Characteristics of extreme temperatures and persistent heat waves over East China from ground station observations and numerical modeling

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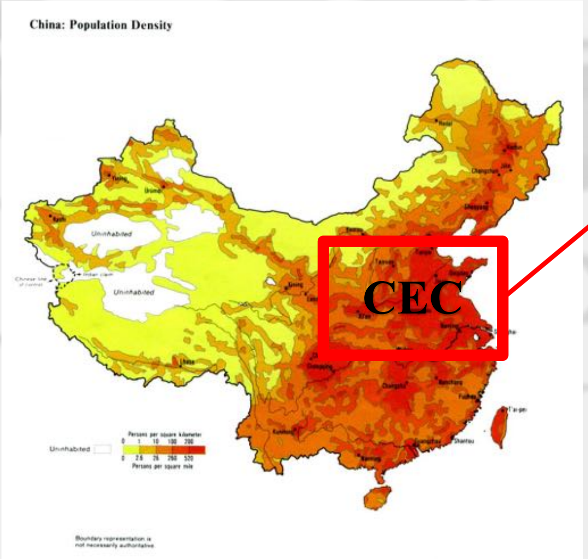
8th GEWEX Conference, Canmore, Canada

CSSP-China

~150 researchers
1 annual general meeting
1 annual UK science meeting

Central-Eastern China (CEC)

- Main characteristics of heat waves over East China?
- Are models consistent with observations and reanalysis?
- Anthropogenic vs natural variability on temperature extremes over this region?



- heavily populated
- urbanisation
- aerosols

→ ***Impact on population***

Regional-scale events
thousands km²

(Our) heat waves definition

- Average **raw** daily temperatures (**Tmin** and **Tmax**) over the CEC.
- Select only May-September from each year, 1979-2010 period.
- A threshold is computed for each variable using the 90^{th} percentile → remove low bias.

Heat wave (HW):

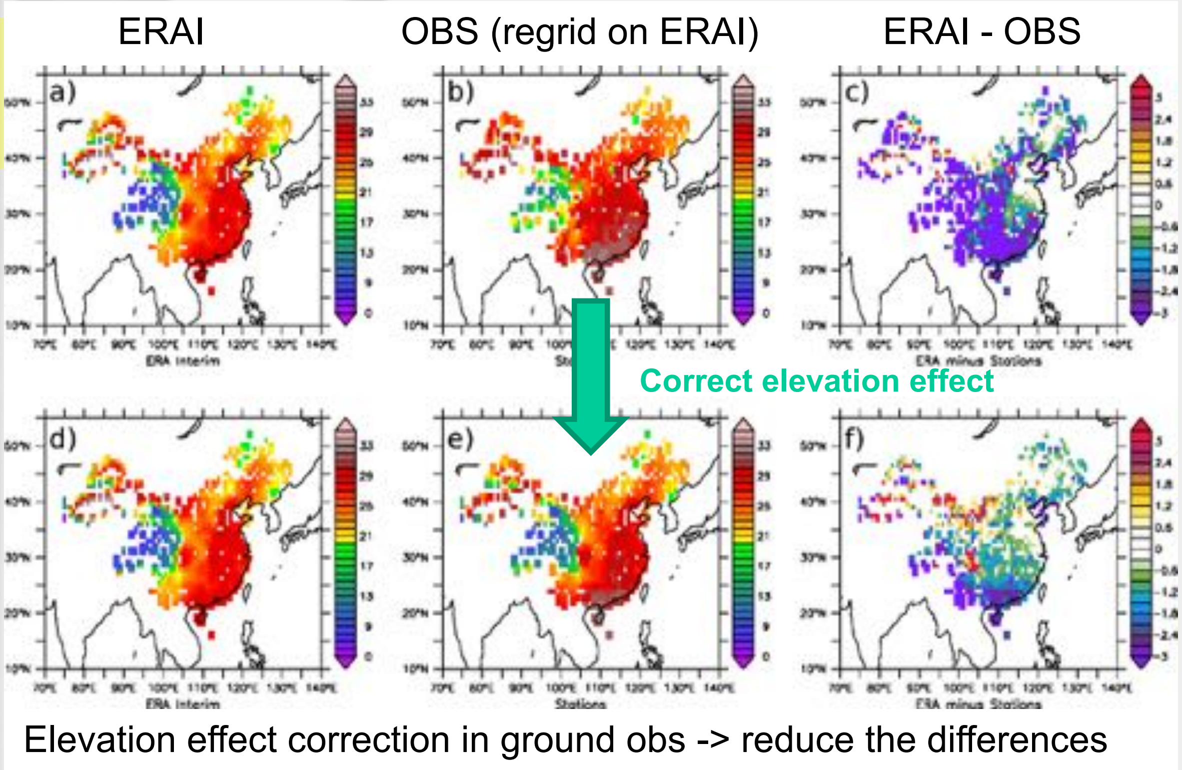
$Tmin_{CEC} > 90^{th}{}_{min}$
$Tmax_{CEC} > 90^{th}{}_{max}$
5+ consecutive days

Large scale
Persistent (day and night)

- ***HW days*** = *Number of days included in HW events.*
  HW events = *Number HW events.*
  Composites = *circulation during HW - climatology circulation – long term trend*

Data

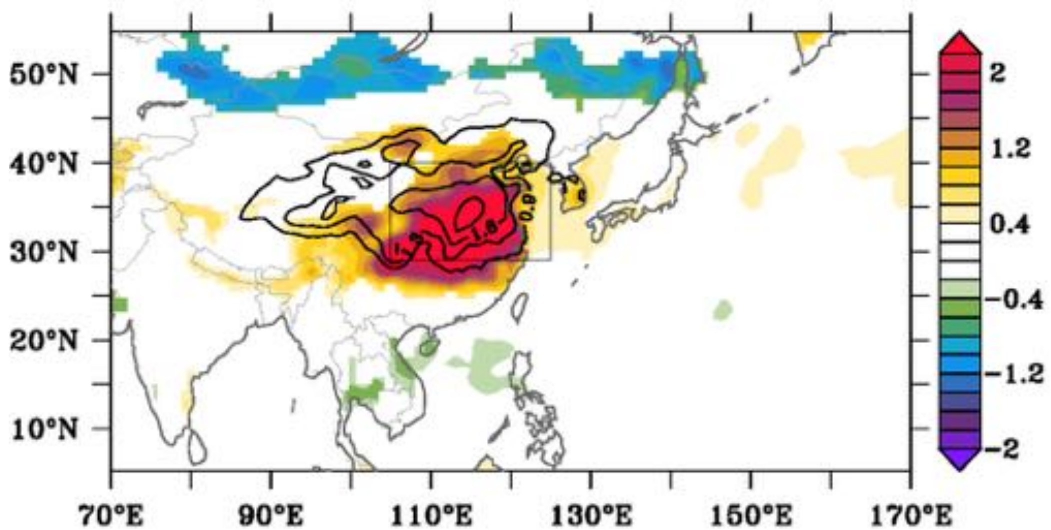
- **ERAI**:
  ERA Interim reanalysis
- **OBS**:
  750 ground station homogenized observations (Li and Yan 2009)



- **AMIP** ensemble: 21 different models / 40 members
- **N216** ensemble: 15 members from the HadGEM3-GA6-N216 model (AMIP style)

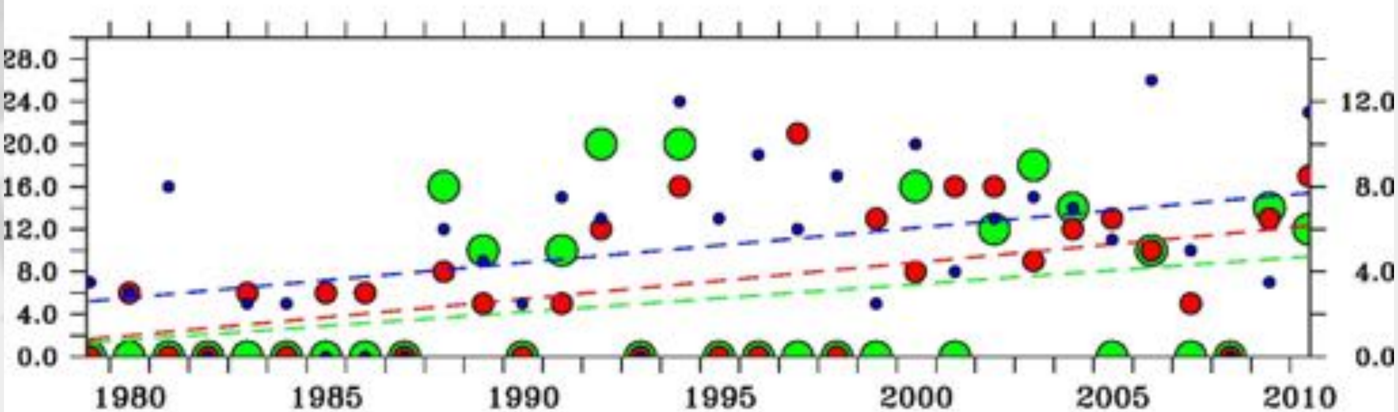
- **Weather@home** experiment: Multi-thousand ensembles (repeating 1 year) from HadAM3 with different conditions (actual forcing, natural world, GHG only)

Heat waves



Composites of **Tmax (shading)** and **Tmin (contours)** during HW.

Anomaly over the whole CEC, and centered over the CEC.

