Extreme and long-lasting events of high **residual load** with long climate model simulations and **rare event algorithm**

ICEM 2023, Session Climate & Energy Modelling

Bastien Cozian

PhD Student at ENS de Lyon, France

Supervised by Corentin Herbert & Freddy Bouchet

27-29 June 2023

PHAST
PHYSIQUE
ET ASTROPHYSIQUE
UNIVERSITÉ DE LYON
ÉCOLE DOCTORALE
52

ENS DE LYON

Introduction

Extreme events with a focus on

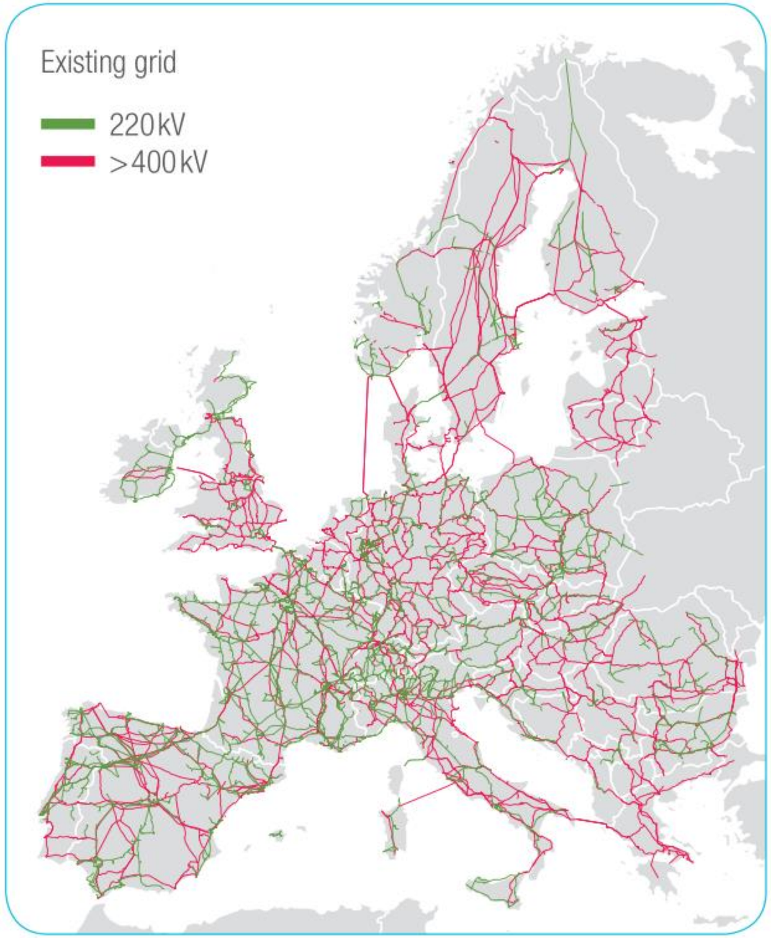
- Long event (from 1 to 30 days), in winter
- Scale of Europe

These extreme events are a combination of:

- low renewable production
- high demand

Questions

- What are the probabilities of such events?
- What are the dynamics associated?



European Power Grid,
e-Highway2050 project (2015)

Climate and energy models

Climate model

- CESM 1.2.2 (NCAR)
- Atmospheric and land components, but no ocean component
- **1000 years** of climate data in stationary conditions (2000s climate)

Simple energy model [1]

European aggregated

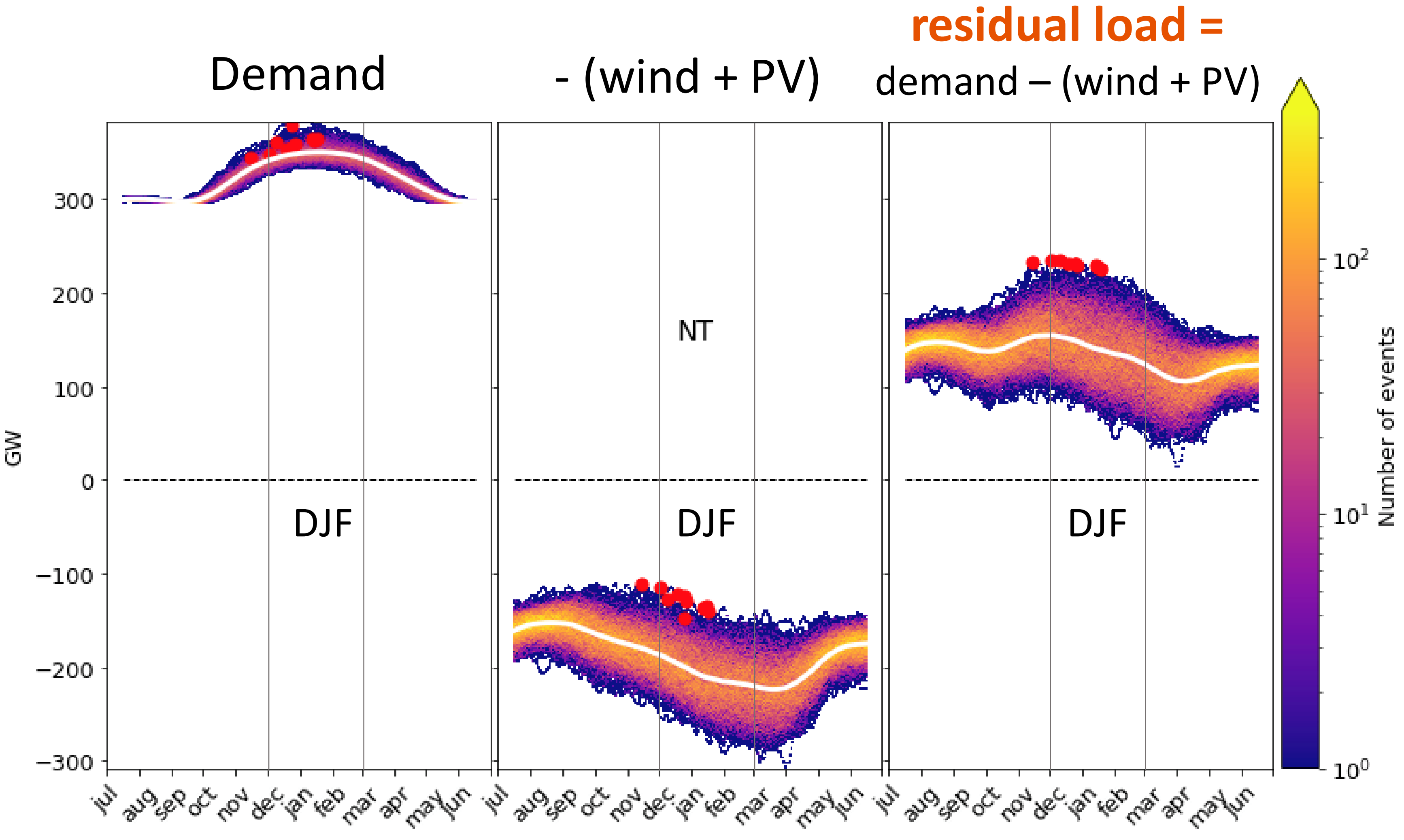
- Wind production
- Solar PV production
- Electricity demand
- National Trend scenario of wind and solar PV installed capacity (TYNDP)

[1] van der Wiel et al. *Environ. Res. Lett.* (2019)

Distribution of monthly residual load events

- High residual load events are challenging for the power system
- Each pixel is a monthly events (30 days)

