INFLUENCE OF CLIMATE CHANGE ON EXTREME WEATHER EVENTS

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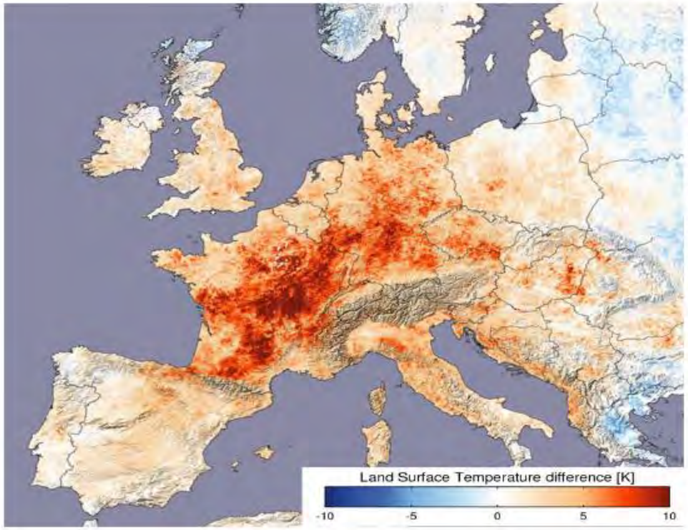
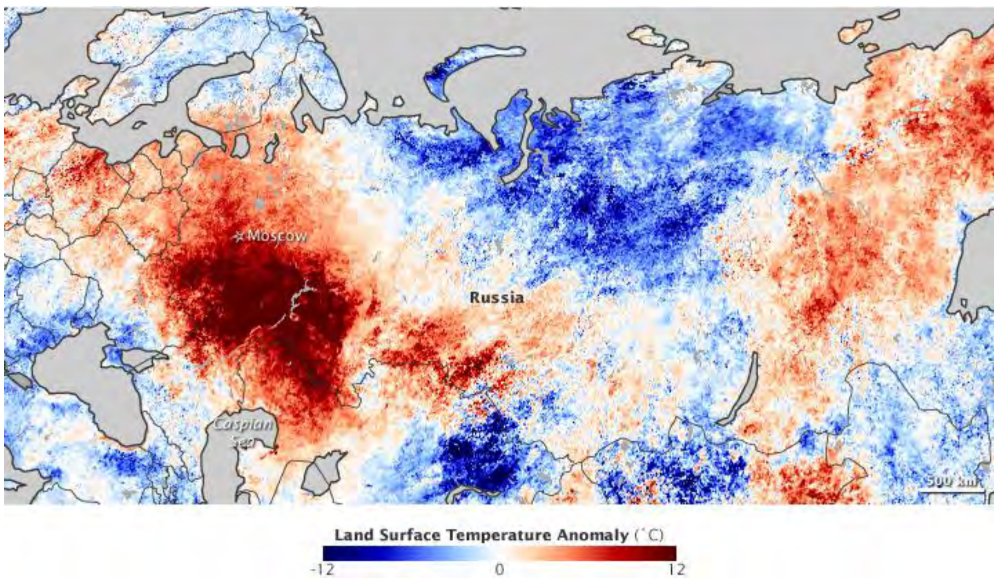
(Joint with Michael Wehner, Lawrence Berkeley Lab)

Extreme Weather Events are of Increasing Concern

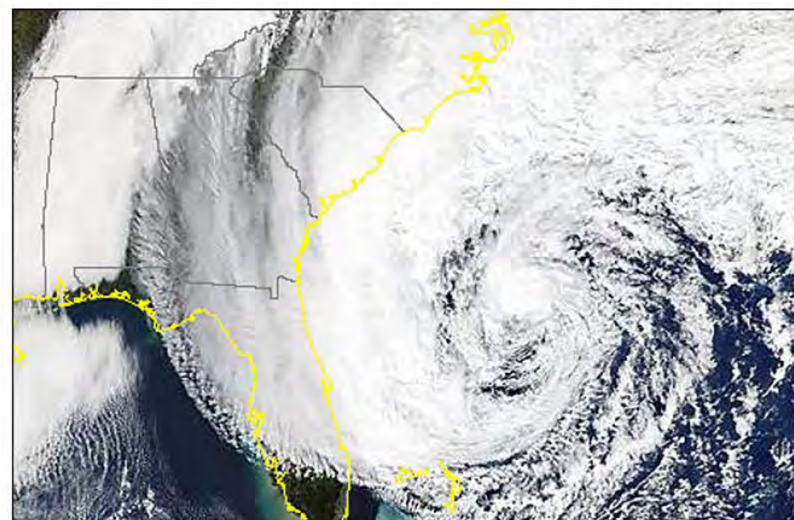


European temperatures in early August 2003, relative to 2001-2004 average

From NASA's MODIS - Moderate Resolution Imaging Spectrometer, courtesy of Reto Stöckli, ETHZ



Russian Heatwave 2010



Superstorm Sandy 2012

Outline of the Problem

- There is empirical evidence that extreme events are becoming more frequent, but there is no universal agreement that it is due to anthropogenic causes
- The challenge is to *quantify* the anthropogenic contribution
- A related problem is to quantify the extent to which extreme events may be expected to become more frequent in the future, regardless of causes (NRC Report on Climate and Social Stress, 2012)