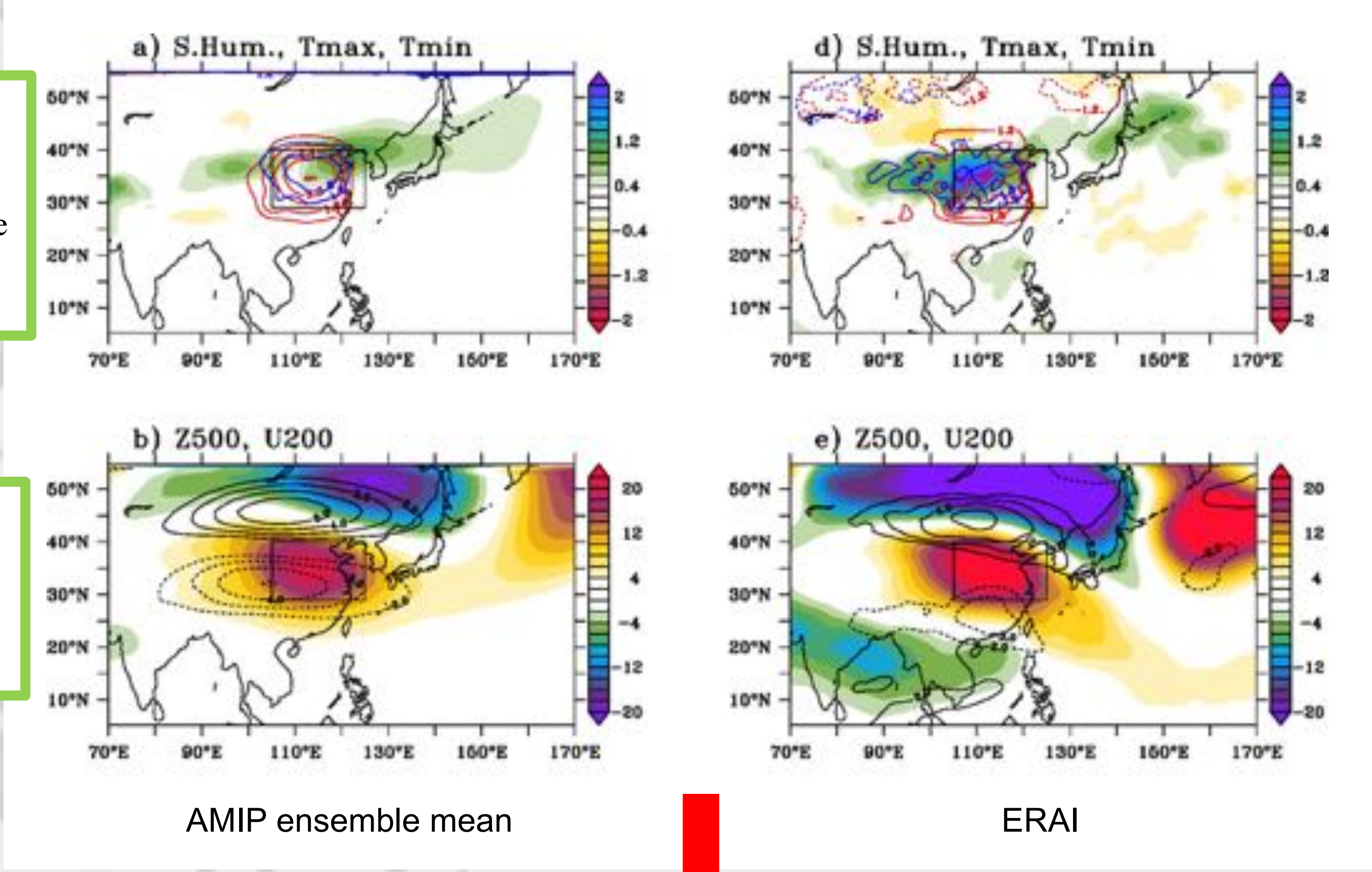


HW days, *EH days* (Tmax) and *TN days* (Tmin).

Heat waves dynamics

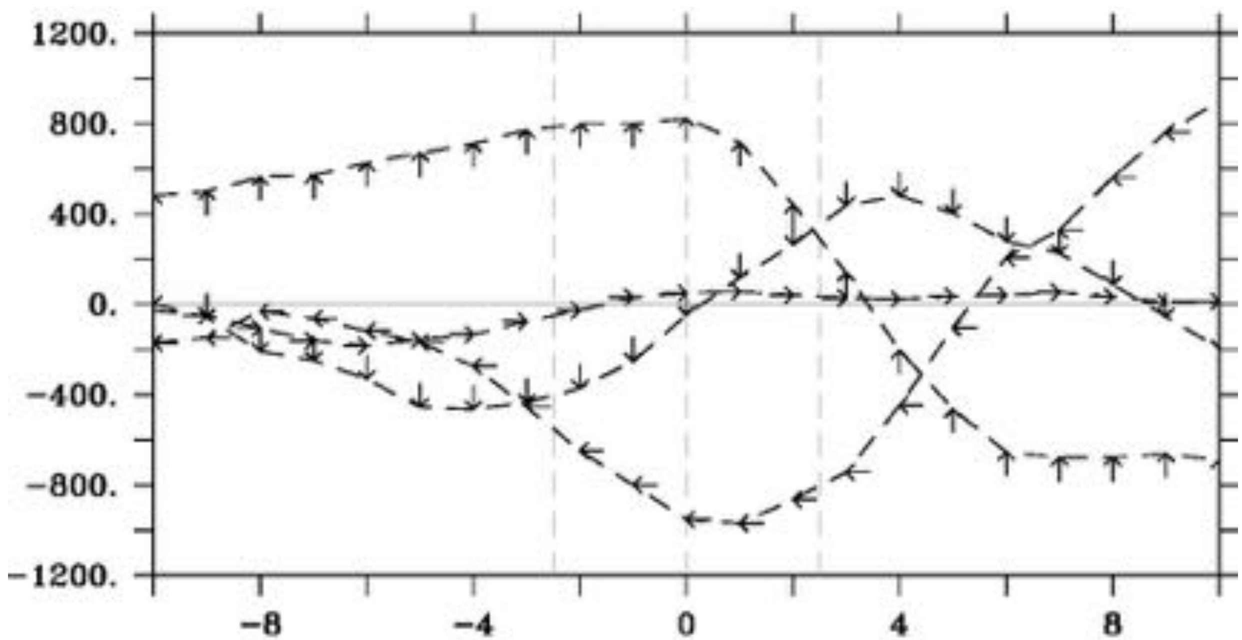
Humid conditions (increase humidity, BUT decrease relative humidity)

High pressure and subsidence



AMIP ensemble can reproduce the shape of the mean signal.

Heat waves dynamics

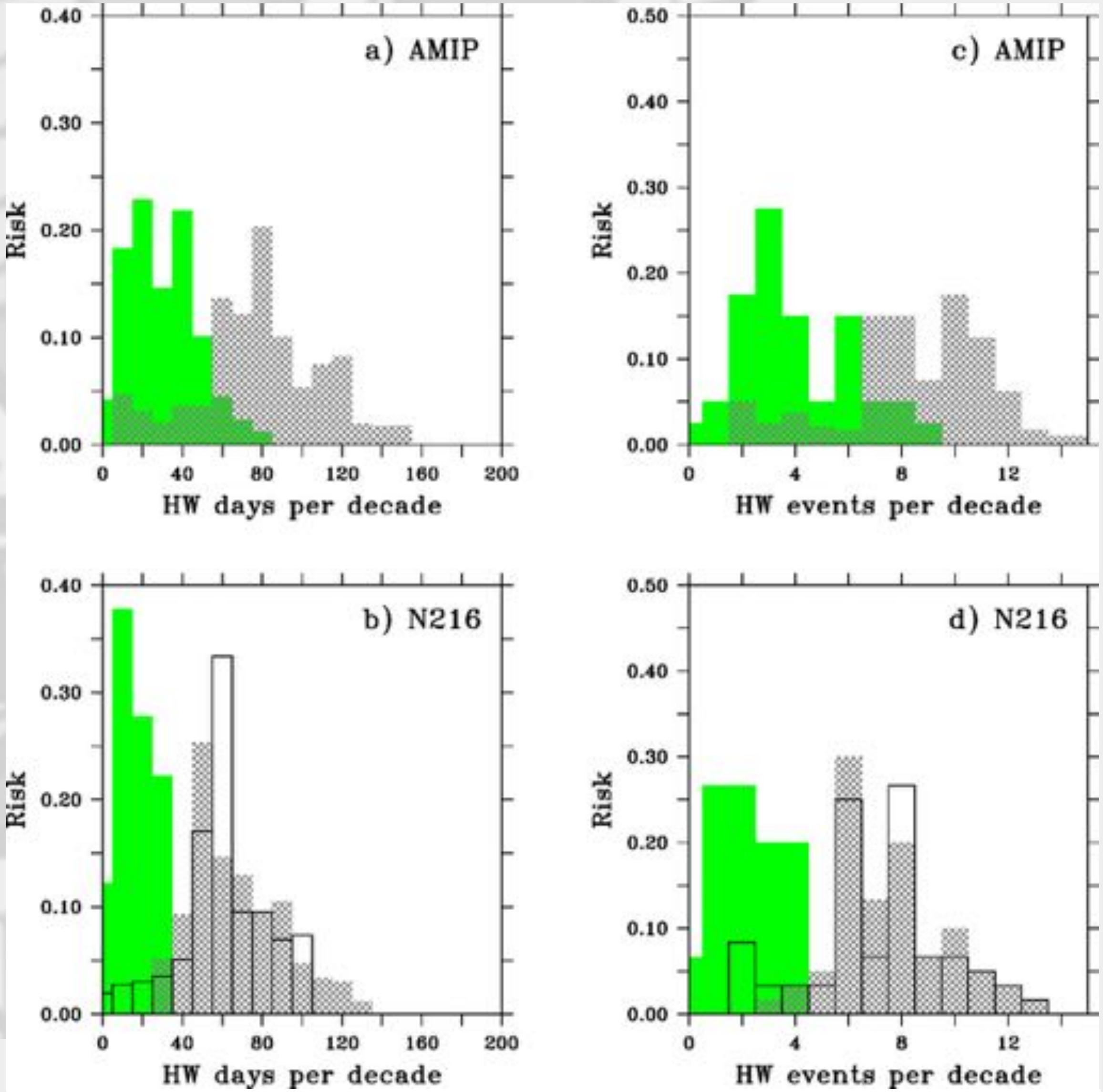


Lag-composites of the atmospheric anomalies during HW events.
(Freychet et al. ERL 2017)

