

# Modeling Earth-surface temperature extremes with physics-informed upper bounds for simulating worst possible cases

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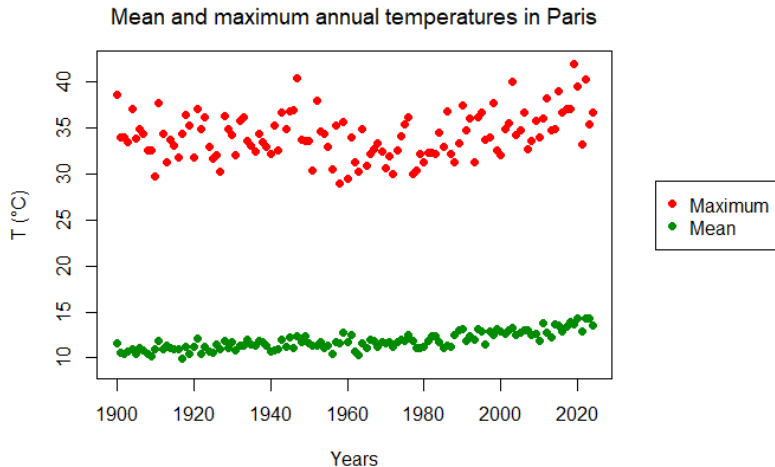
## Context:

- Strong statistical and physical evidence for a finite land temperatures upper bound
- This upper bound depends on local climate, large-scale atmospheric conditions and spatial variations
- Difficulty in estimating this upper bound due to the scarcity of data on extreme events

## Goals:

- Combining statistical and physical modelling
- Taking into account spatial and temporal trends of the climate
- Generating large amounts of data at low cost for extreme events

# Observed daily mean and maximum temperatures



Sources: Extreme Weather Watch,  
OpenData Paris

Statistical bound and physical bound

# GEV upper bound

Let us define  $T(t)$  the annual maximum temperature in year  $t$ .  
Extreme-Value Theory suggests:

$$T(t) = \max_{1 \leq i \leq 365} T_i(t) \approx \text{GEV}(\mu, \sigma, \xi)$$

with  $(\mu, \sigma, \xi) \in \mathbb{R} \times \mathbb{R}_+^* \times \mathbb{R}$ .

Distribution function of a GEV distribution (Generalized Extreme Value)

$$G(x) = \mathbb{P}(T(t) \leq x) = \exp \left( - \left[ 1 + \xi \left( \frac{x - \mu}{\sigma} \right) \right]^{-1/\xi} \right)$$

with  $x$  such that  $1 + \xi \left( \frac{x - \mu}{\sigma} \right) > 0$ .

$$\text{For } \xi < 0, \quad 1 + \xi \left( \frac{x - \mu}{\sigma} \right) > 0 \quad \Leftrightarrow \quad x < \mu - \frac{\sigma}{\xi} =: B_{\text{GEV}}$$

# Statistical bound

For a given location, we model the annual maximum temperatures by:

$$T(t) \approx \text{GEV}(B_{\text{stat}}(t), \sigma, \xi)$$

with  $B_{\text{stat}}(t)$  the statistical bound for year  $t$  estimated by maximum likelihood

Plausible models must satisfy:

$$\mathbb{P}(T(t) > B_{\text{stat}}(t)) = 0$$

Possible violations of the upper bound:

- Model error: the temperatures  $T(t)$  do not follow exactly a GEV distribution
- Parameter uncertainty

# Physically-informed upper bound determined by atmospheric variables

According to physical laws derived by Zhang and Boos 2023 and Noyelle et al. 2024, the maximum surface temperature satisfies the following equation:

$$T_{\max} = T_{500} + \frac{L_v}{c_p}(Q_{\text{sat}}(T_{500}) - Q) + \frac{g}{c_p}(Z_{500} - Z_s)$$

with:

- $T_{500}$  the air temperature at 500hPa
- $Q$  the surface specific humidity of the air parcel
- $Z_{500}$  the geopotential height at 500hPa

## Physically-informed upper bound determined by atmospheric variables

Let us define  $Y_j = T_{500}, Z_{500}$  or  $-Q$ . Let  $Y_j(t)$  be the annual maximum value of  $Y_j$  for year  $t$ . Then, we assume:

$$Y_j(t) \approx \text{GEV}(B_j(t), \sigma_j, \xi_j)$$

with  $B_j(t)$  the statistical bound for year  $t$  achieved by maximum likelihood