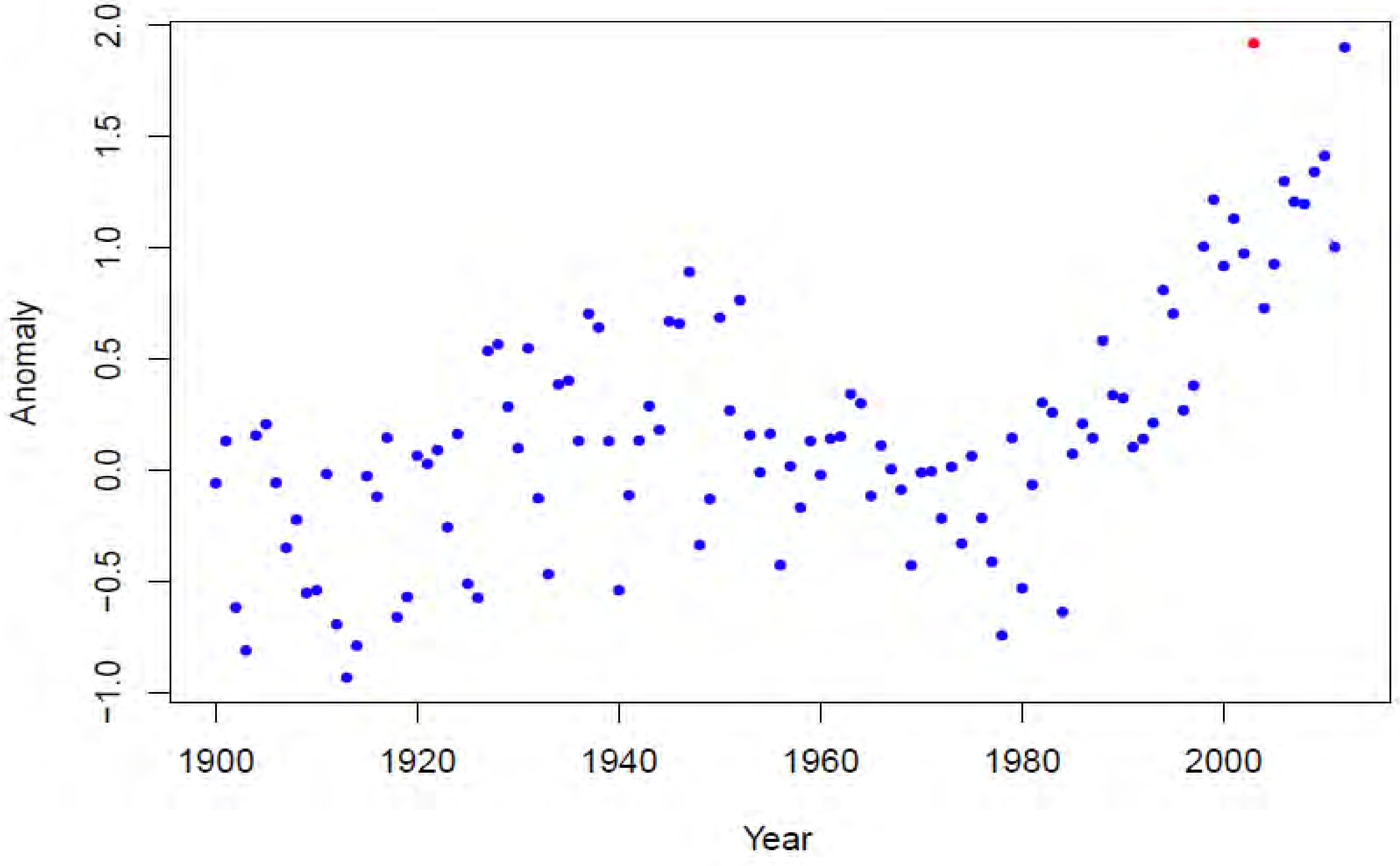
Current Approaches

- The most popular measure is fraction of attributable risk or FAR (Stott, Stone and Allen, 2004)
- First we have to define an event of interest, e.g. a specific space-time average of temperature or precipitation above a threshold
- Let P_1 be the probability of this event under a model that includes all known forcing factors, including anthropogenic; let P_0 be the corresponding probability using natural forcings only
- The FAR is defined to be $1-P_0/P_1$.
- Example for 2003 European heatwave: they estimated $P_1=1/250$, $P_0=1/1000$, so FAR=0.75. They also said it was "very likely" (confidence level at least 90%) that the FAR was at least 0.5.
- I prefer to use risk ratio, $RR=P_1/P_0$, or its logarithm.
- Several other approaches in the intervening years, but they are all somewhat questionable in their statistical assumptions. Pall et al. (2011) gave the most comprehensive approach to date, but it is very data intensive and assumed complete fidelity of model predictions to observations
- This paper offers a new approach combining *extreme value theory* and *hierarchical models*