Moisture transport (South boundary) increases before the events

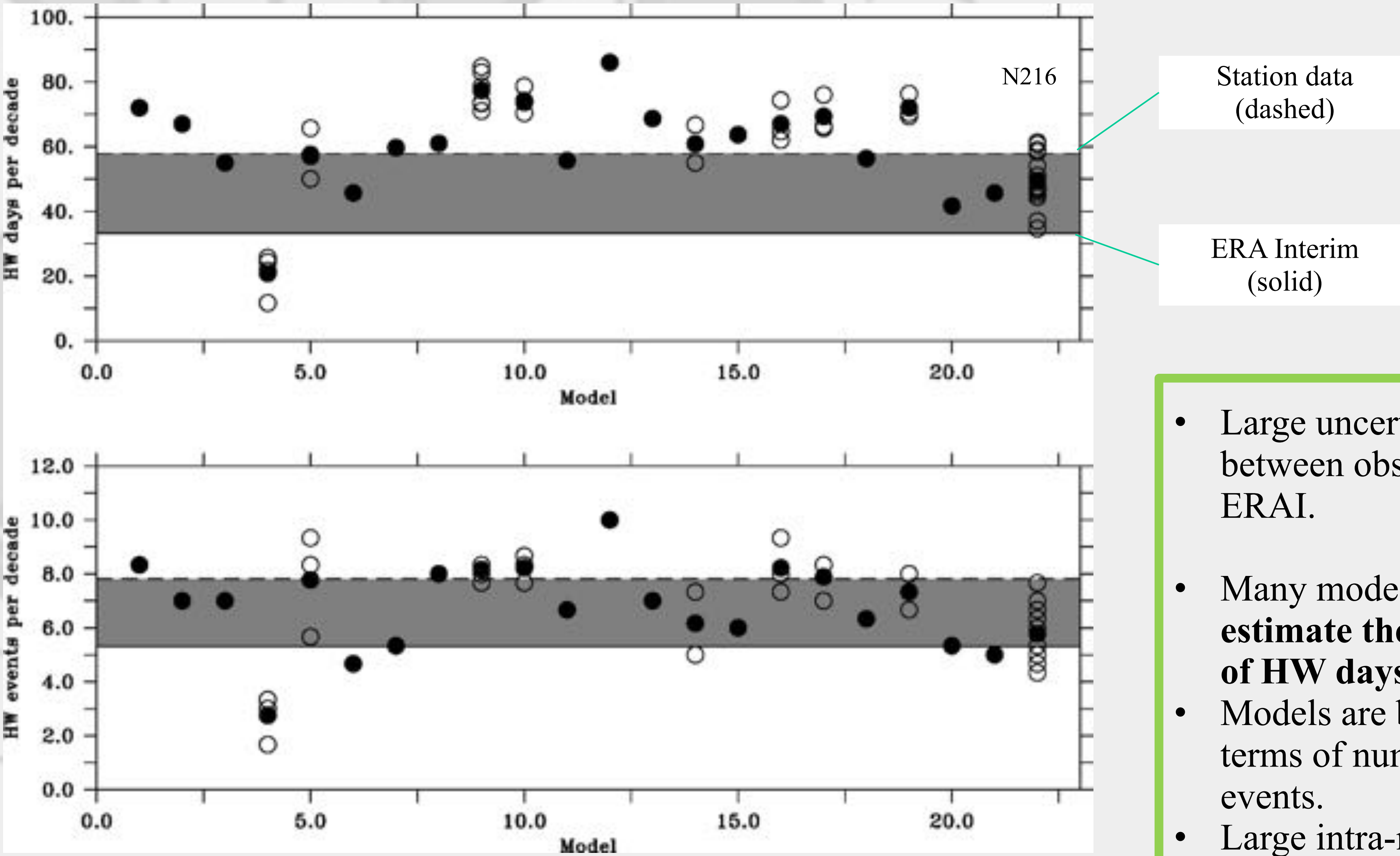
"Humid" Heat Waves

Change in the risk of HW events



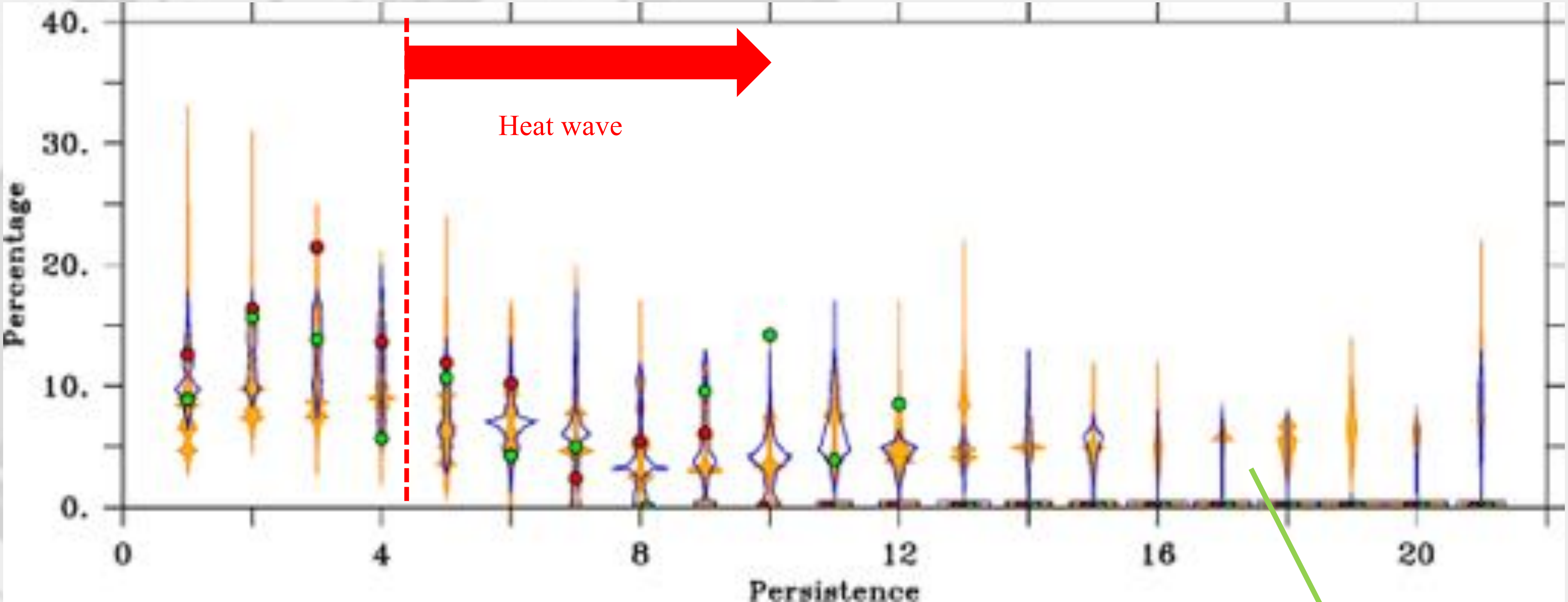
1979-1988 1999-2008 2009-2013

Do the models estimate the good signal?



- Large uncertainties between obs and ERAI.
- Many models **over-estimate the number of HW days**
- Models are better in terms of number of events.
- Large intra-model variability.

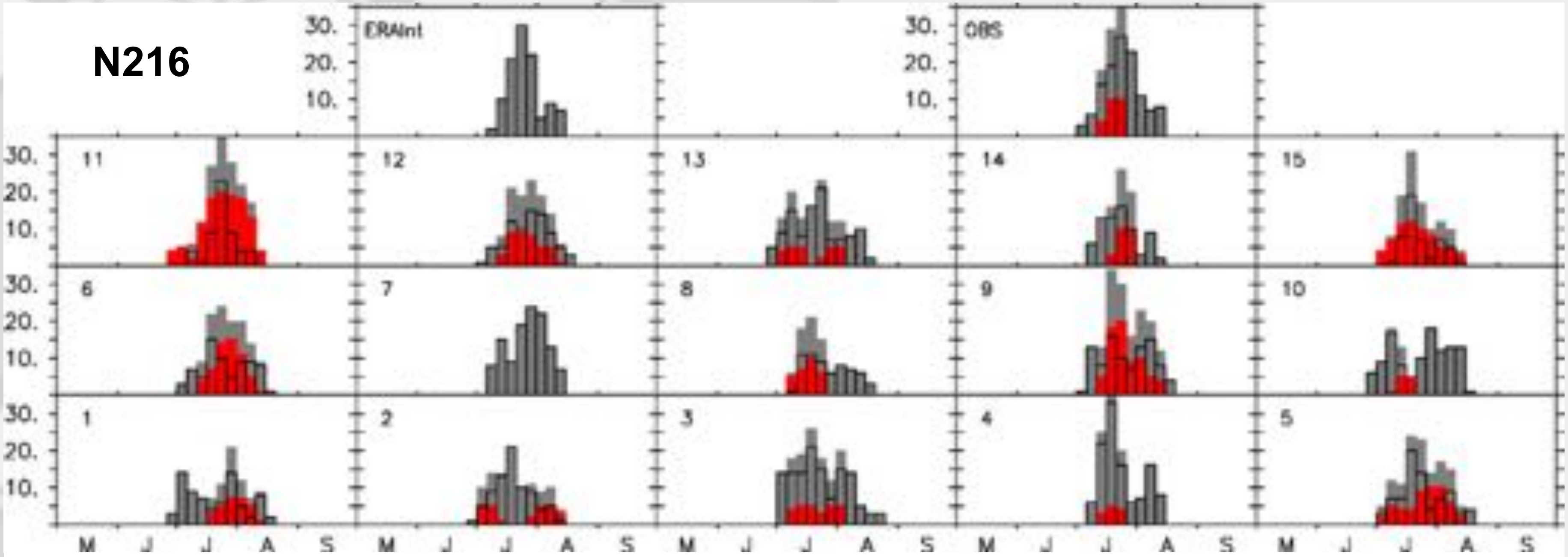
Do the models estimate the good signal?



Persistence of warm events, ratio (in percent) of the warm event that last X days.
Circles: **ERAI**, **OBS**
Violin diagram: **AMIP**, **N216**

Models can produce very persistent events.

Do the models estimate the good signal?