Therefore, we define an upper bound for  $T_{max}$  at year  $t$  as the following physical quantity:

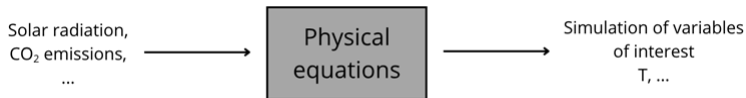
$$B_{phy}(t) = B_{T_{500}}(t) + \frac{L_v}{c_p}(Q_{sat}(B_{T_{500}}(t)) + B_{-Q}(t)) + \frac{g}{c_p}(B_{Z_{500}}(t) - Z_s)$$



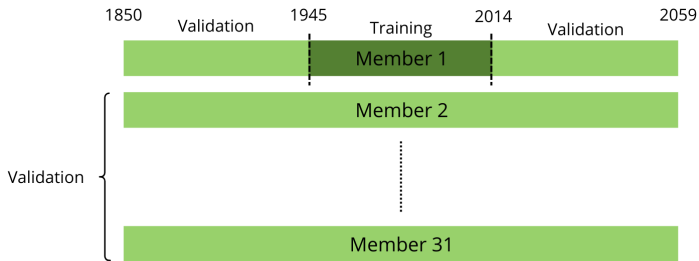
Data

# Data simulated by a physical climate model

Climate model IPSL-CM6A-LR:

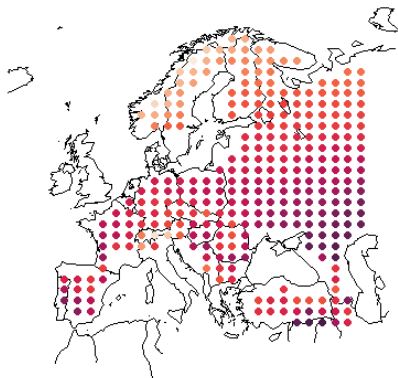


31 independent members:

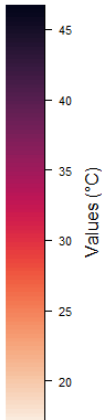
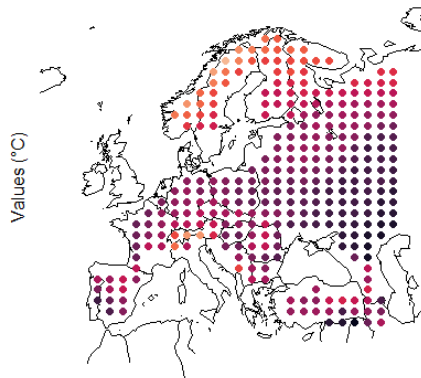


# Data simulated by a physical climate model

Average of maximum annual temperatures  
over 1945-2014 (member 1)



Maximum of maximum annual temperatures  
over 1945-2014 (member 1)



## Results

# Models

For a given location, the estimated parameters come from the model:

$$\begin{cases} B(t) \\ \sigma(t) = \sigma_0, \sigma_0 > 0 \\ \xi(t) = \xi_0, \xi_0 < 0 \end{cases}$$