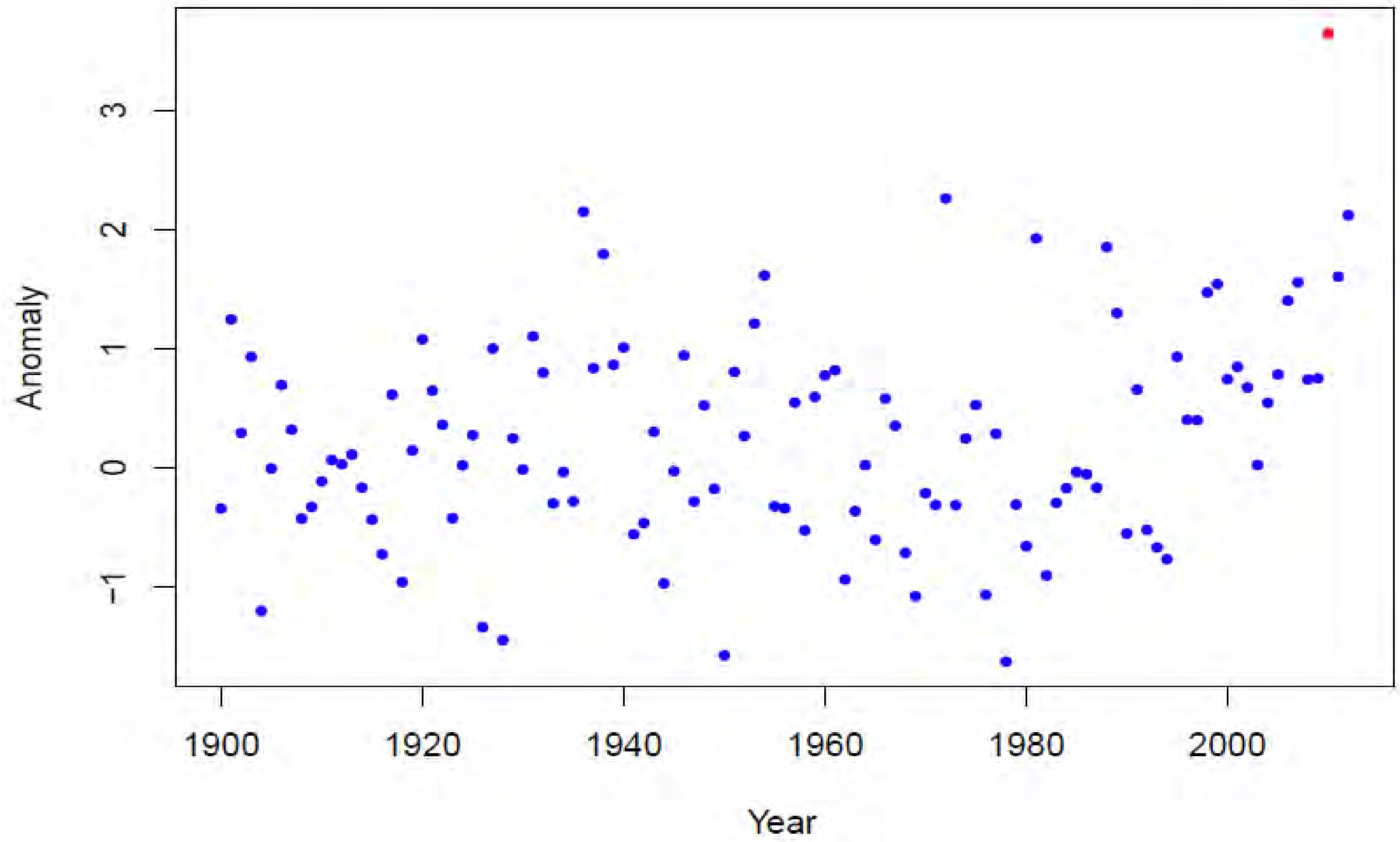
Data

- Observational data from CRU (Climate Research Unit, University of East Anglia, UK) – monthly averages on 5°x5° grid boxes, aggregated to JJA average anomalies over
  - Europe: spatial averages over 10°W-40°E, 30°N-50°N (2003 value was 1.92K but 2012 almost the same)
  - Russia: spatial averages over 30°E-60°E, 45°N-65°N (2010 value 3.65K)
  - Central USA (including Texas and Oklahoma): spatial averages over 90°W-105°W, 25°N-45°N (2011 value 2.01K)
- Climate model data from CMIP3
  - 14 climate models
  - Total of 64 control runs, 44 twentieth century runs, 34 future projections under A2 scenario
  - Same spatial regions as observational data, converted to anomalies