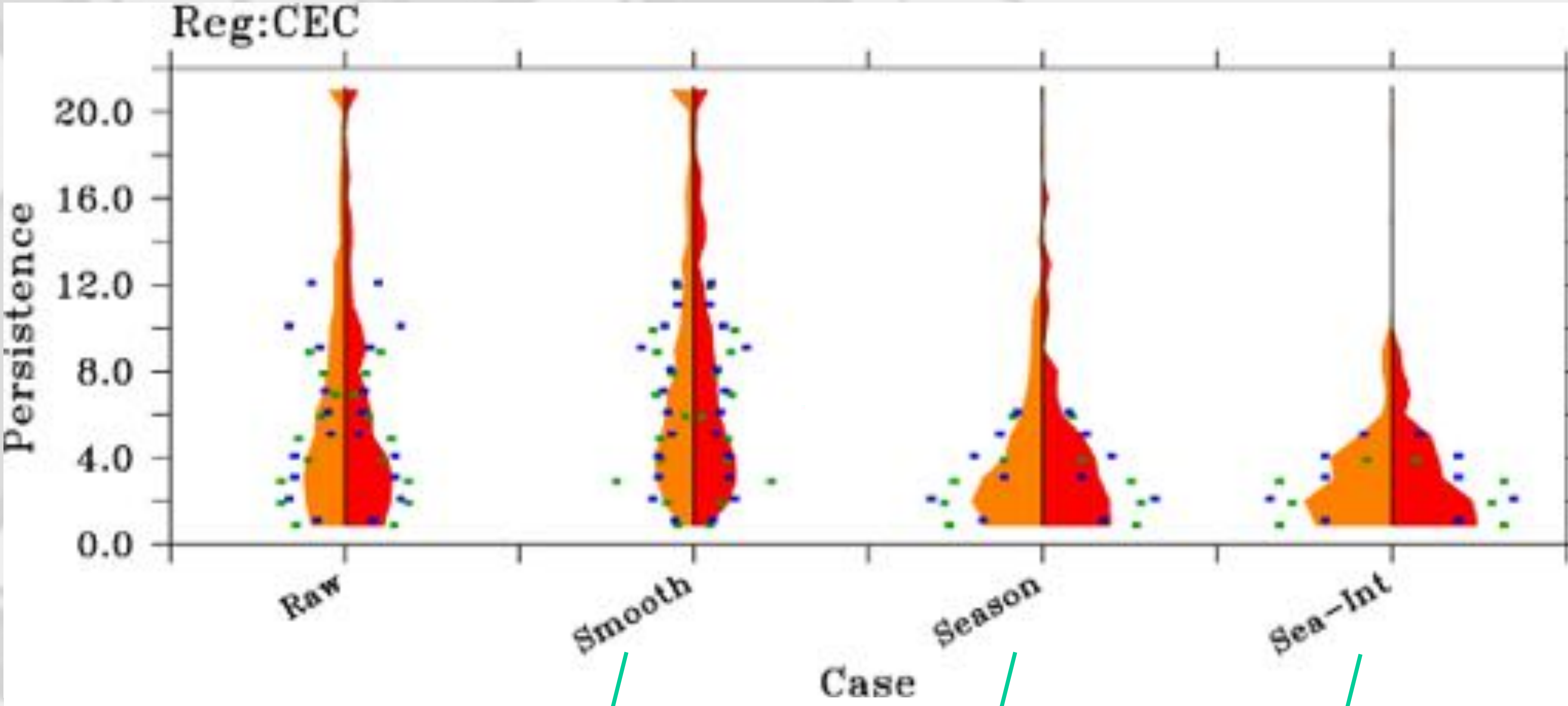
Pentad-sum of HW occurence during the 30 years (after correcting seasonal climatology).

Gray = total
Black contours = 5-10 days
Red = 11+ days

Intra-model variability + observations error:

16 days duration (for a single member) would be reasonable.

Do the models estimate the good signal?



Persistence of warm events.
Square symbols: **ERAI**, **OBS**
Violin diagram: **AMIP**, **N216**

3-days running mean

Anomaly relative to daily seasonal signal

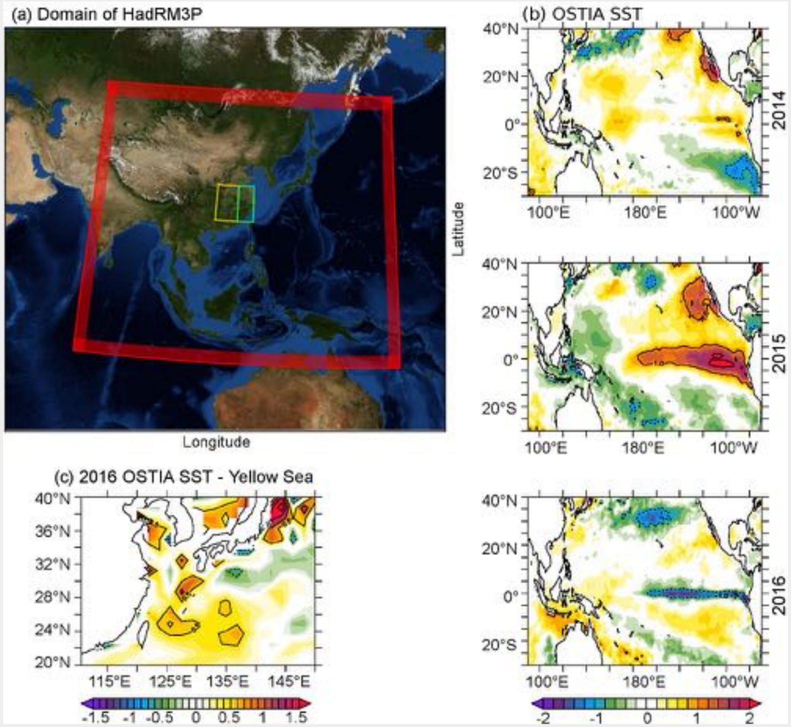
Anomaly relative to daily seasonal signal + remove long term changes

Anthropogenic influence vs natural variability

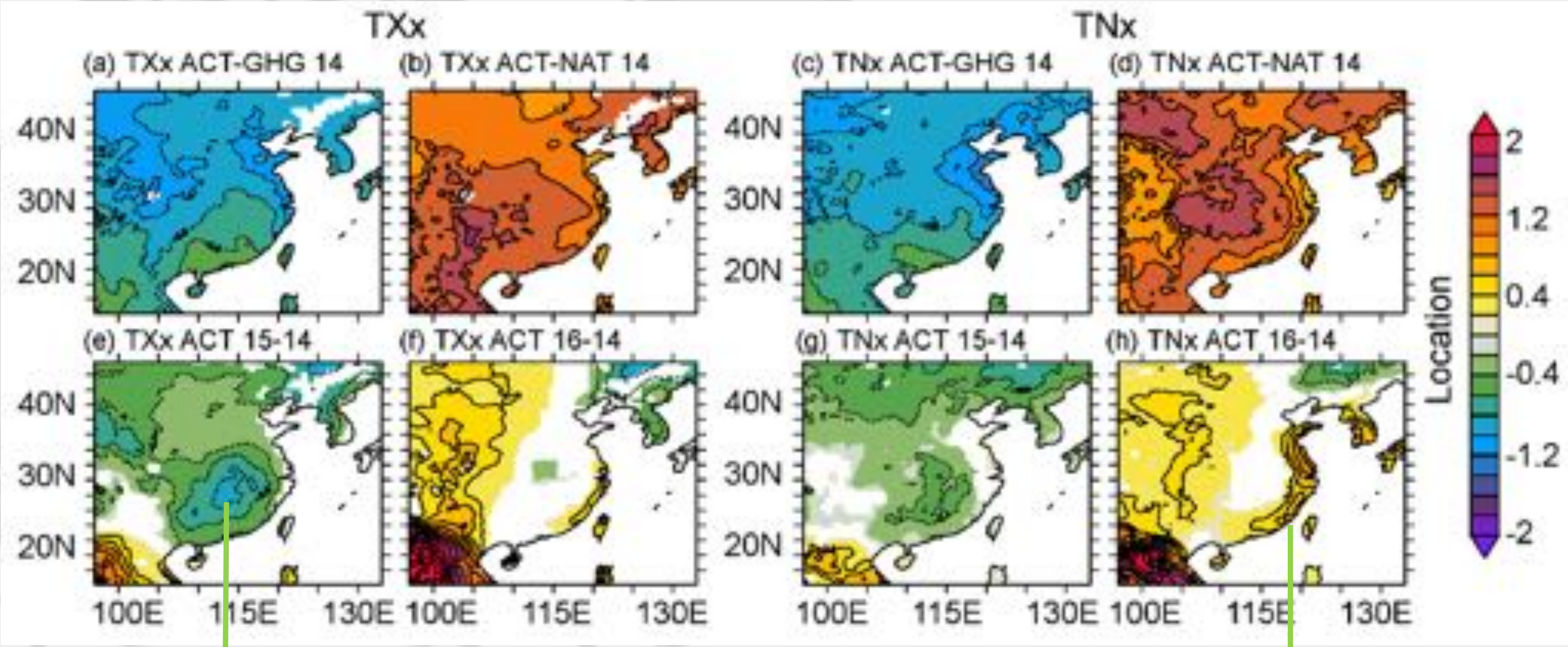
- weather@home experiment:
  - *global 2° model + regional (Asia) 50km model*
  - *multi-thousands members*
  - *repeating the same years 2014 [normal], 2015 [El-Niño], 2016 [post-ENSO]*
  - *3 ensembles: **ACT**ual world, **NAT**ural world, **GHG** only*

- Each member: **Summer** warm extremes (**TXx** and **TNx**)

- GEV fit to compare summer extremes under different conditions (*for all comparison 2014 ACT is the reference*).



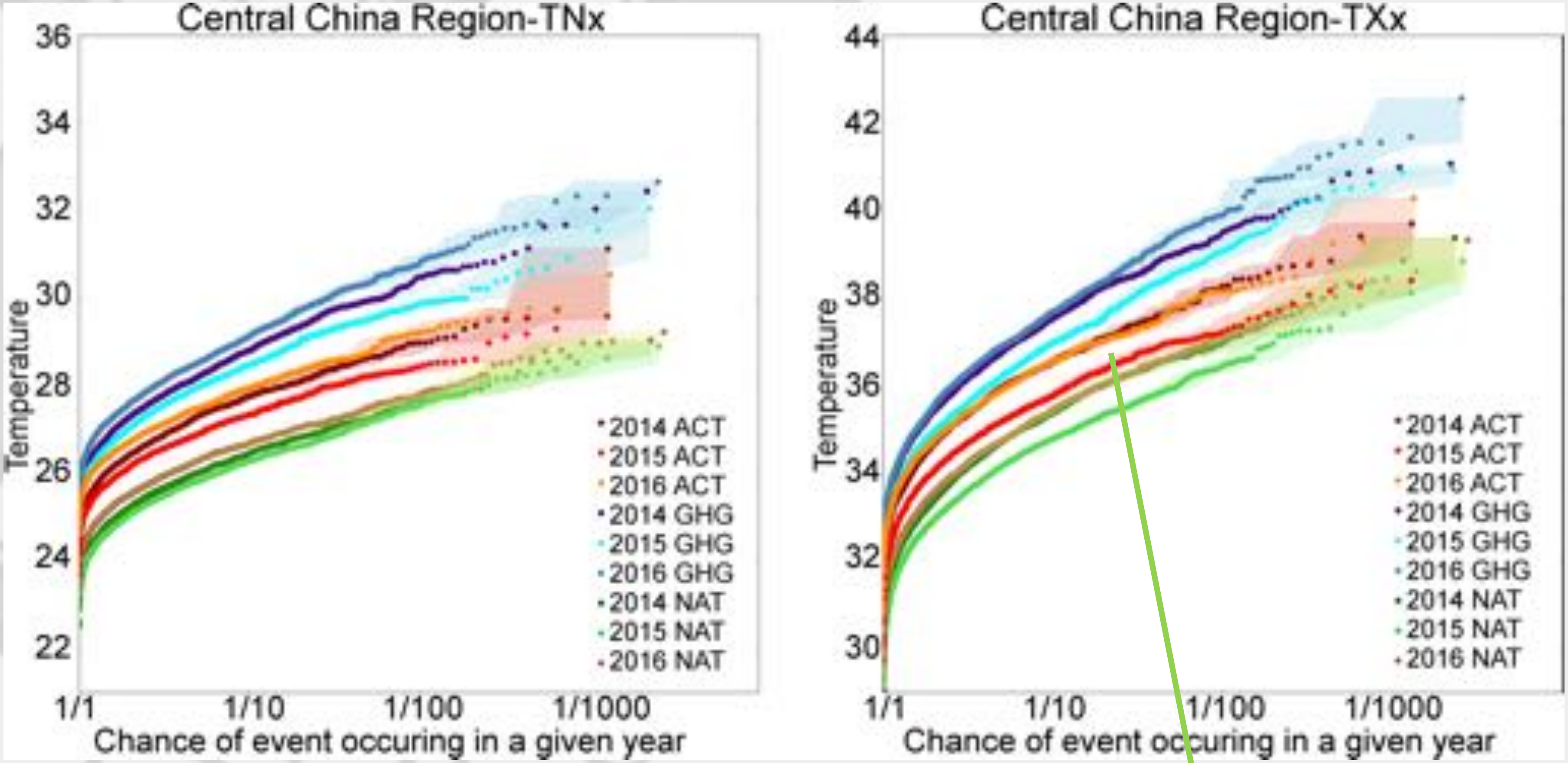
Anthropogenic influence vs natural variability



Decrease risk of TXx.