**Statistical upper bound:**

$$B(t) = \hat{B}_0 + \hat{B}_1 \times \widetilde{GMST}(t)$$

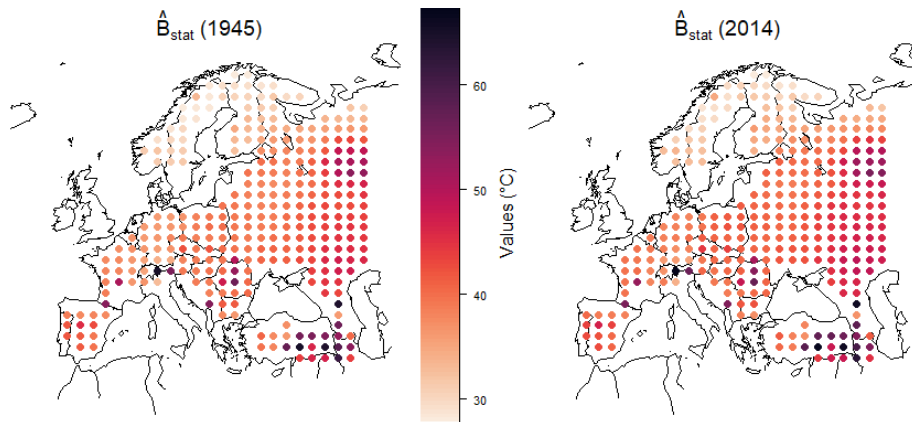
**Physically-informed upper bound**

$$\begin{aligned} B(t) = & \hat{B}_{0,T_{500}} + \hat{B}_{1,T_{500}} \times \widetilde{GMST}(t) \\ & + \frac{L_v}{c_p} \left[ Q_{sat} \left( \hat{B}_{0,T_{500}} + \hat{B}_{1,T_{500}} \times \widetilde{GMST}(t) \right) + \hat{B}_{0,-Q} + \hat{B}_{1,-Q} \times \widetilde{GMST}(t) \right] \\ & + \frac{g}{c_p} \left[ \hat{B}_{0,Z_{500}} + \hat{B}_{1,Z_{500}} \times \widetilde{GMST}(t) - Z_s \right] \end{aligned}$$

defining  $\widetilde{GMST}(t) = GMST(t) - \overline{GMST}_{train}$   
(Global Mean Surface Temperature)

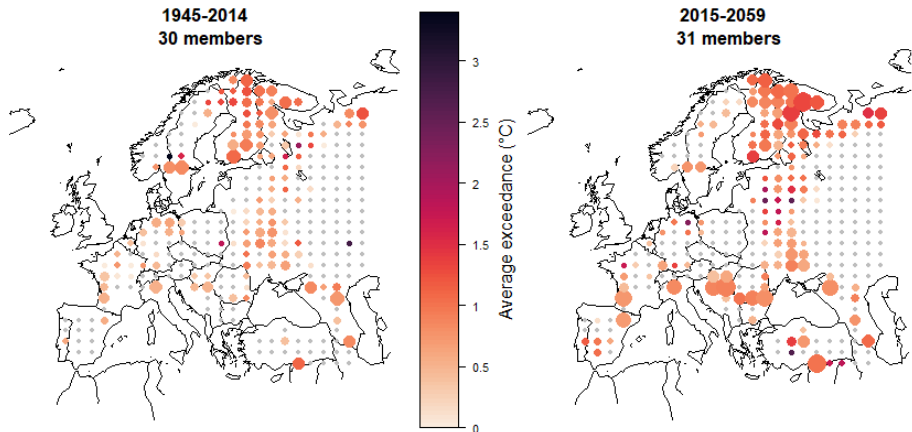
# Statistical upper bound: results

MLE considering the nearby locations and penalizing  $\xi$  when close to 0



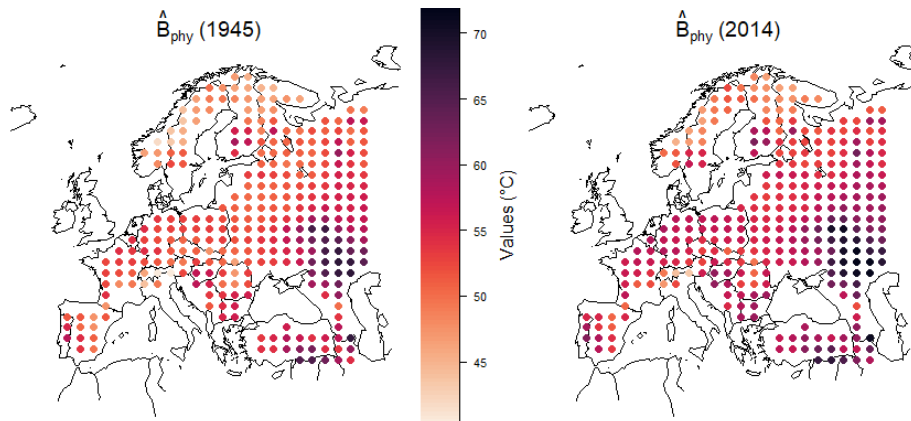
# Statistical upper bound: exceedances

Point size: number of exceedances for the location studied



# Physical upper bound: results

MLE considering the nearby locations and penalizing  $\xi$  when close to 0



→ No exceedance over 1850–2059 for all members of the climate model



Data simulation

# Data simulation: annual maximum temperatures in Grenoble

Generating data in Grenoble for years  $t \in \llbracket 2015; 2059 \rrbracket$  from:

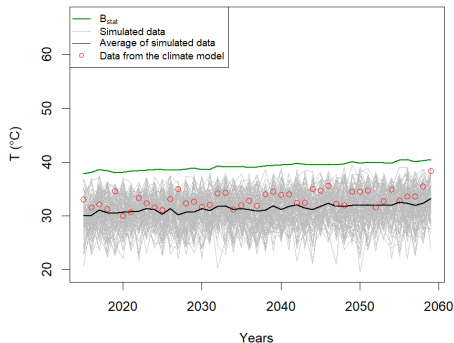
- $GEV(\hat{B}_{stat}(t), \hat{\sigma}, \hat{\xi})$
- $GEV(\hat{B}_{phy}(t), \hat{\sigma}, \hat{\xi})$



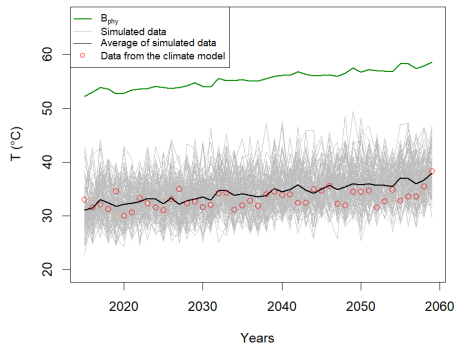
# Data simulation: annual maximum temperatures in Grenoble

GMST from the member 1 of the climate model from 2015 to 2059  
100 trajectories (grey)

Maximum annual temperatures simulated with  $B_{stat}$

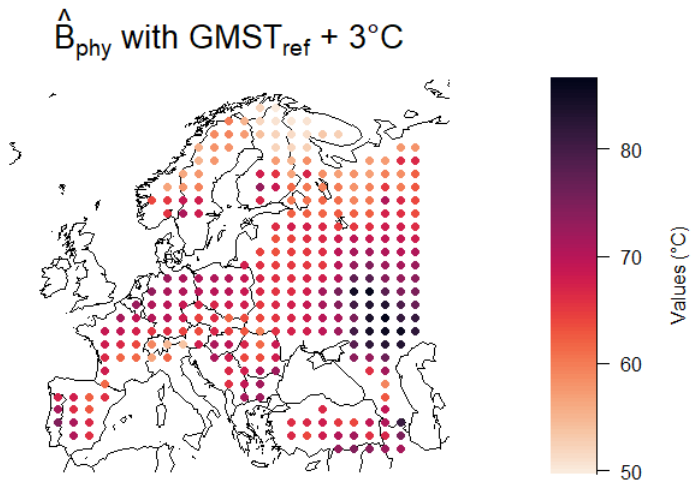


Maximum annual temperatures simulated with  $B_{phy}$

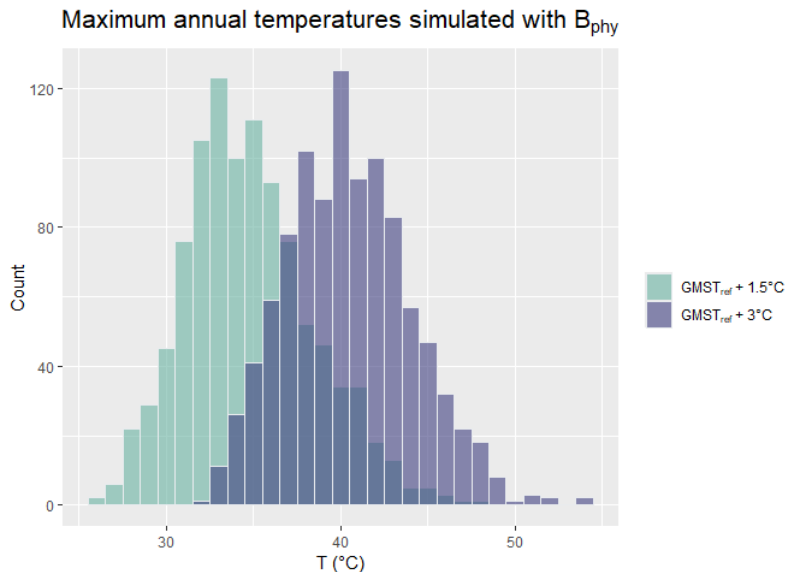


# Data simulation: TRACC scenario for Europe

Scenario: Global warming will reach +3°C in 2100 compared to pre-industrial levels