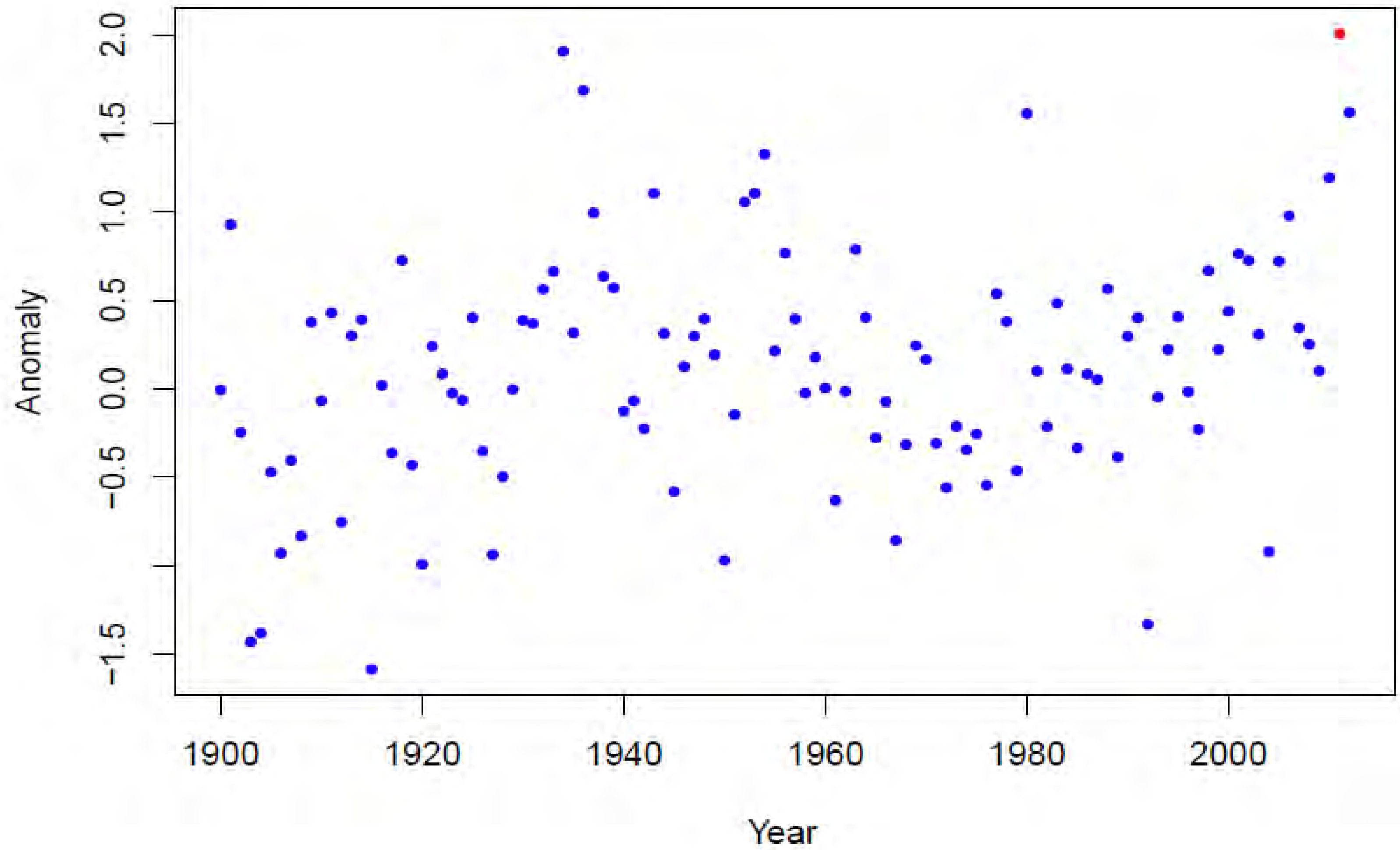
Europe Summer Mean Temperatures



Russia Summer Mean Temperatures



Central USA Summer Mean Temperatures



Introduction To Extreme Value Theory

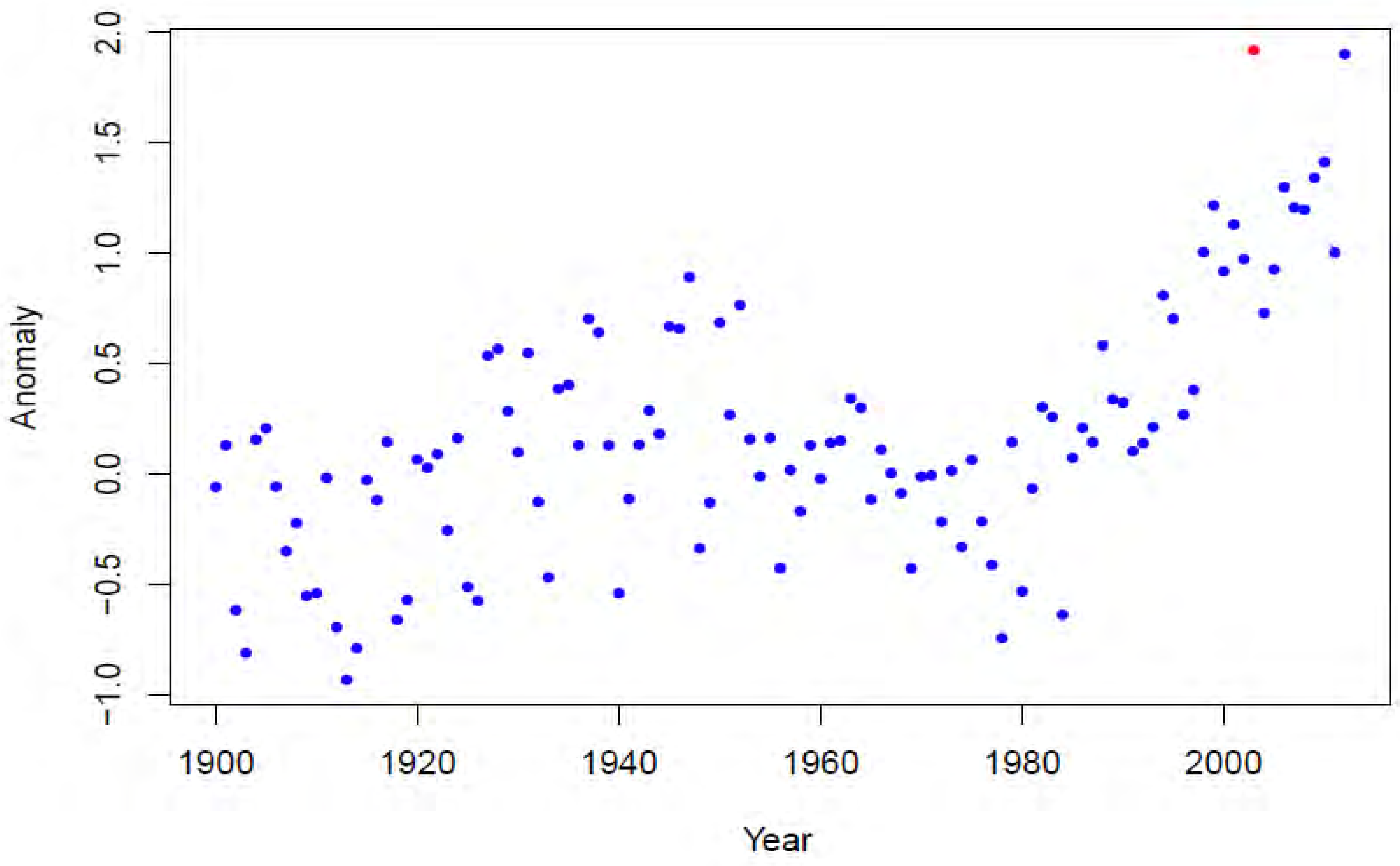
Key tool: *Generalized Extreme Value* Distribution (GEV)