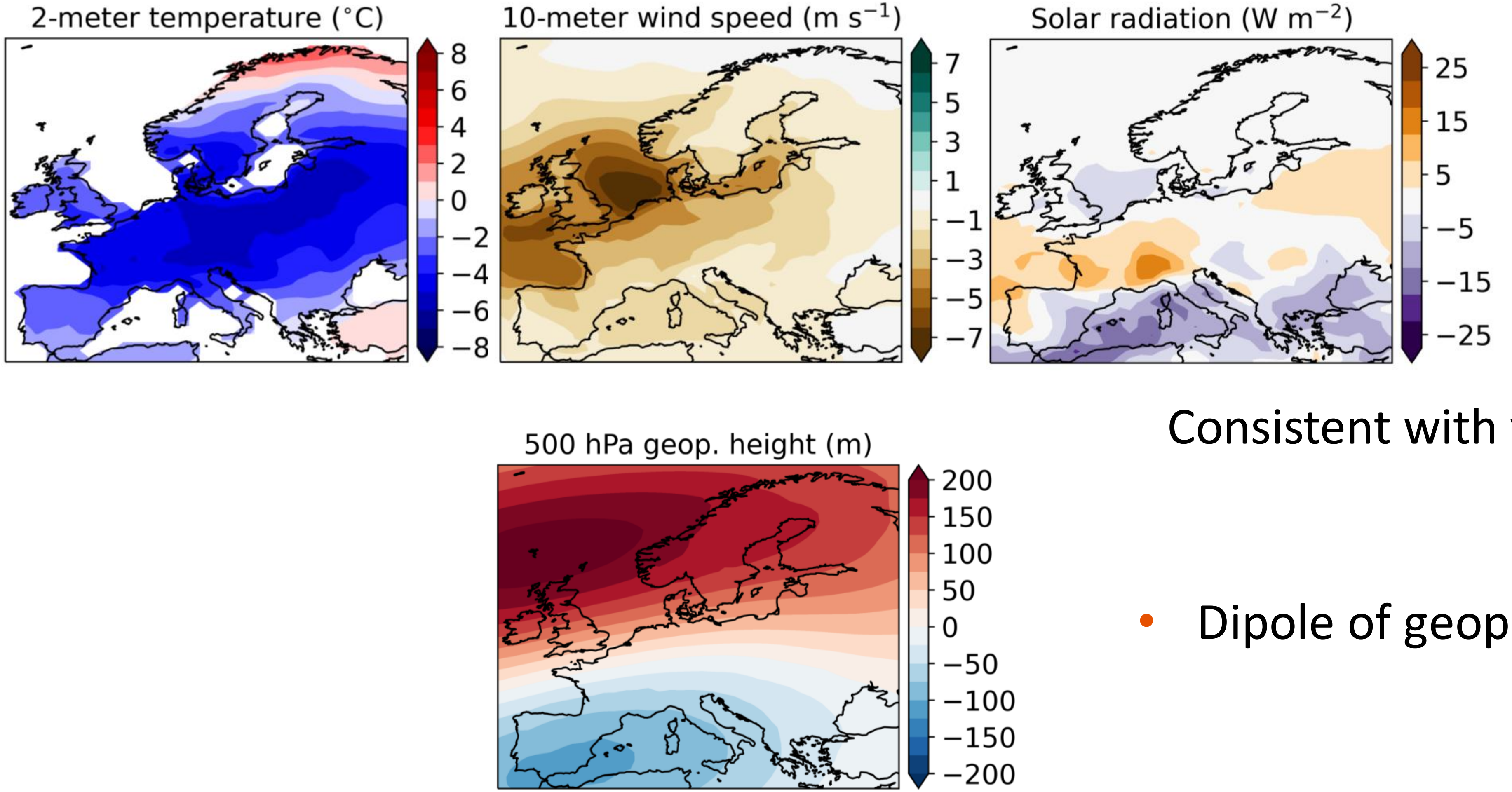
We look at
- 10-year events
- 100-year events (red dots)



Compound events

r = 10 years

Composite maps of 10-year daily events



Compound events:

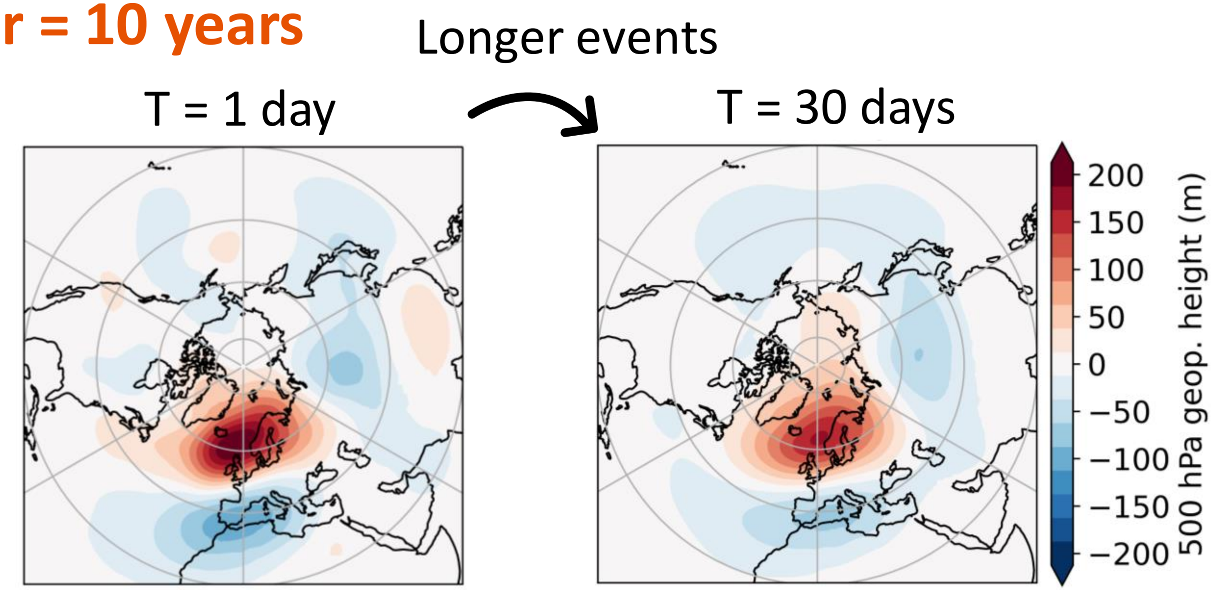
- Low wind speed
- Low temperature
- Low solar radiation in Southern Europe

Consistent with van der Wiel et al. (2019)

- Dipole of geopotential height anomaly

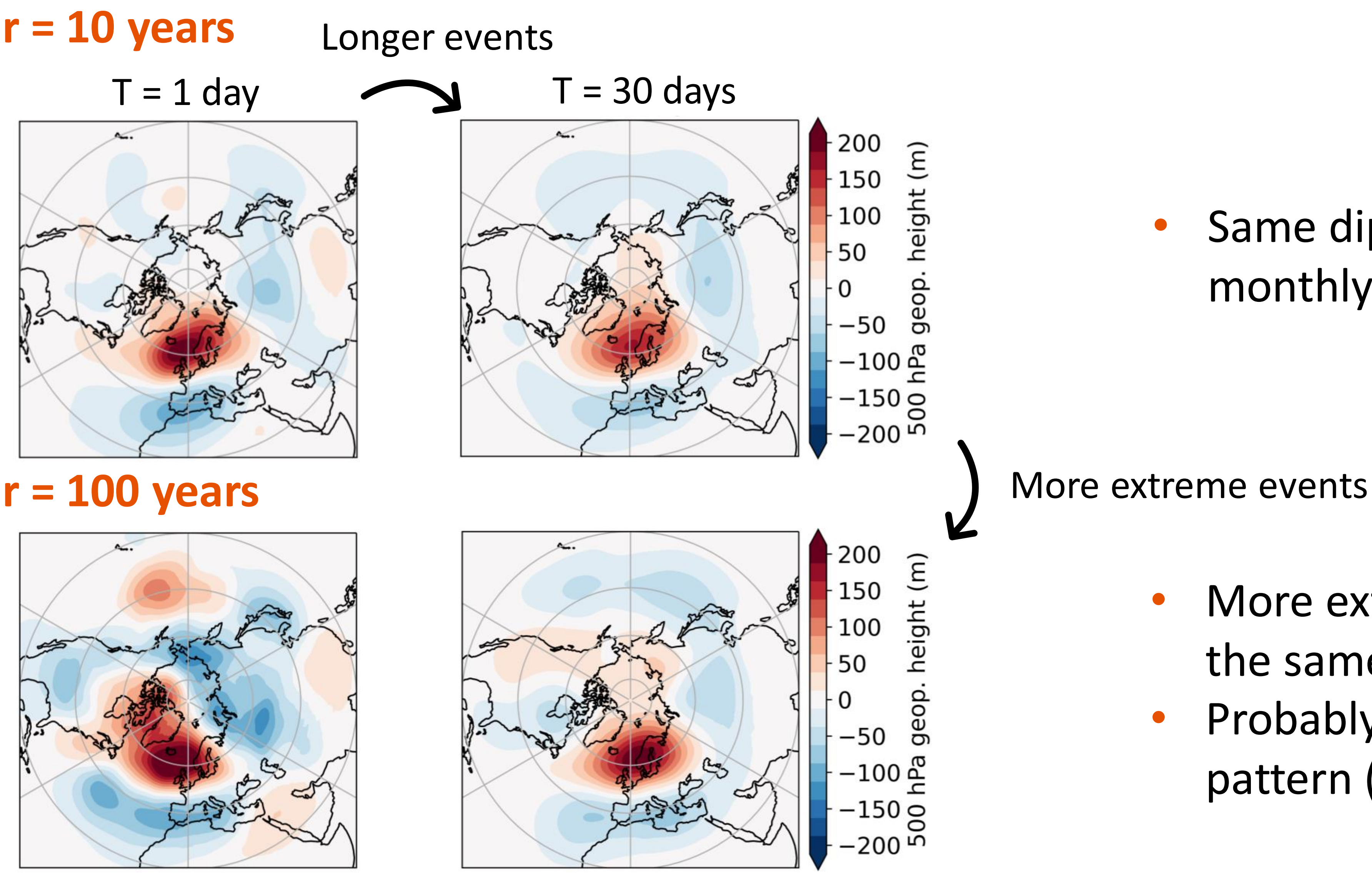
Influence of event duration and amplitude