Increase coastal TNx.

Anthropogenic influence vs natural variability



Impact of ENSO same scale as anthropogenic.

Key points

- ERAI and OBS have some differences → **observation uncertainties**.
- AMIP models can reproduce the dynamics identified in ERAI.
- AMIP and N216 models produce too persistent HW.
- N216 members highlight the intra-model variability
  → **using a single member may lead to unreliable results**.
- Risk increased clearly during the past few decades.
- ENSO can impact temperatures on the same scale than anthropogenic impact.
- Tmax and Tmin have different spatial responses to ENSO.

Freychet et al 2017: Summer heat waves over Eastern China: Dynamical processes and trend attribution, ERL.
Freychet et al 2018a: Central-Eastern China heat waves in AMIP models, Journal of Climate.
Freychet et al 2018b: Impacts of Anthropogenic Forcings and El-Nino on Chinese Extreme Temperatures, Advance in Atmospheric Sciences.

What's next?

Urban effect

Aerosol interaction

Extreme precipitation attribution

Develop partnership and exchanges with Chinese research community

Service: develop indices/risks

CSSP-China

Work Package 1: Monitoring, attribution and reanalysis
Detection and attribution of extreme events, models and reanalysis evaluation.

Work Package 2: Global dynamics of climate variability and change
This work package aims to further our understanding of global climate dynamics with the overall aim of improving regional climate predictions

Work Package 3: East Asian climate variability and extremes
Regional modes of climate variability, their teleconnections and impacts on regional water cycle and climate extremes within East Asia

Work Package 4: Development of models and climate projection systems
Model evaluation and development activities and aims to develop UK-China collaborations

Work Package 5: Climate Services
Climate services provide climate information in a way that assists decision-making by individuals and organisations

LOTUS

WP1 - Long Term Undulations versus secular change in Chinese Climate

Edinburgh:
Simon Tett, Gabi Hegerl, Mike Mineter, Nicolas Freychet

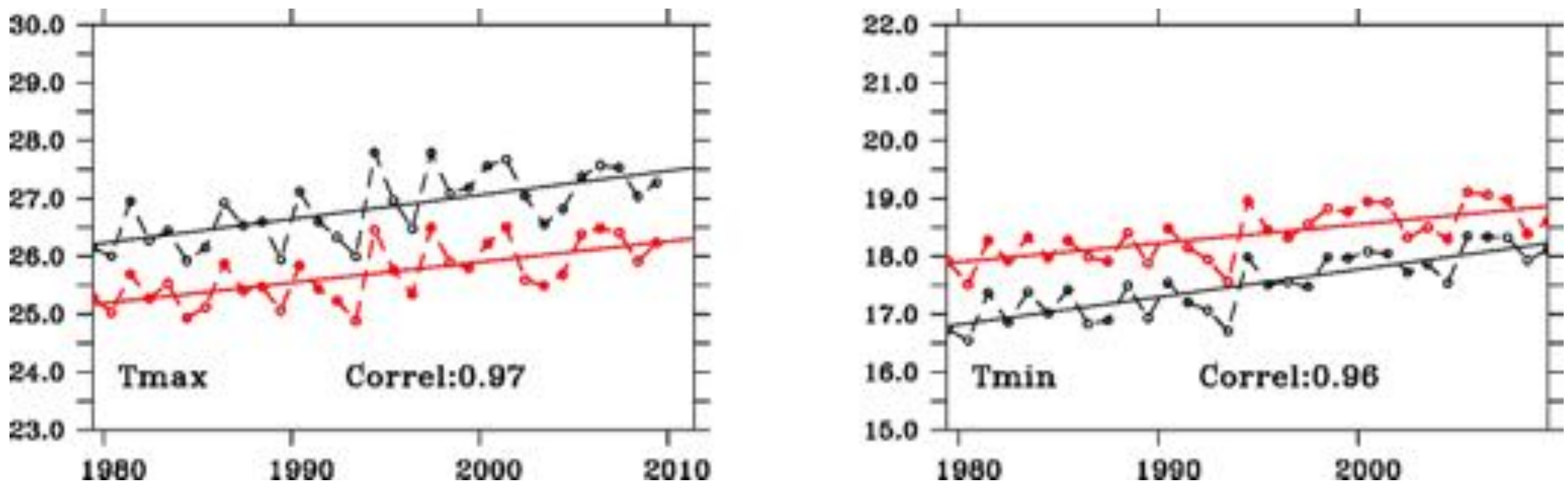
Reading:
Buwen Dong, Rowan Sutton, Fangxing Tian

Oxford:
David Wallom, Myles Allen, Sarah Sparrow

Met. Office:
Peter Stott , Lizzie Good, (Claire Burke, Fraser Lott)

China:
Panmao Zhai, Zhongwei Yan, Jun Wang, Riyu Lu, Ying Sun, Kaicun Wang.

Reanalysis vs Observations?

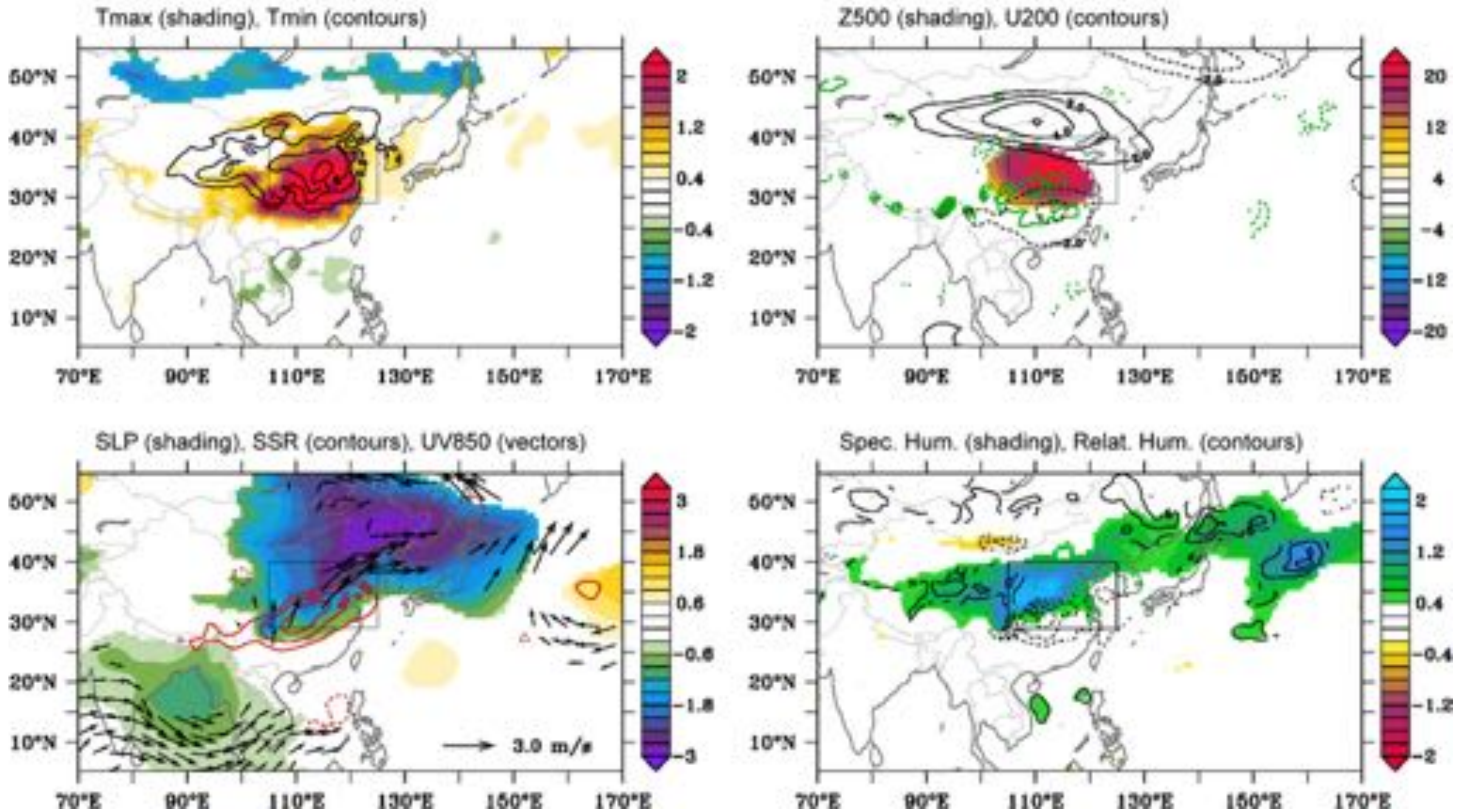


ERA Interim (red) vs homogenized ground observation (black, Li and Yan 2009) after elevation correction. Tmin and Tmax (summer-mean) averaged over 105°E-125°E/20°N-45°N

Reanalysis underestimates the intensity of temperatures (especially Tmax).

But trends and variability are realistic.

