounted for by appropriate statistical methods (i.e. block maxima, peak over threshold).**
- **Consideration of impacts (natural hazards) usually requires the use of impact and/or damage models, or at least the consideration of appropriate impact indices.**
- **Model biases are particularly crucial (biases in distribution, fixed thresholds).**
- **High computational resolution is desirable.**
- **Uncertainties due to model physics are more important than when considering means, better understanding needed, large ensembles useful.**

References

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