r = 10 years



- Same dipole pattern for daily and monthly events

Influence of event duration and amplitude

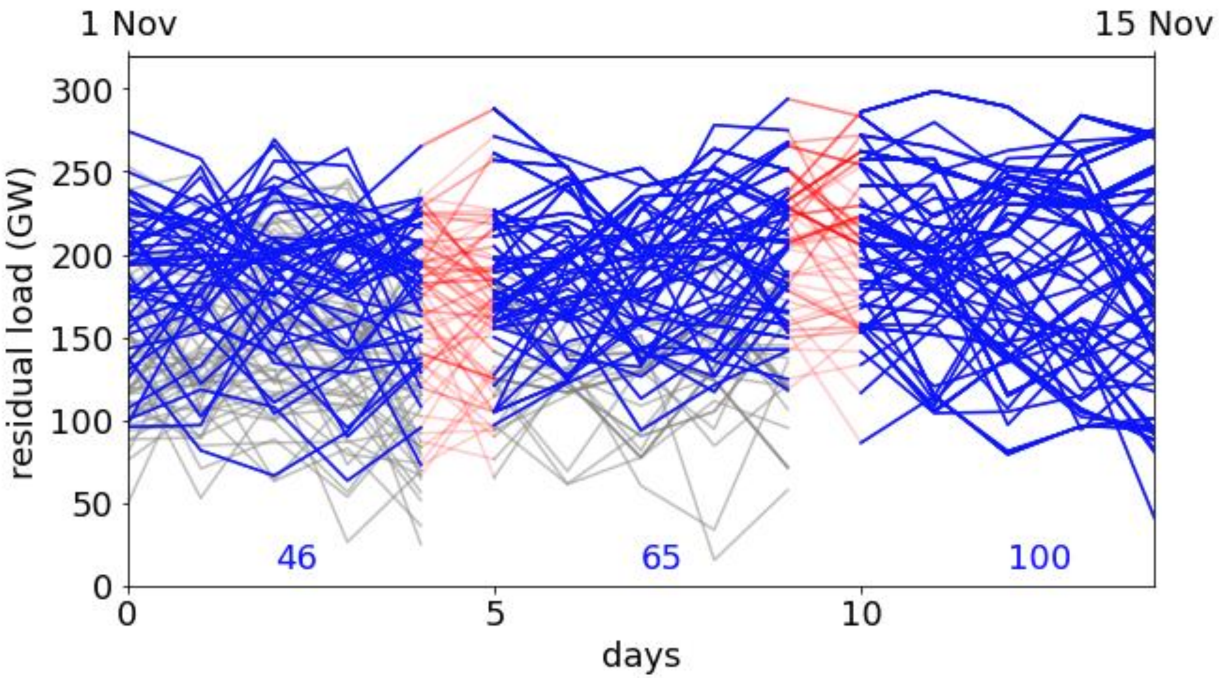


- Same dipole pattern for daily and monthly events

- More extreme events also show the same pattern
- Probably stronger teleconnection pattern (need more data)

Rare event algorithm: principle

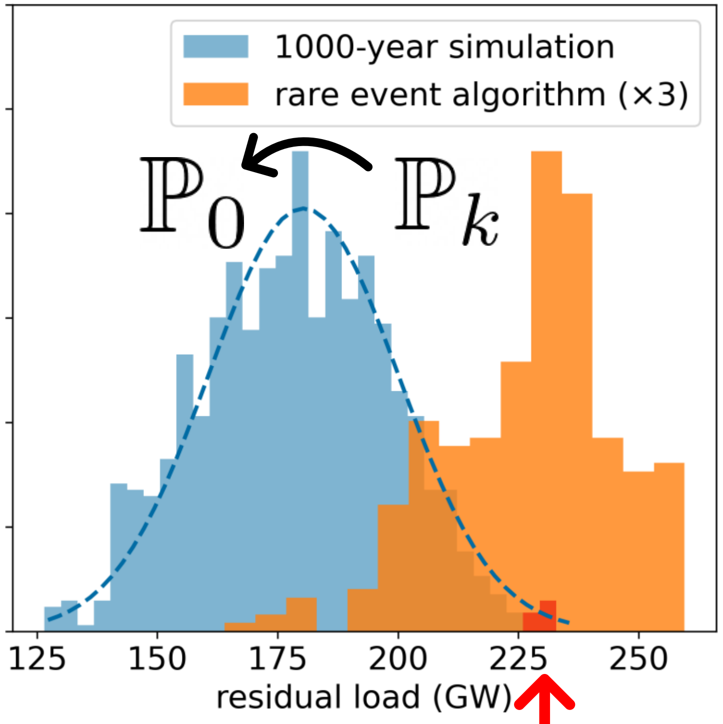
- Algorithm originally developped using statistical physics ideas
- Each trajectory is a simulation of the climate model
- 100 trajectories, with 100 independent initial conditions
- Every 5 days, trajectories that « perform » the best (according to a score function) are cloned, the others are killed



First 15 days of a rare events algorithm experiment.

Improved sampling of rare events

PDF of 30-day events



r = 100-year events

Computational cost

Control simulation

1000 years of climate simulation for

10 independent 100-year events.

Rare event algorithm

33 years (+100 years) of climate simulation for

8 independent 100-year events.

- We can sample the same number of extreme events at lower numerical cost

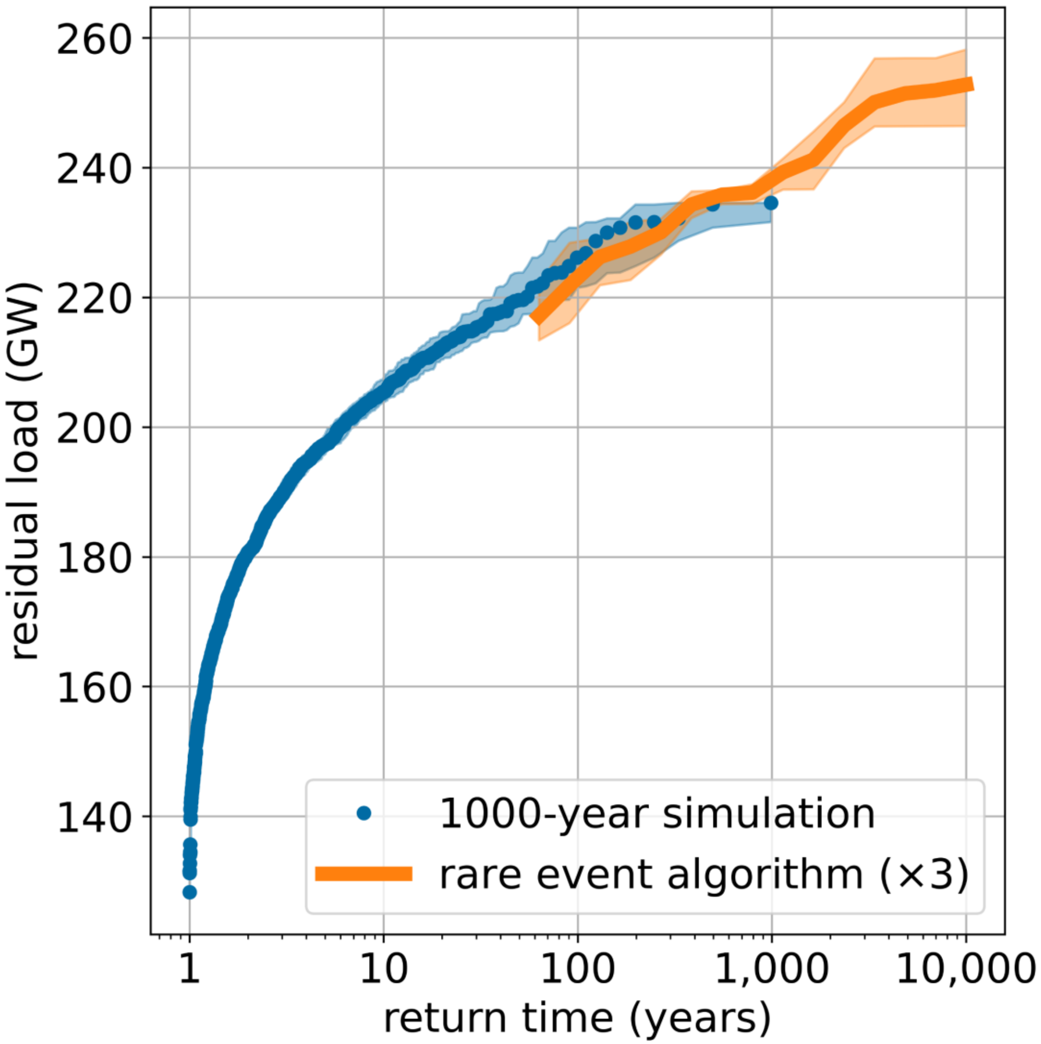
Or

- We can sample more extreme events with the same numerical cost.