Heat waves dynamics

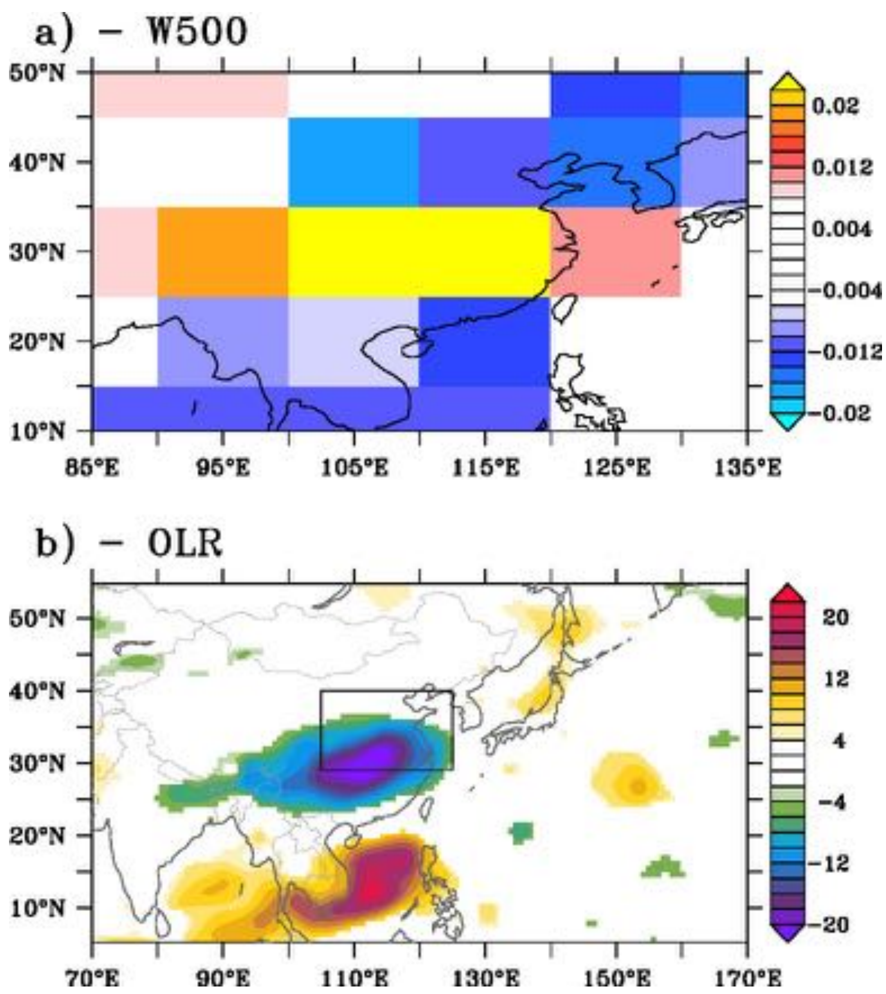


High pressure and subsidence

Humid conditions
(increase humidity, BUT decrease relative humidity)

Composites of the atmospheric anomalies during HW events.
(Freychet et al. ERL 2017)

Heat waves dynamics



Subsidence – meridional cell

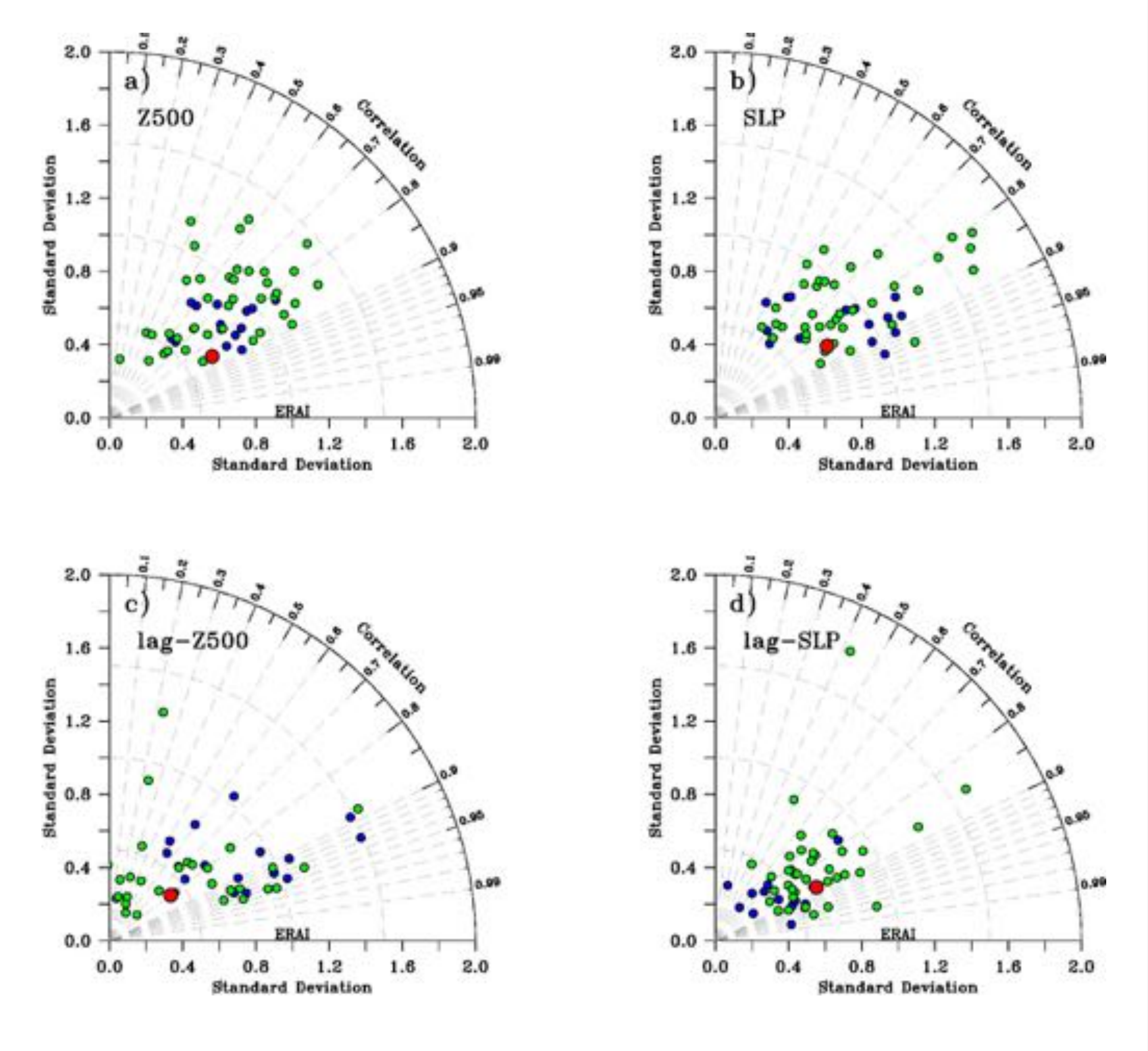
Humid conditions

-

Decrease in OLR

Composites of the atmospheric anomalies during HW events.
(Freychet et al. ERL 2017)

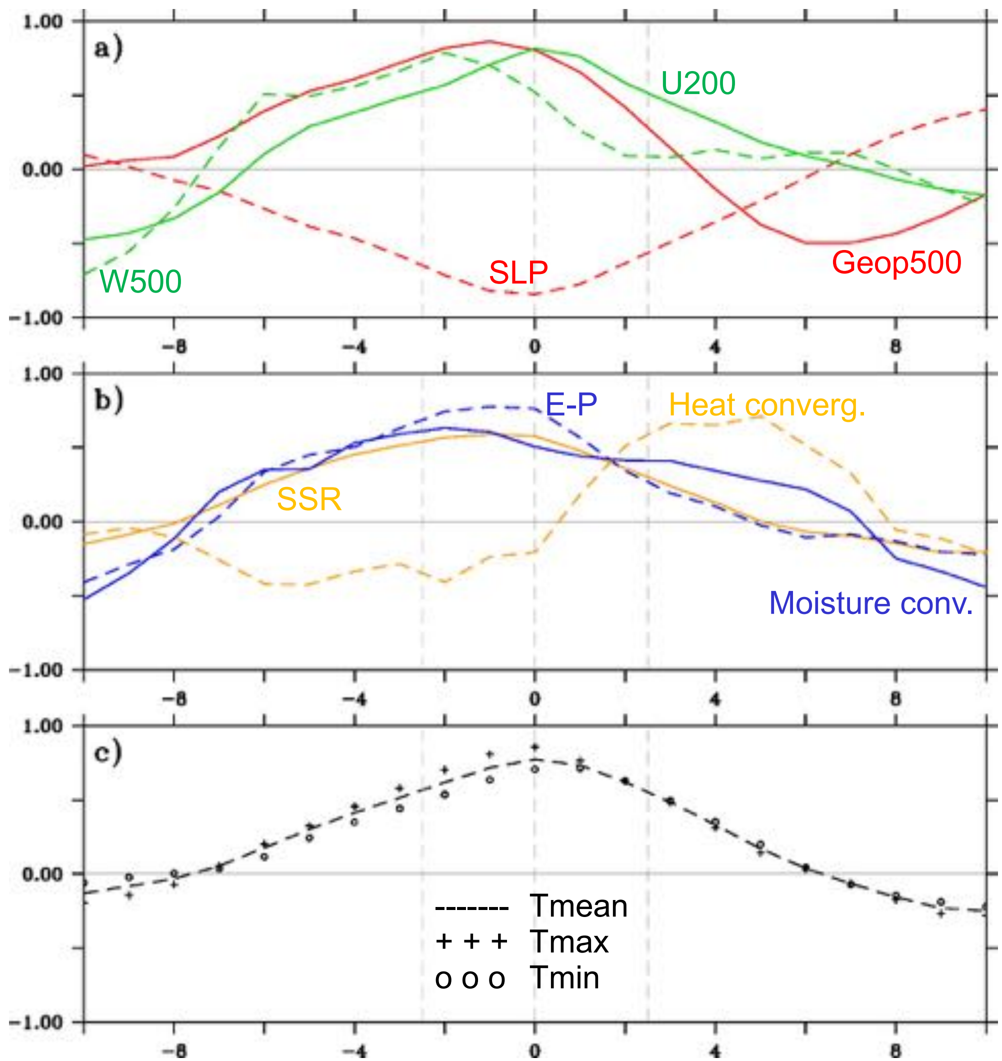
Heat waves dynamics



Ensemble mean is good in terms of correlation.

Individual members can be less consistent.