- Three-parameter distribution, derived as the general form of limiting distribution for extreme values (Fisher-Tippett 1928, Gnedenko 1943)
- μ, σ, ξ known as location, scale and shape parameters
- $\xi > 0$ represents long-tailed distribution, $\xi < 0$ short-tailed

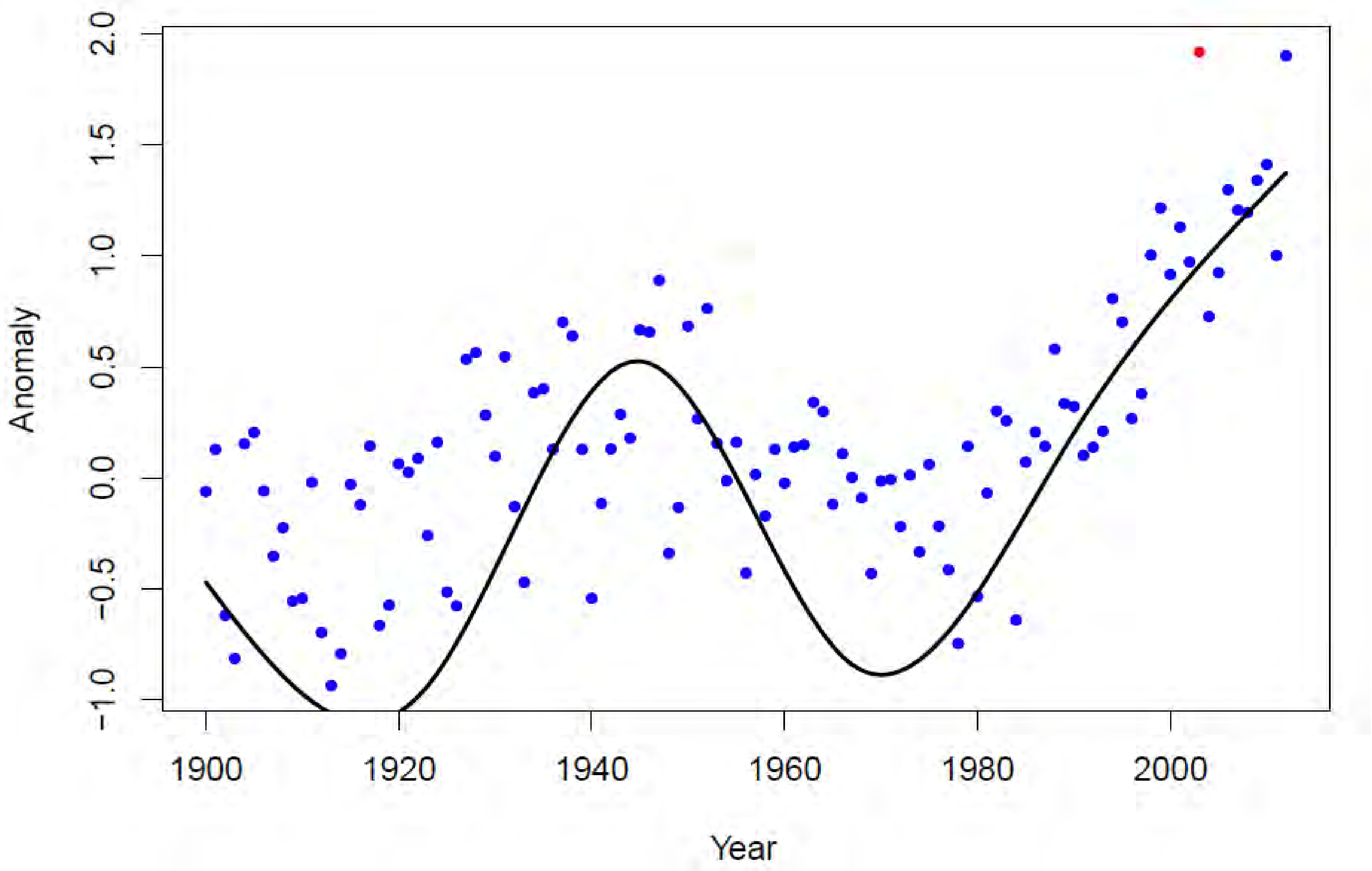
$$\Pr\{Y \le y\} = \exp\left[-\left\{1+\xi\left(\frac{y-\mu}{\sigma}\right)\right\}_{+}^{-1/\xi}\right].$$