Estimation of the return time

- We can estimate the return time of monthly events up to 10,000 years

Return time curves for 30-day events

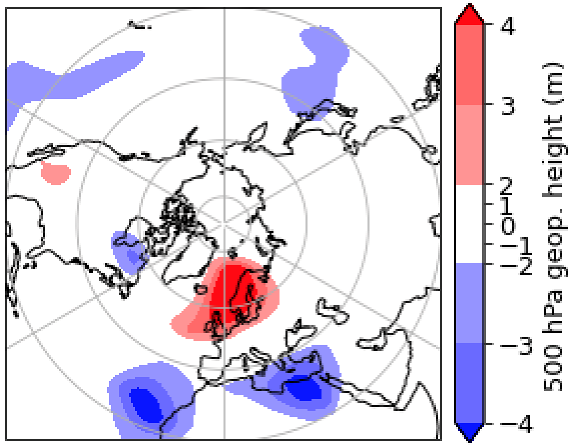


Teleconnection patterns are more significant

One sample t-test: $t = \dfrac{\hat{\mu}(a) - \mu_0}{s/\sqrt{M}}$

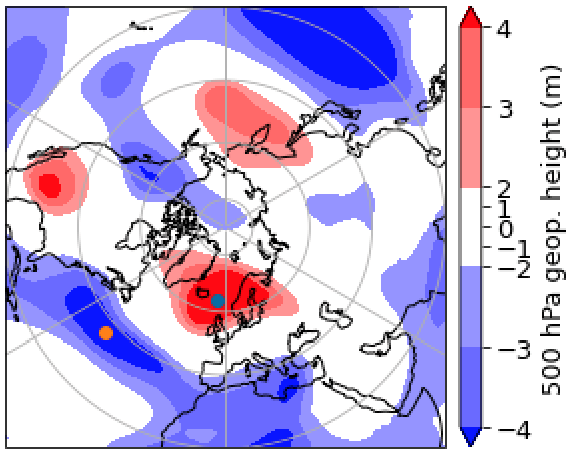
r = 100 years

T = 30 days



1000-year
control simulation

T = 30 days



Rare event algorithm

- Extreme 100-year events show a significant teleconnection pattern, highlighting characteristic large-scale dynamics.
- A large-scale pattern could lead to stronger predictability.

Conclusions

- Extreme 10-year daily and monthly events of residual load are associated with a geopotential height dipole in Europe.
- There is a lack of data to study extreme 100-year events.

- Rare event algorithm can sample more extreme events with a smaller numerical cost.
- We can estimate the return time of monthly events up to 10,000 years.
- Extreme 100-year events show significant teleconnection patterns, potentially predictable

bastien.cozian@ens-lyon.fr

Appendix

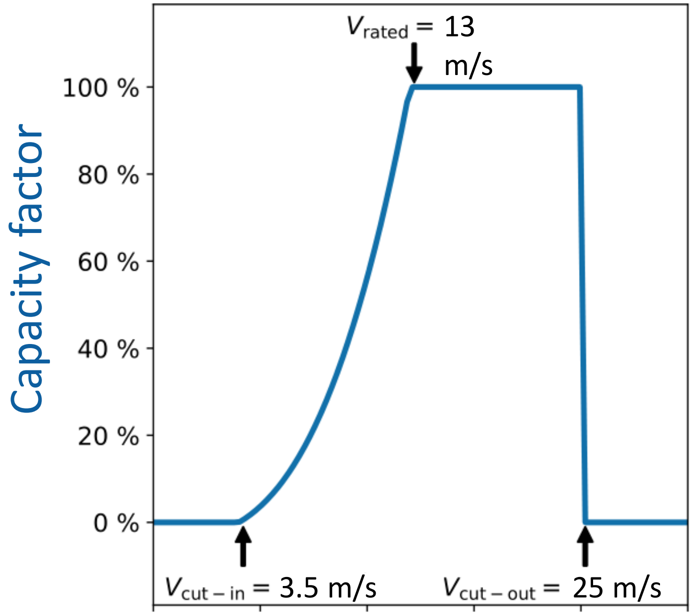
Renewable production and demand model

Simple model [1]

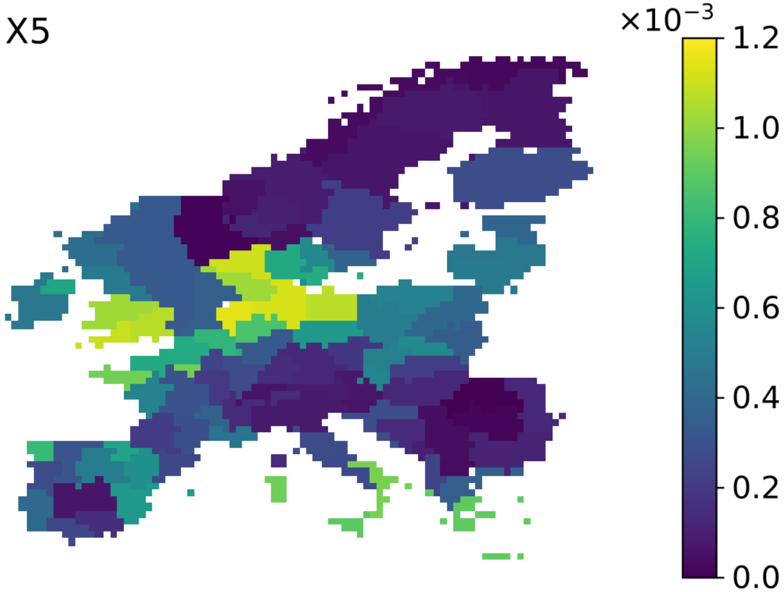
- Wind production
- Solar PV production
- Electricity demand

With 8 scenarios of wind and solar PV installed capacity.

Illustration of the wind model



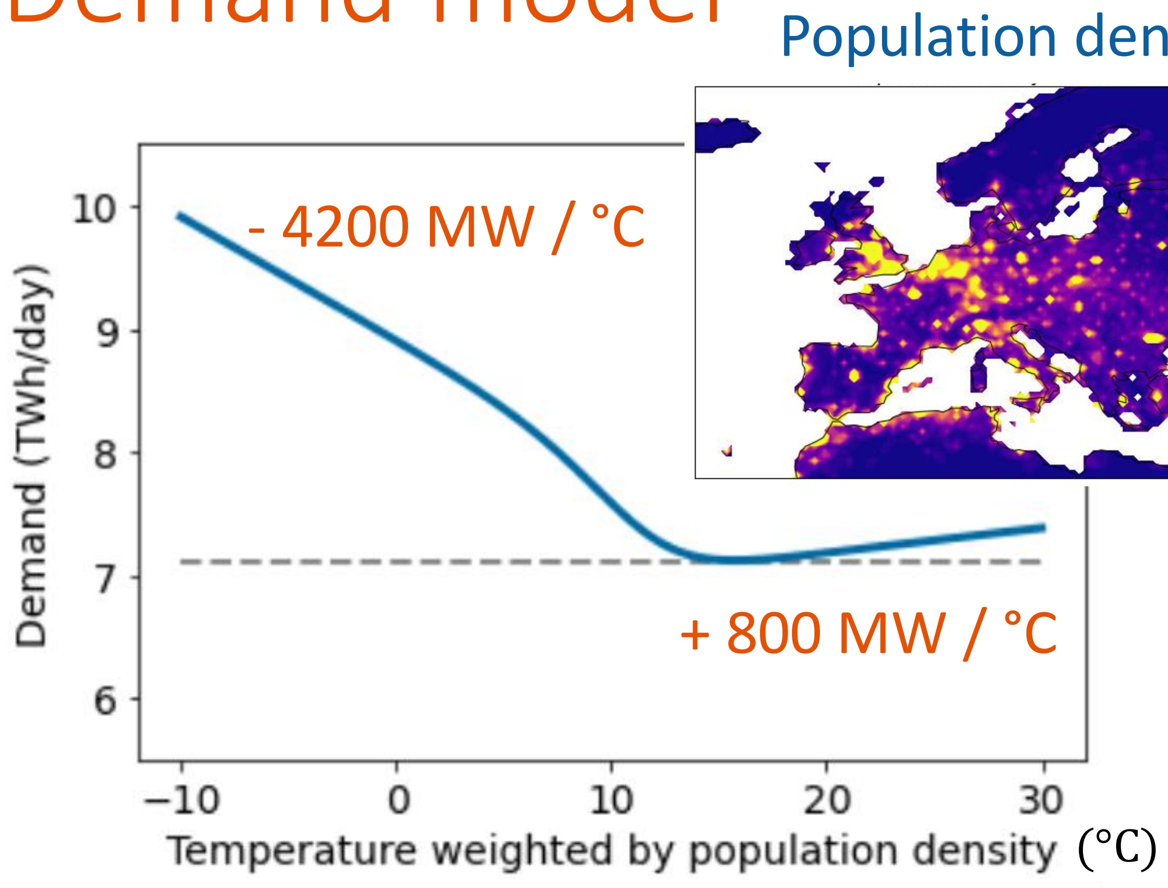
Local onshore 80-m wind speed (m/s)

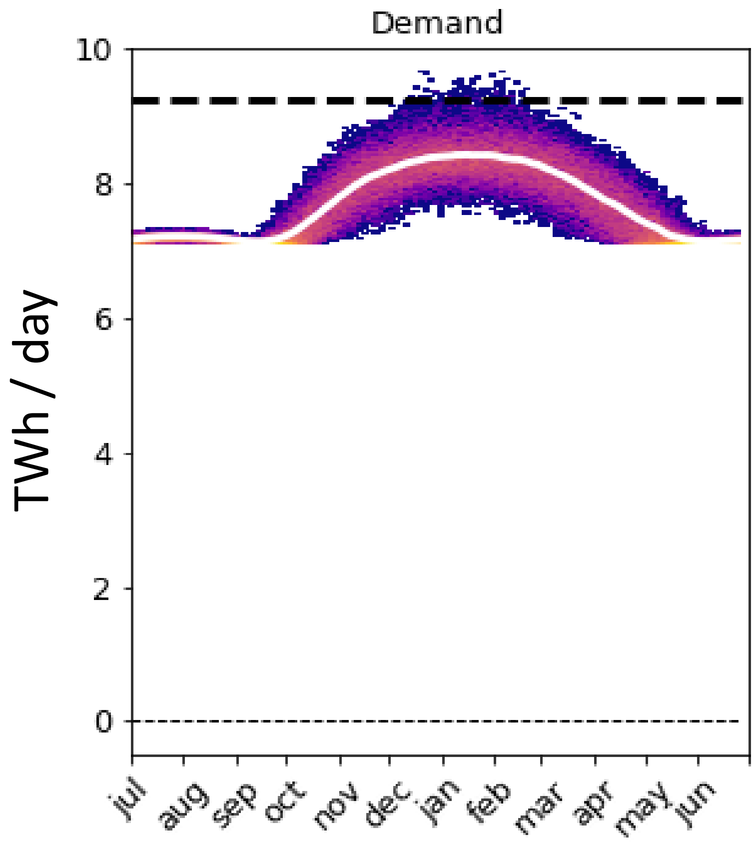


Installed capacity density (in %) of one of the 8 scenarios

[1] van der Wiel et al. *Environ. Res. Lett.* (2019)