Heat waves dynamics

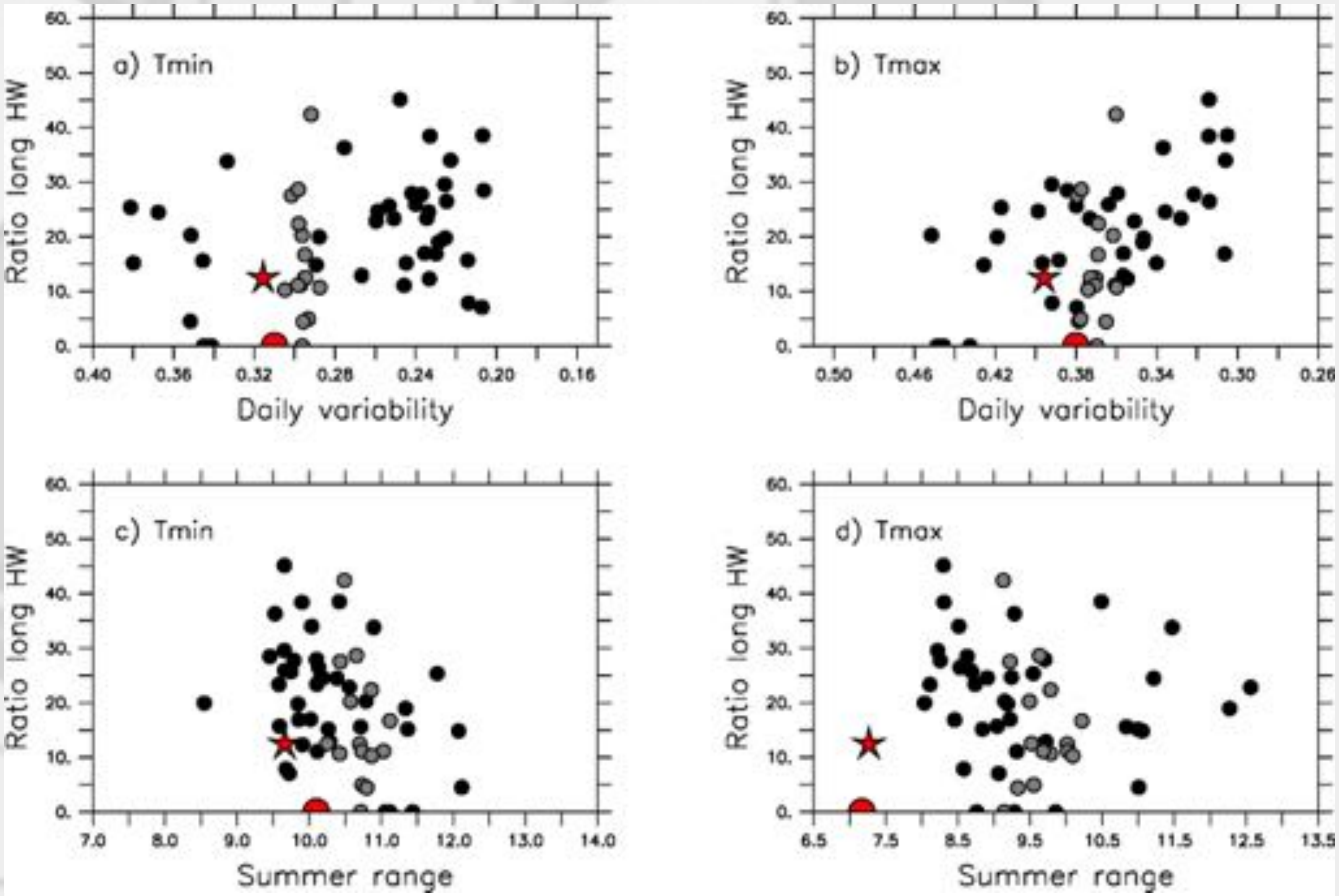


Lag-anomalies before and after the HW.

Leading role of the dynamics + moisture advection before the HW.

Feedbacks have important effects:
- evaporation (increases moisture)
- low pressure leads to convergence of heat (foenh effect at the North boundary)

Do the models estimate the good signal?

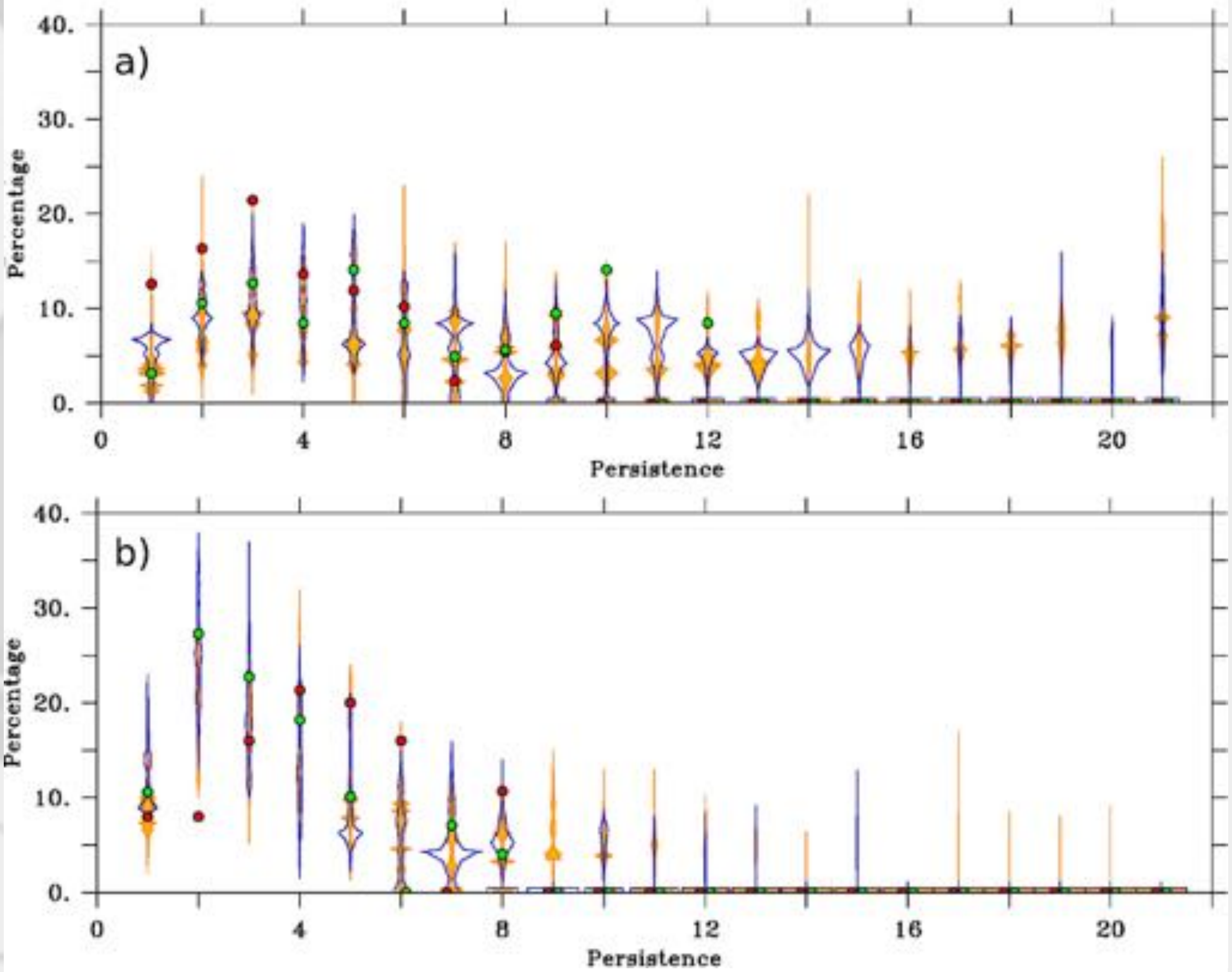


Ratio of long/short HW days vs Daily Variability (daily STD) and Summer Range (diff between warmest and coldest period of the summer climatology).

ERAI (*circle*), OBS (*star*), **AMIP**, **N216**

No clear relationship except for the daily Tmax variability (inter-model differences, but not intra-model differences)

Do the models estimate the good signal?

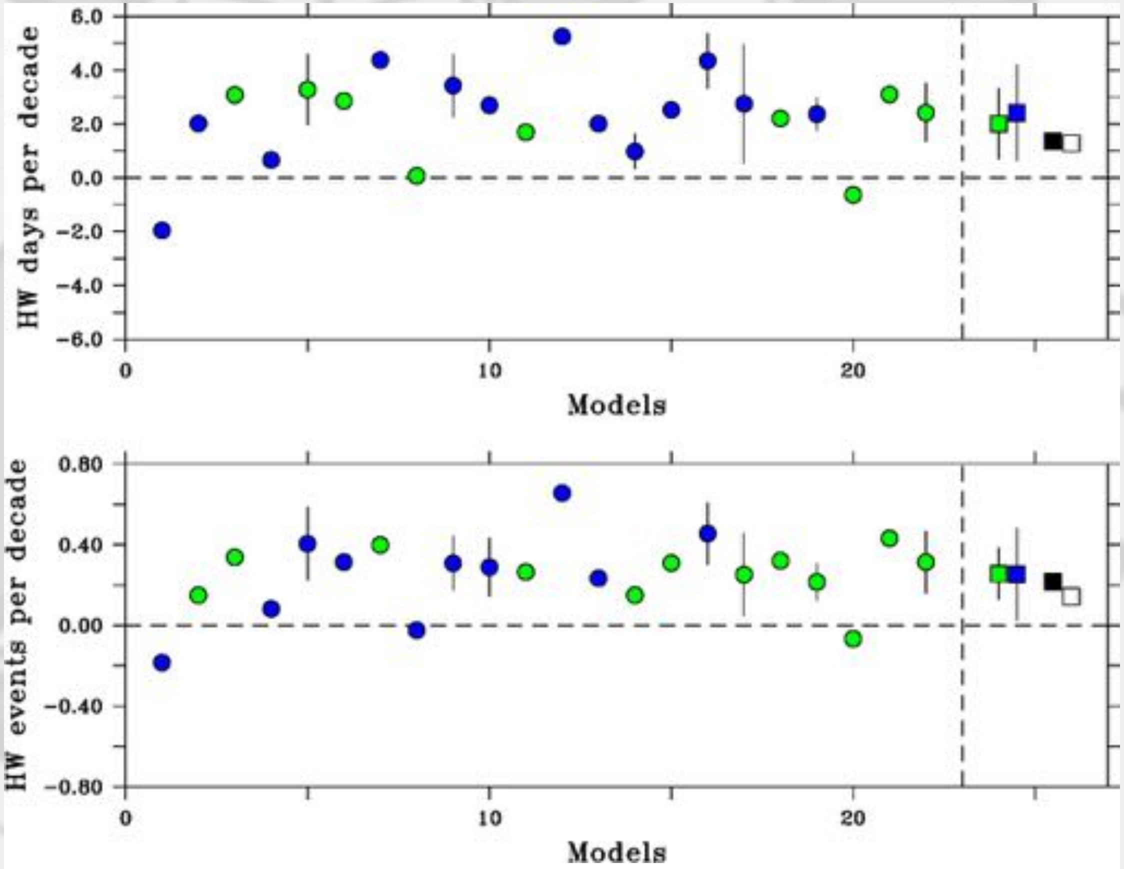


Persistence of warm events, ratio (in percent) of the warm event that last X days.
a) Corrected climatological signal (apply ERAI climato. instead).
b) Removed climatological signal.
Circles: **ERAI**, **OBS**
Violin diagram: **AMIP**, **N216**

After correcting the climatological signal, HW are still too persistent in the models.