# Data simulation: TRACC scenario for Grenoble



## Conclusion

# Conclusion





In this work:

- Combining estimation of covariate bounds and physical equation gives greater upper limits
- No exceedance of the physics-informed upper bound while maintaining a reasonable goodness-of-fit
- Generating new data is easy and low-cost computing

Work in progress:

- Bayesian framework: defining more appropriate, principled priors for key parameters
- Estimate and propagate uncertainty of the physical bound by joint estimation of all parameters
- Spatial copula model for generating new data

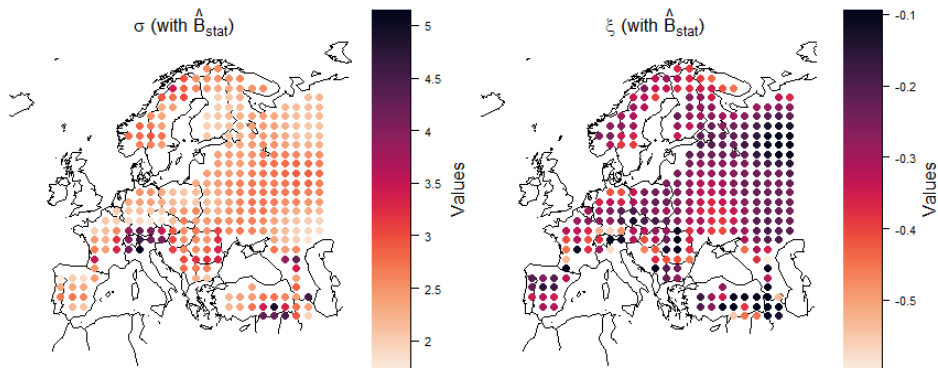
# References

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-  Coles, Stuart (2001). *An introduction to statistical modeling of extreme values*. Vol. 208. Springer.
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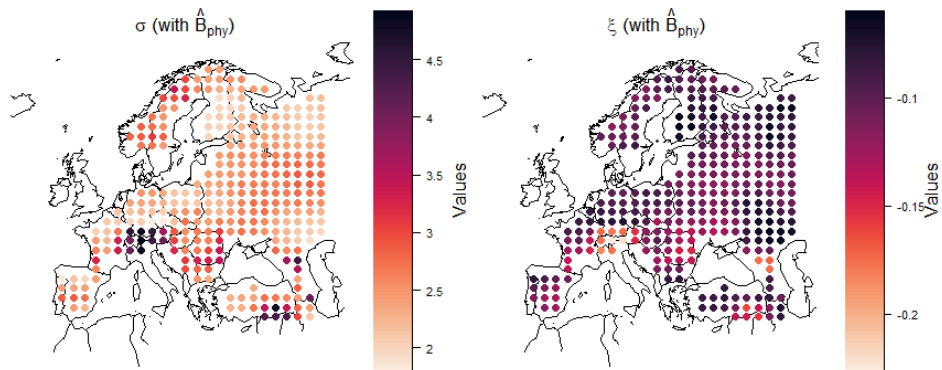


## Appendices

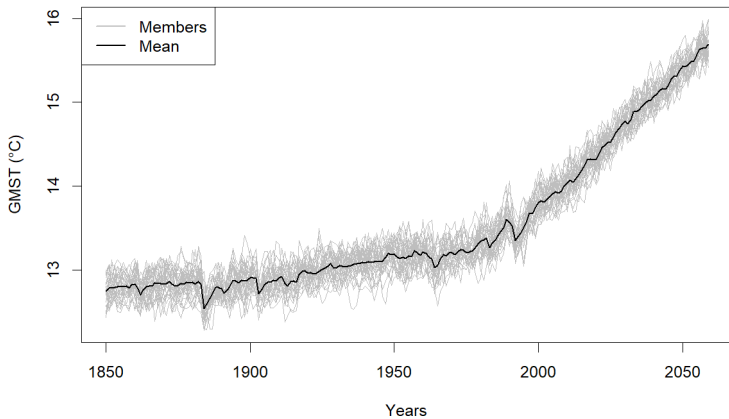
# Statistical upper bound: scale and shape parameters



# Physical upper bound: scale and shape parameters



# Appendices



# Appendices

GLOBAL AVERAGE SURFACE TEMPERATURE