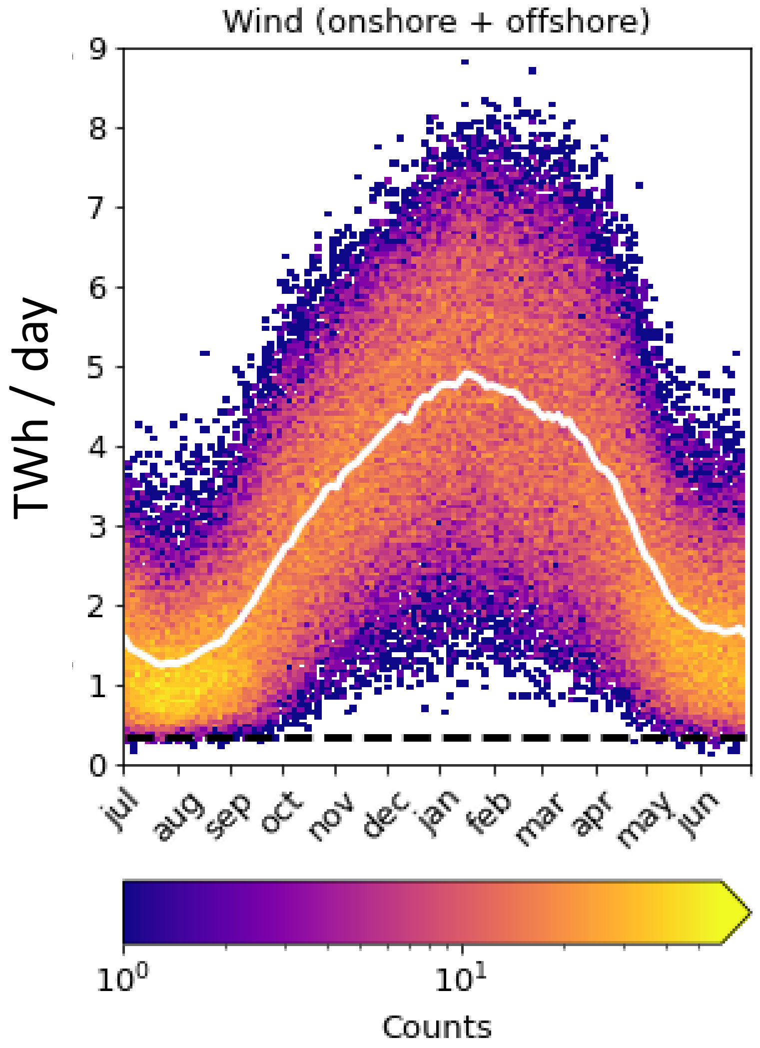
Demand model



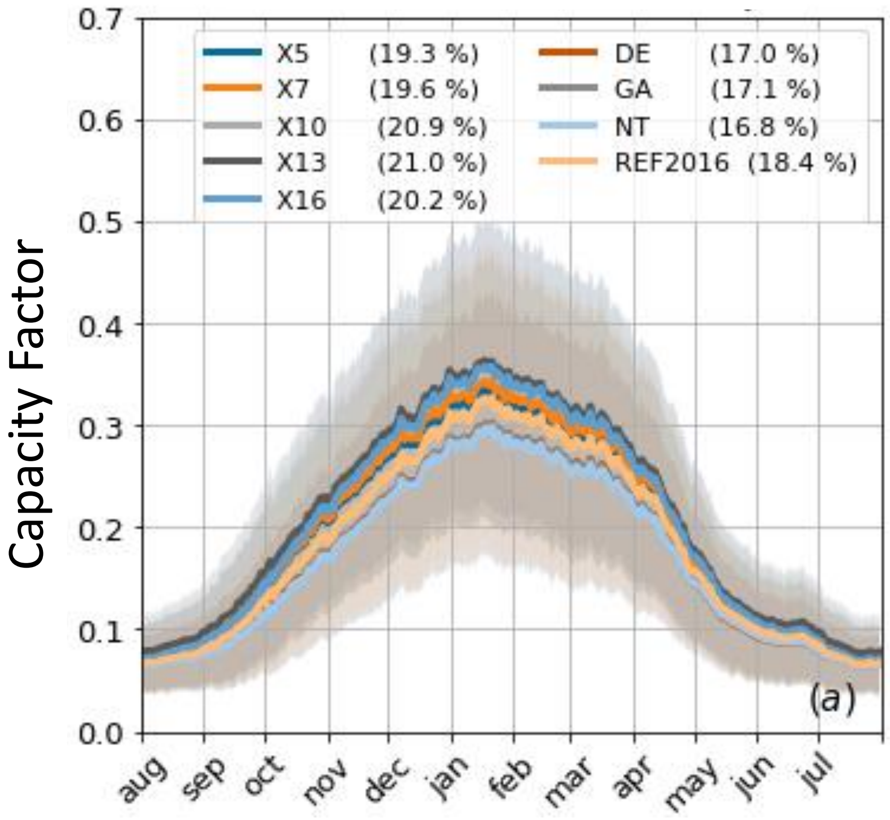


Energy demand model for 15 European countries, based on 2006-2015 ENTSO-e data. Van der Wiel et al. (2019a)