After removing climato., signal better but still too persistent (HW detection may be **too sensitive to the seasonal transition** in the models).

Change in the risk of HW events

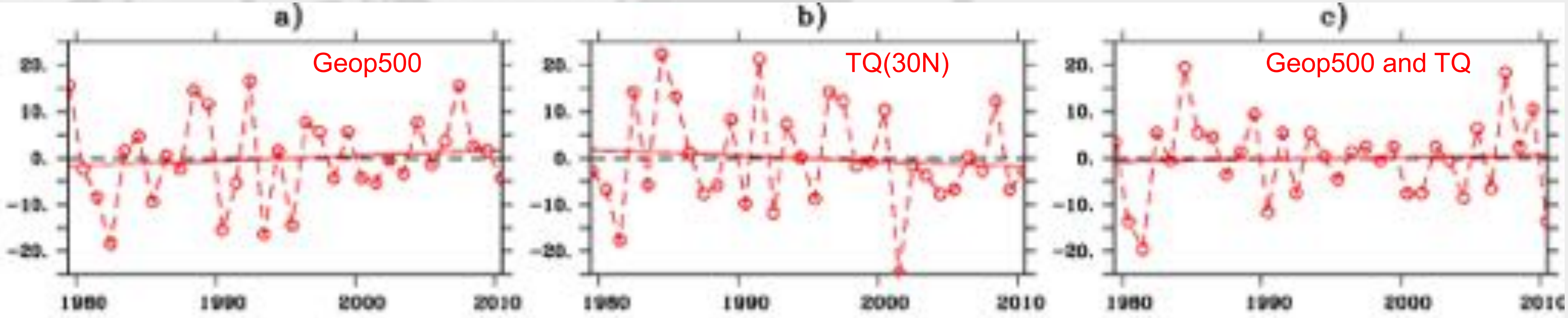


Linear trend for each **good** or **bad** model (circles), ensemble mean (squares), **ERAI** (white square) and **OBS** (black square).

Selection of good and bad models based on their closeness to ERAI and OBS in terms of HW days or events.

To filter the good and bad models do not lead to significantly different trend estimations.

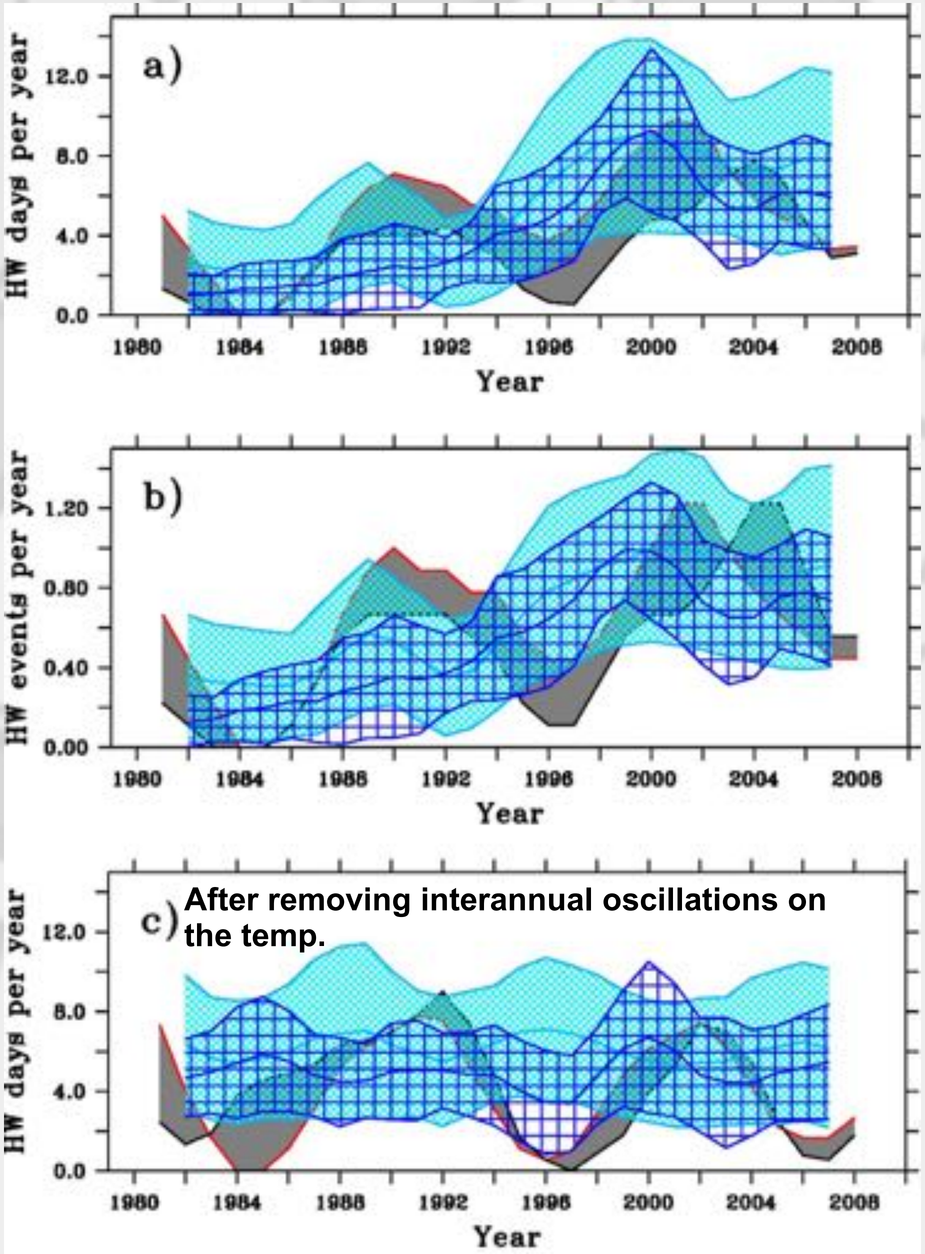
What leads the trend in heat waves?



(a) Yearly sum (during the extended summer) of the number of days with a positive anomaly of Z500 over the CEC region. The signal is centered by removing its 1979-2010 mean. (b) Same as (a) but for TQ at the southern border of the domain. (c) Same as (a) but for positive anomalies on Z500 and TQ occuring at a same day.

No significant trend in the frequency of dynamical anomalies.

Change in the risk of HW events



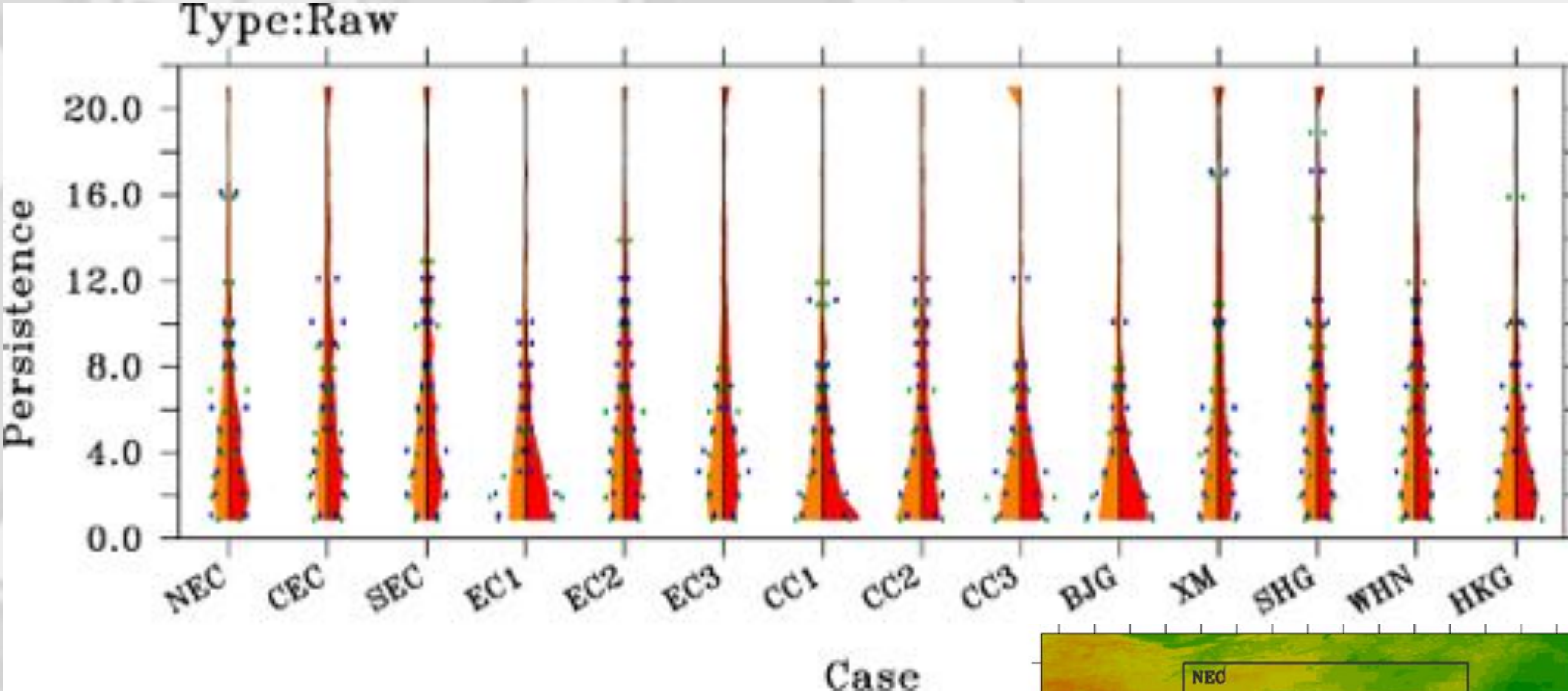
Models reproduce positive trend in HW days or events.

Decadal oscillation is less clear in models, especially after removing the interannual oscillations.

ERAI and **OBS**, and **range** between the two.

AMIP ensemble mean + STD.
N216 ensemble mean + STD.

Do the models estimate the good signal?



Persistence of warm events.
Square symbols: ERAI, OBS
Violin diagram: AMIP, N216