Wind production model

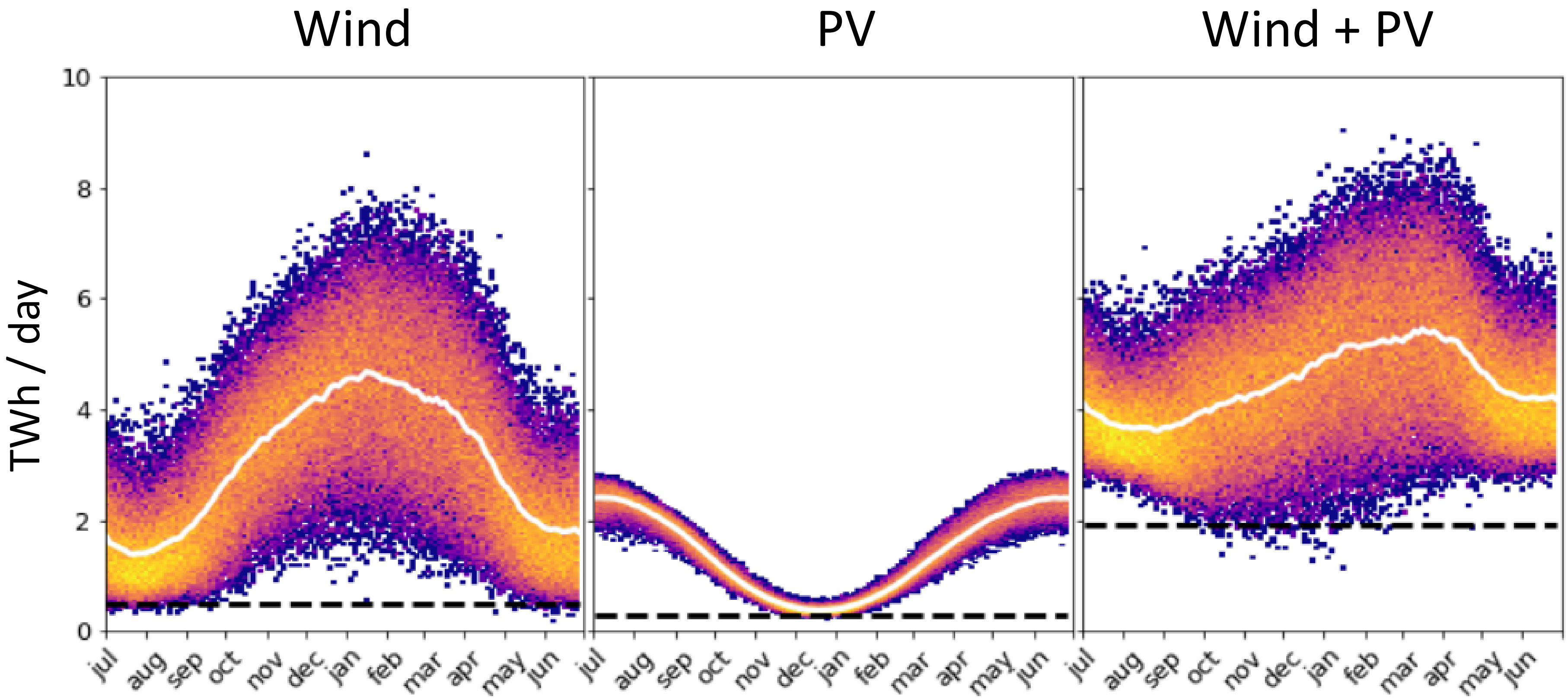


Scenario eHighway2050 - X10



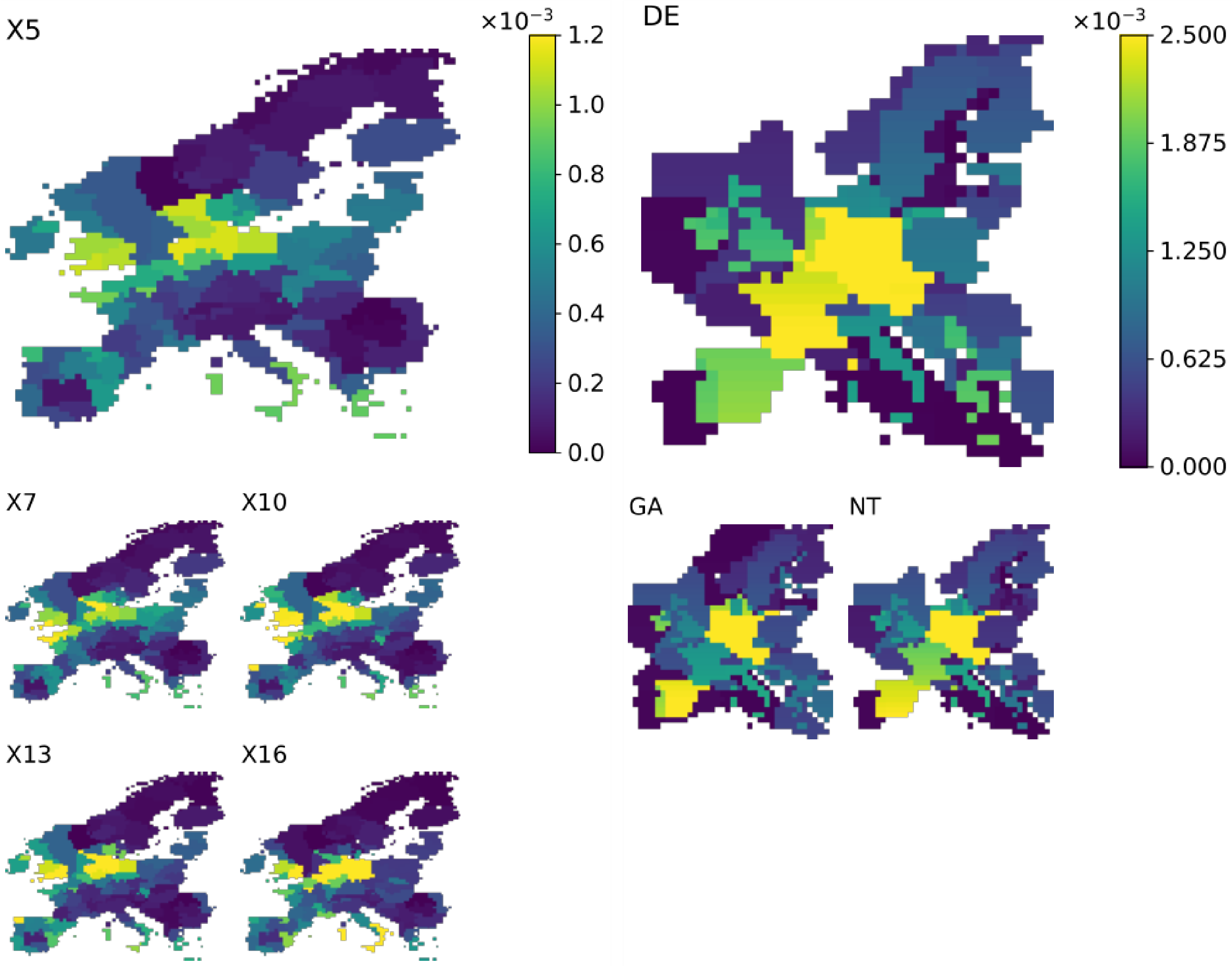
Mean and standard deviation of capacity factor for all scenarios

Solar PV production model

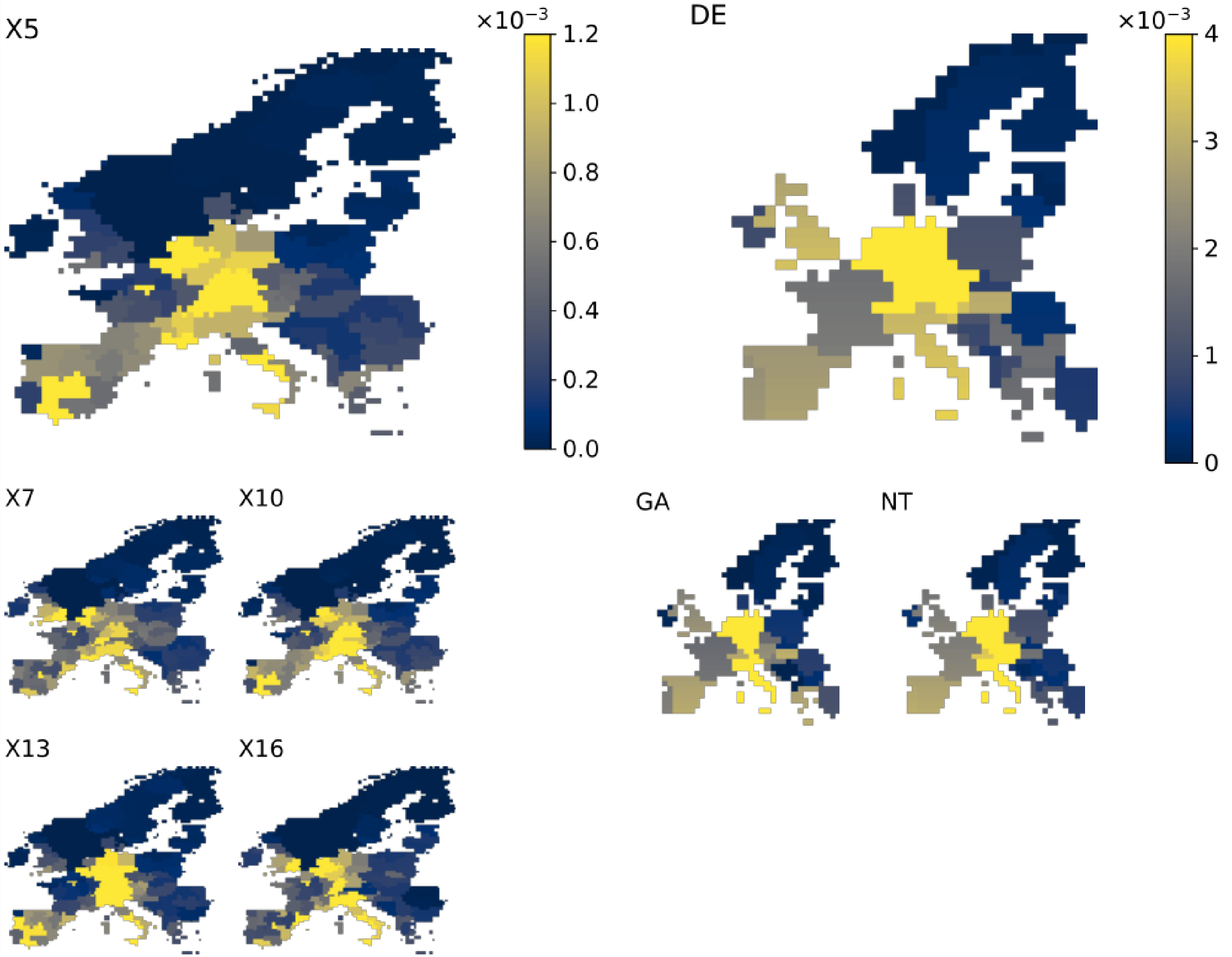


- Solar PV production = $f(W_{radiation},\ T_{air}, \boldsymbol{WS})$

Wind installed capacity



Solar PV installed capacity



Definition of 30-day residual load events

We define the random variable t_* as the date when the maximum T-day average of the observable A occurs:

$$t_* = \underset{t \in [0, T_a - T]}{\text{argmax}} \left\{ \frac{1}{T} \int_t^{t+T} R(u)\, \mathrm{d}u \right\}. \tag{10}$$

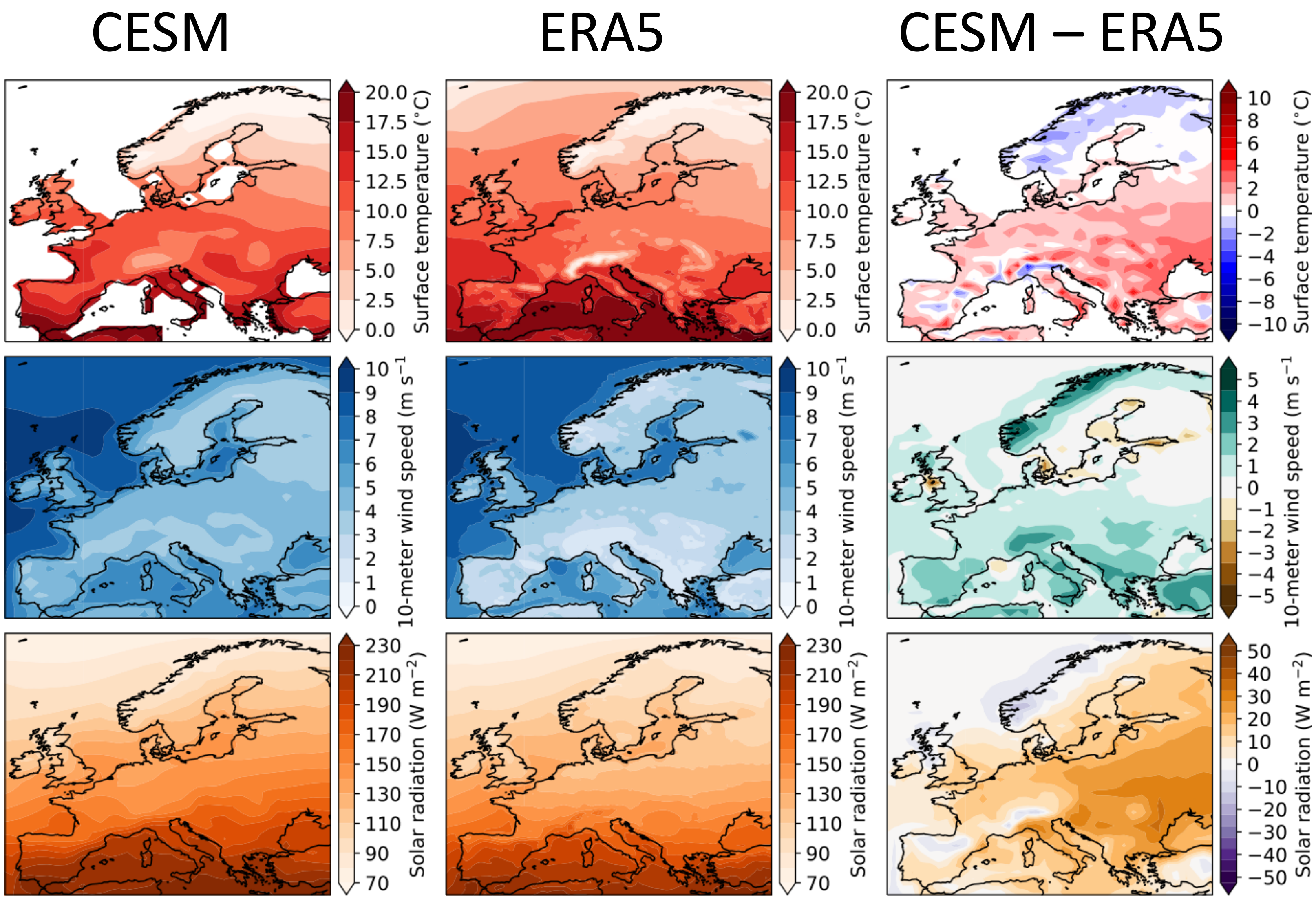
We note A_* and X_* the T-day average values:

$$A_* = \max_{t \in [0, T_a - T]} \left\{ \frac{1}{T} \int_t^{t+T} R(u)\, \mathrm{d}u \right\} = A_T(t_*) \tag{11}$$

$$X_* = X_T(t_*) \tag{12}$$

- Composite map = $\mathbb{E}[X | A \geq a]$

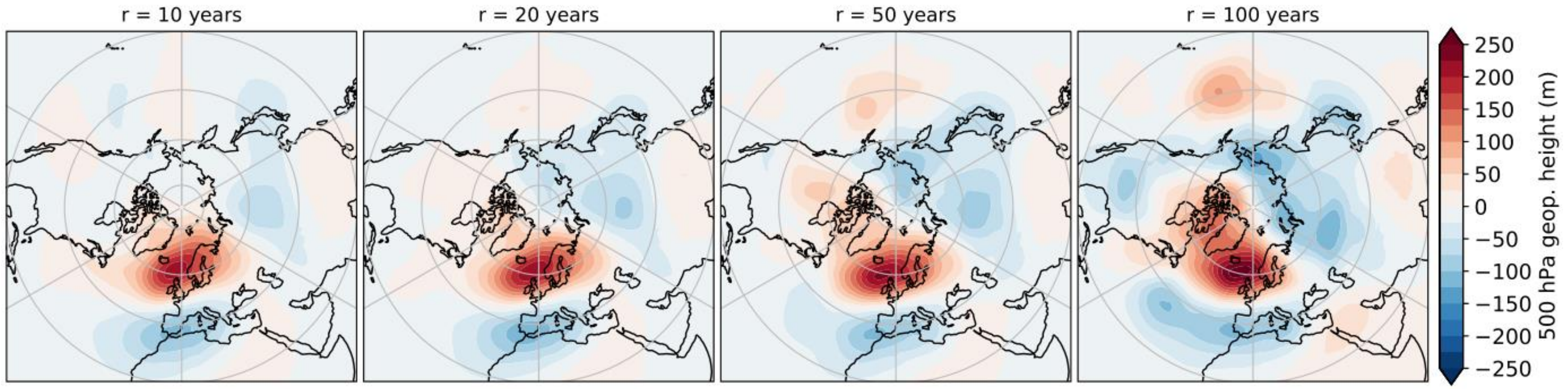
Bias of our climate model w.r.t. reanalysis



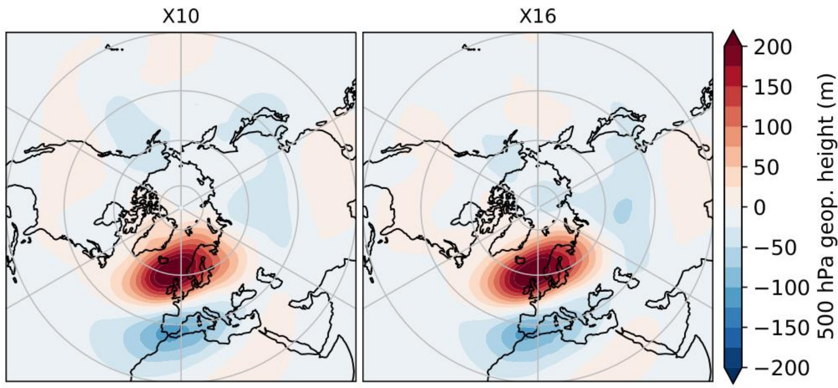
Climatology of CESM and 1980-2020 ERA5 (left and middle panel), and difference (right panel).

Composite maps pattern depends little on r, T or sce

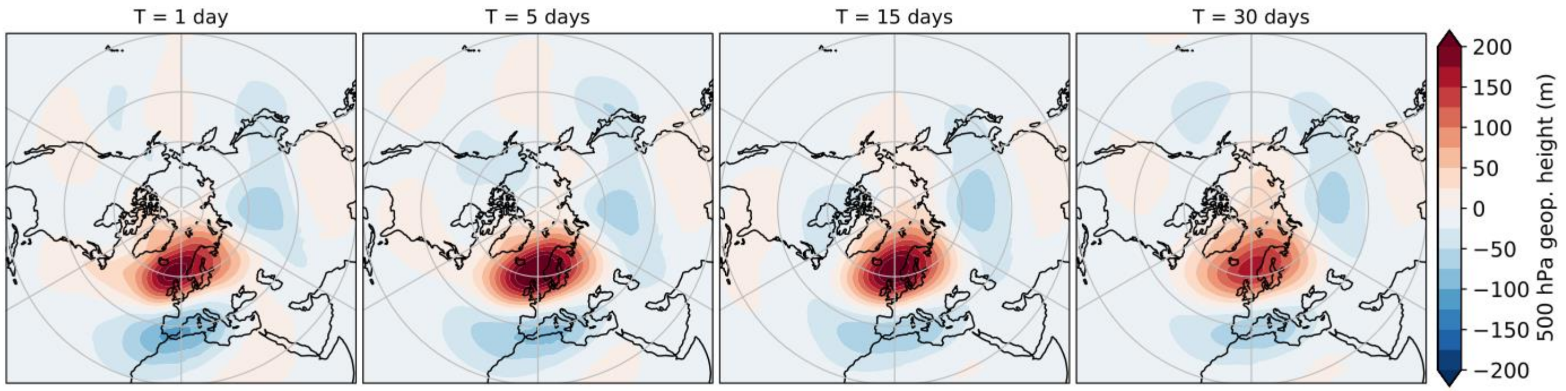
Return time ↗



Change scenario

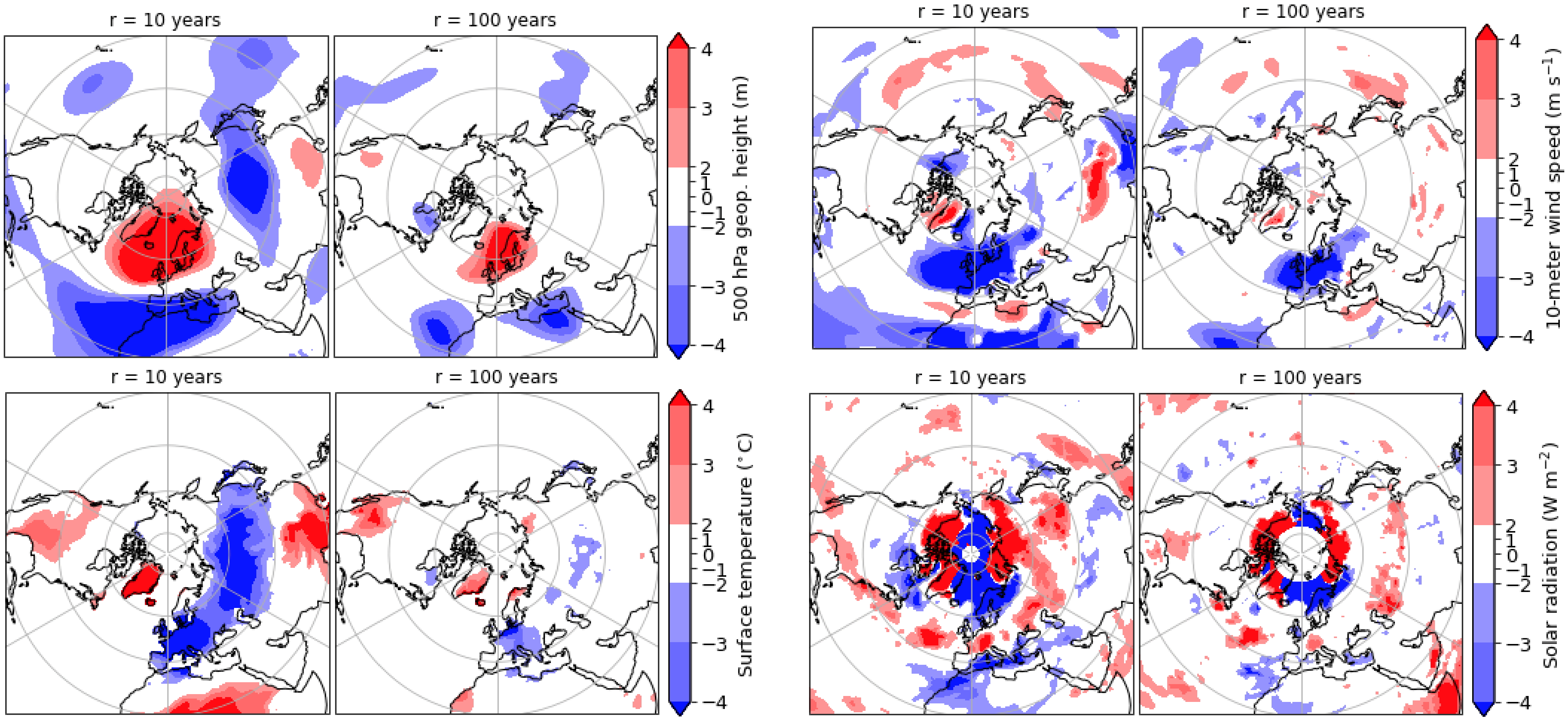


Duration T ↗

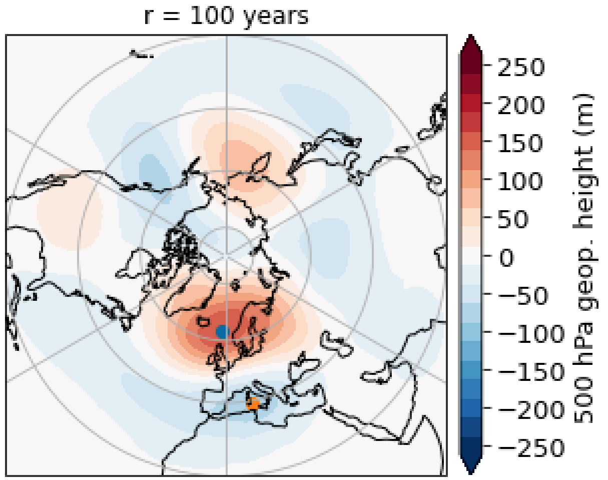


Significance map for control run

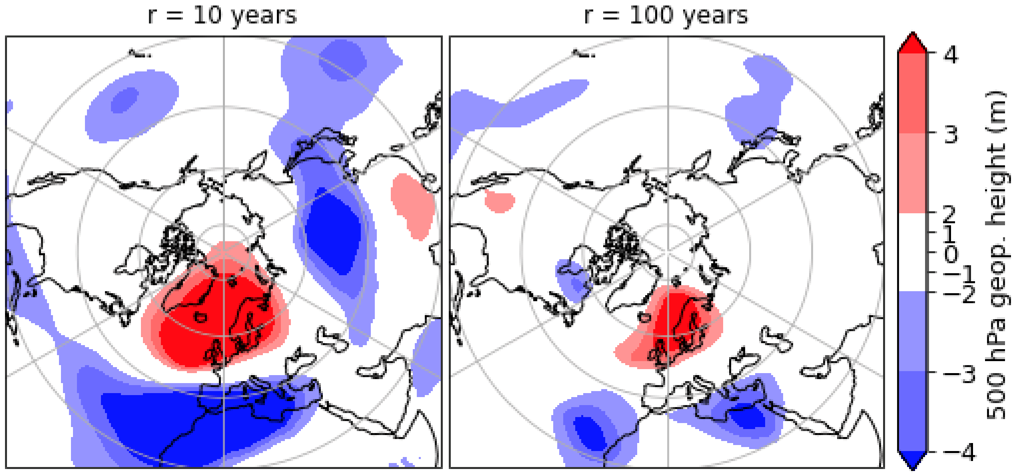
$$t = \frac{\hat{\mu}(a) - \mu_0}{s/\sqrt{M}}$$



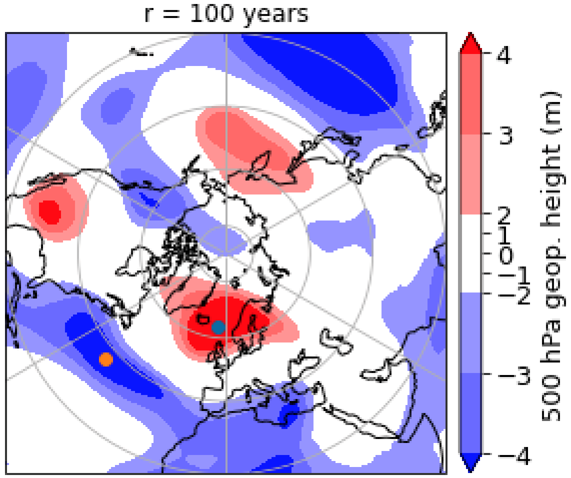
Significance map for GKTL



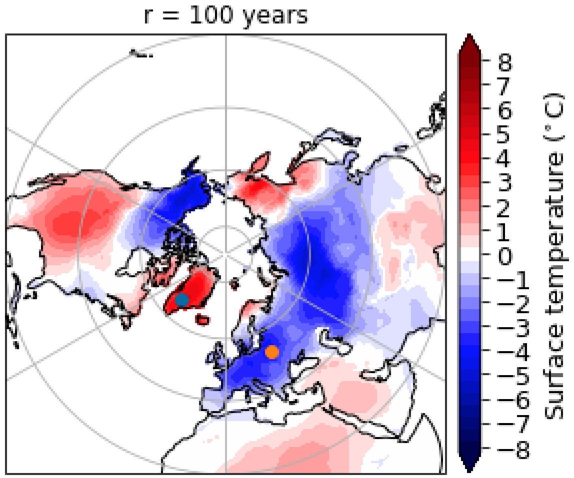
CTRL



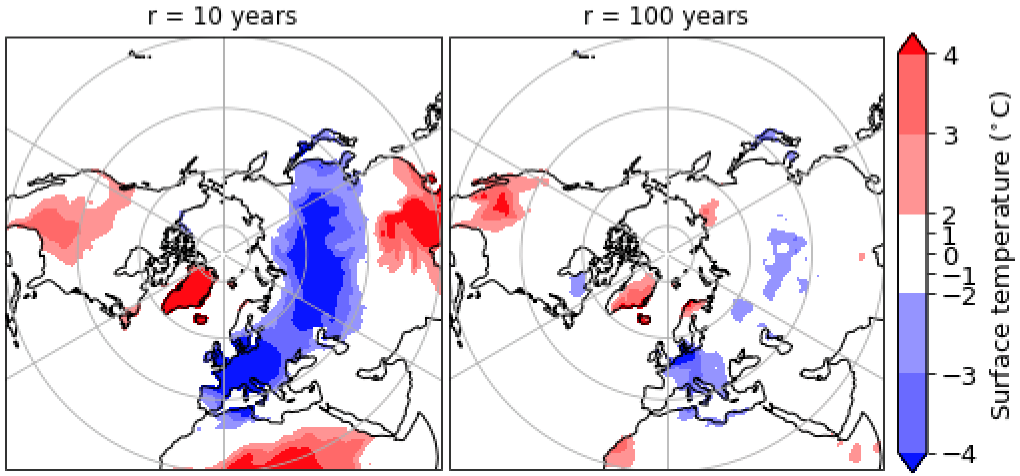
GKTL



Significance map for GKTL



CTRL



GKTL