- *Peaks over threshold* approach implies that the GEV can be used generally to study the tail of a distribution: assume GEV holds exactly above a threshold u and that values below u are treated as left-censored
- Time trends by allowing μ, σ, ξ to depend on time
- *Example:* Allow $\mu_t = \beta_0 + \sum_{k=1}^{K} \beta_k x_{kt}$ where $\{x_{kt},\ k = 1, ..., K,\ t = 1, ..., T\}$ are spline basis functions for the approximation of a smooth trend from time 1 to T with K degrees of freedom
- Critical questions:
  - Determination of threshold and K
  - Point and interval estimates for the probability of exceeding a high value, such as 1.92K in the case of the Europe time series

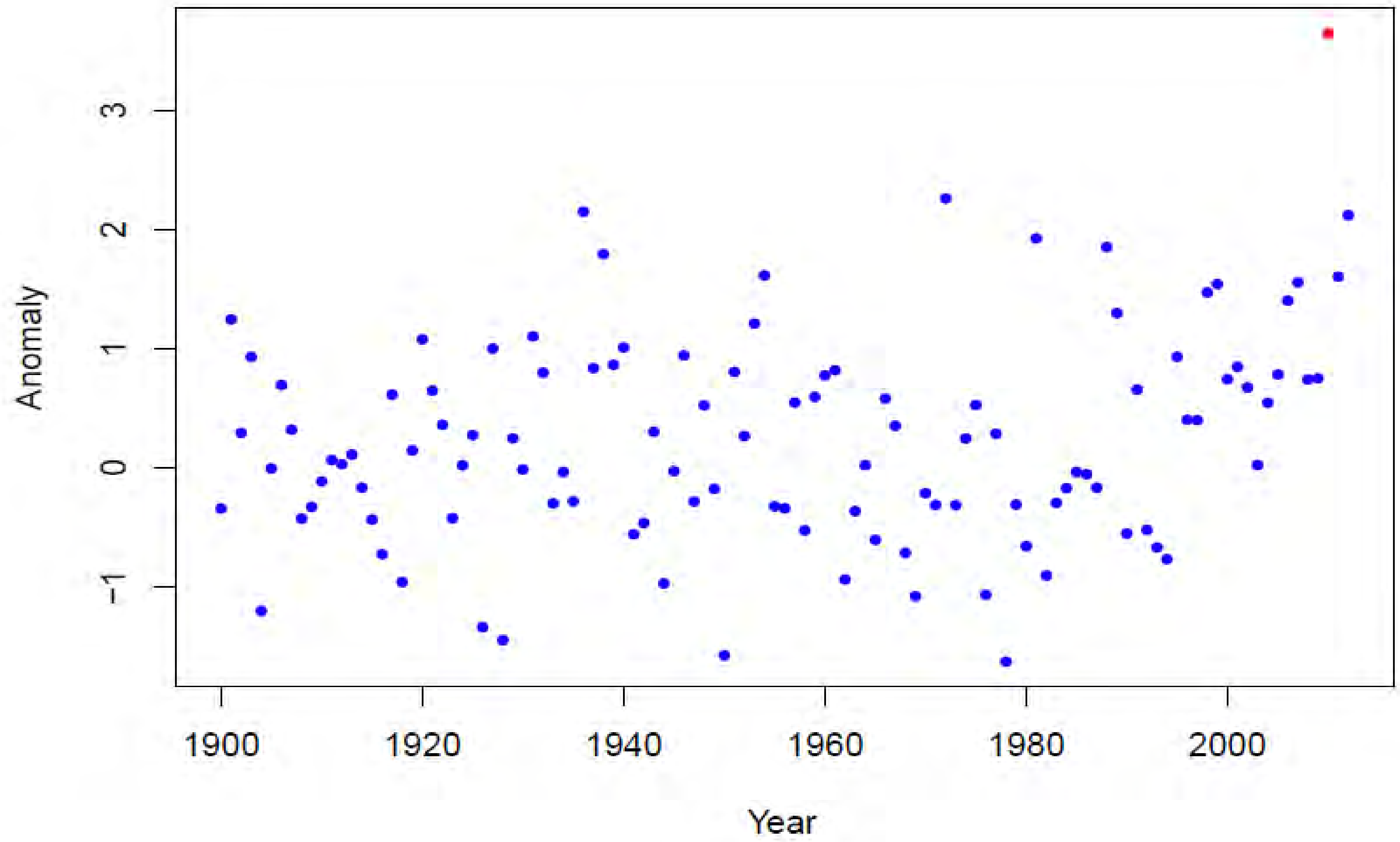
Europe Summer Mean Temperatures



Europe Summer Mean Temperatures With Trend



Russia Summer Mean Temperatures



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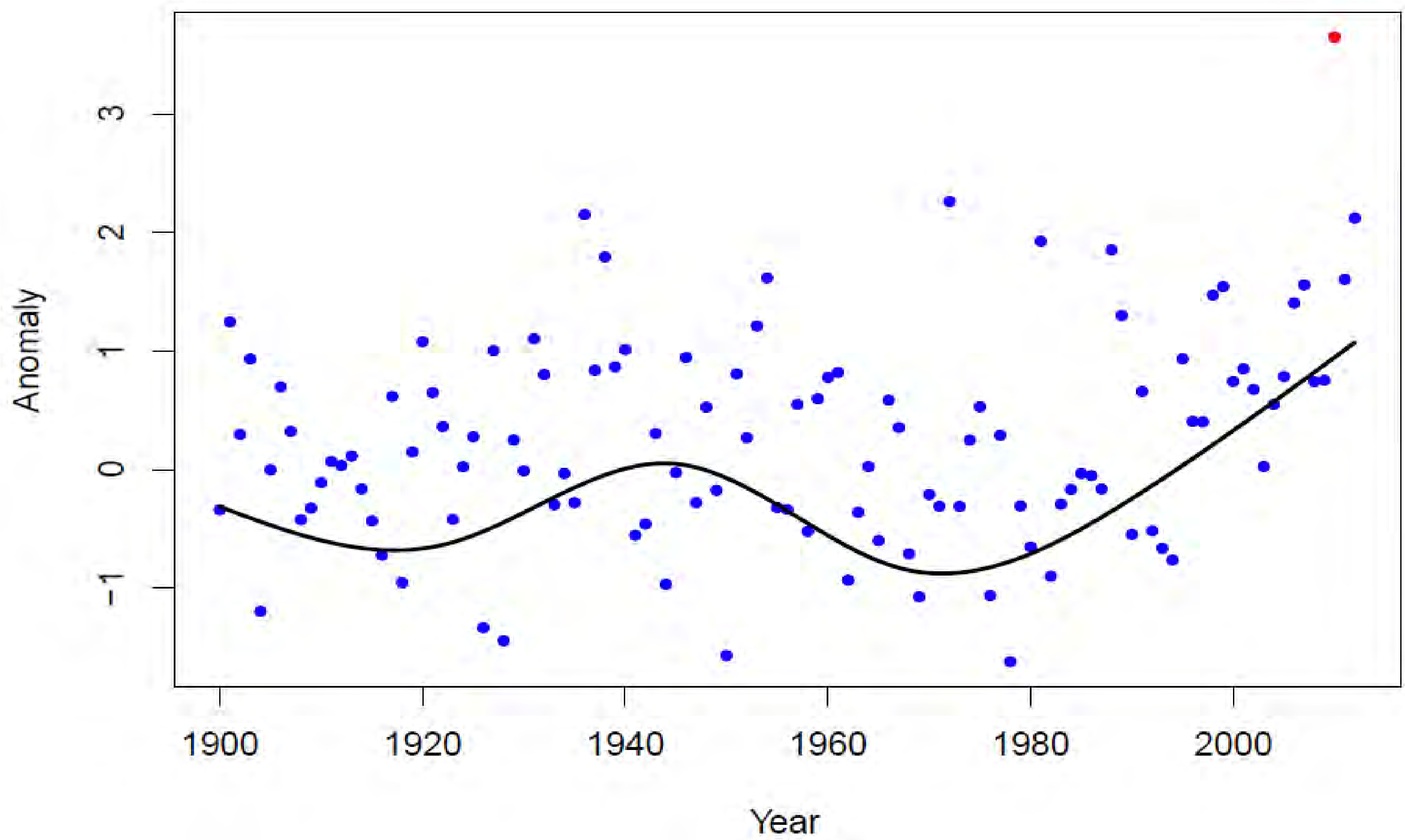
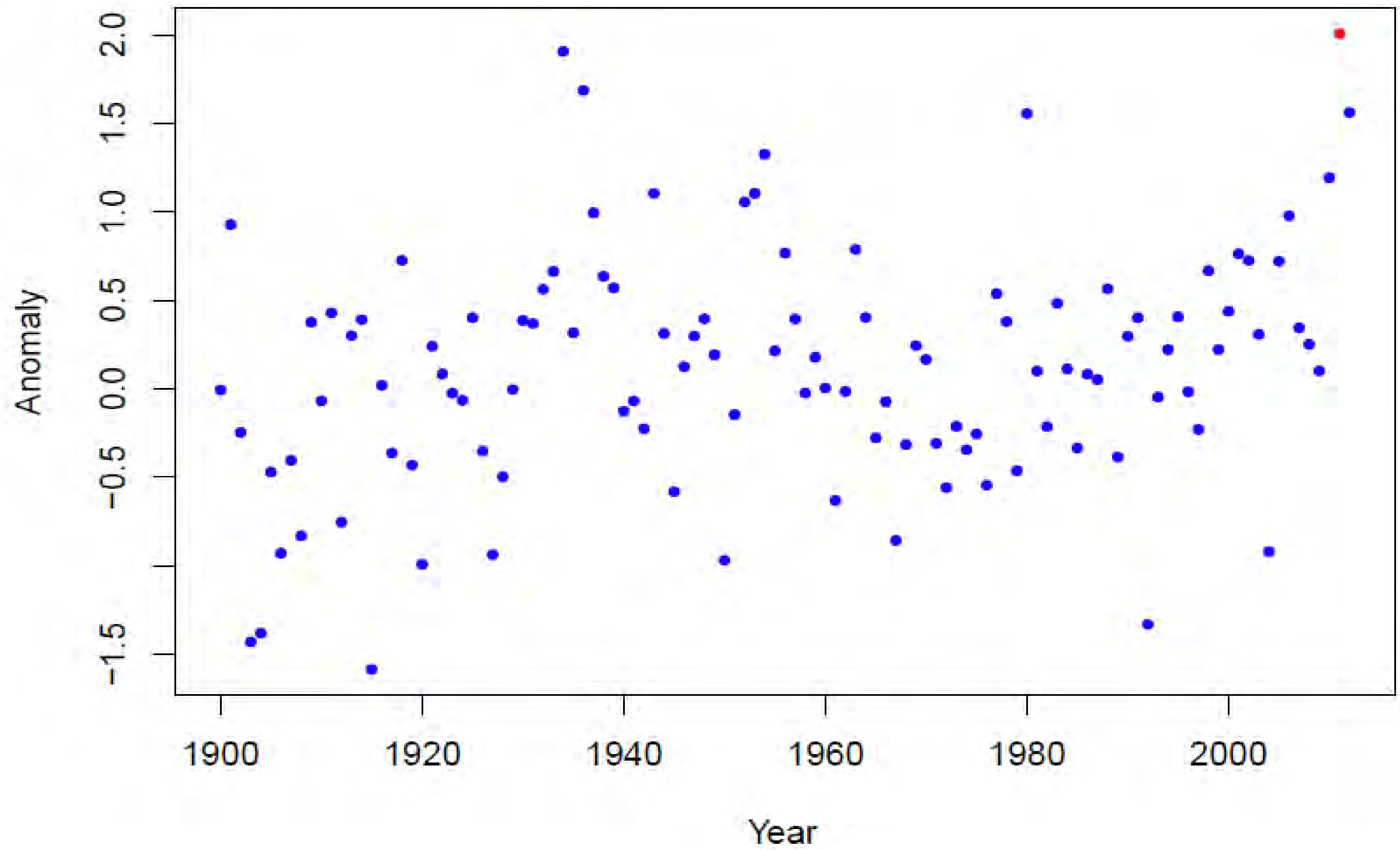
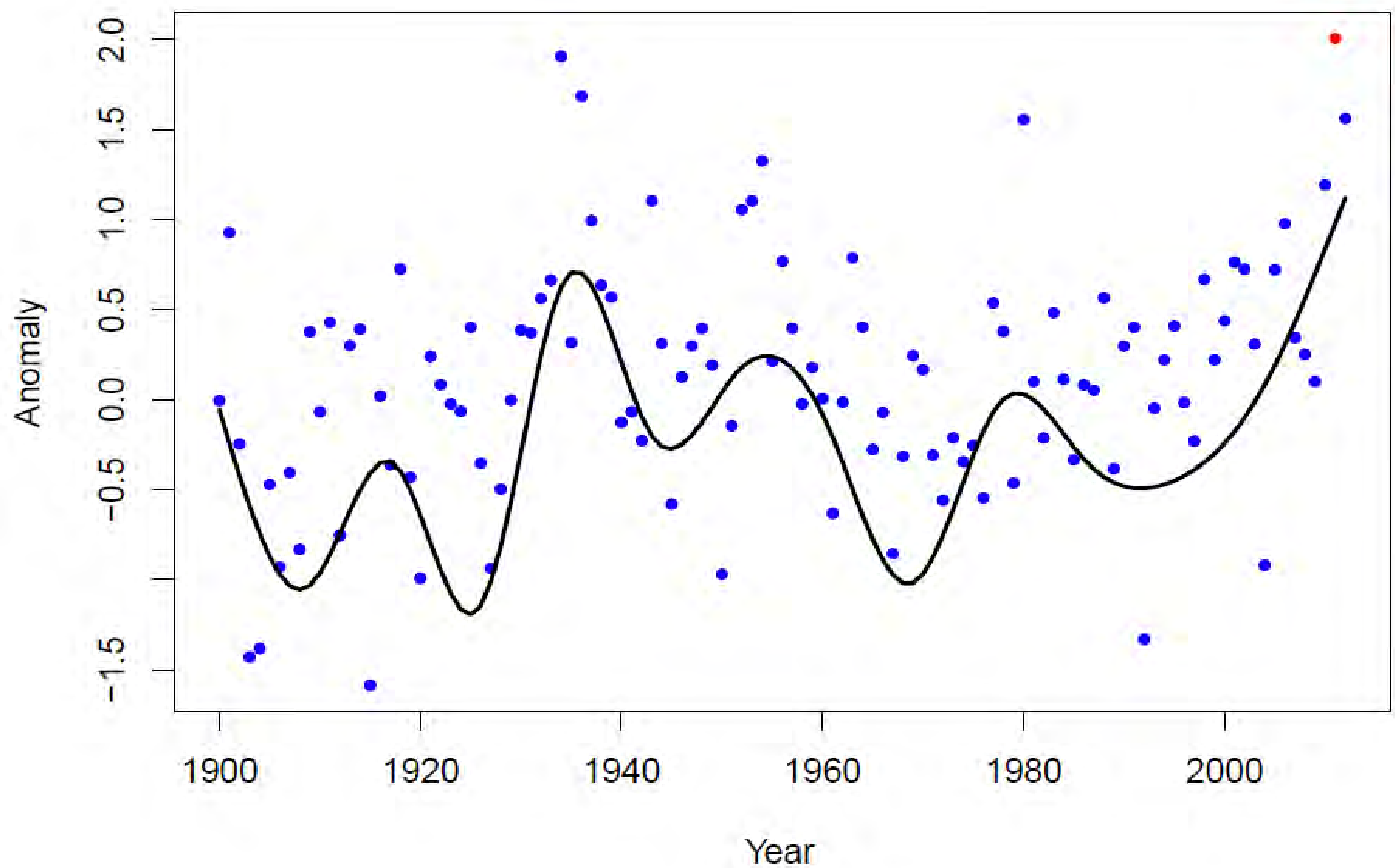


Central USA Summer Mean Temperatures

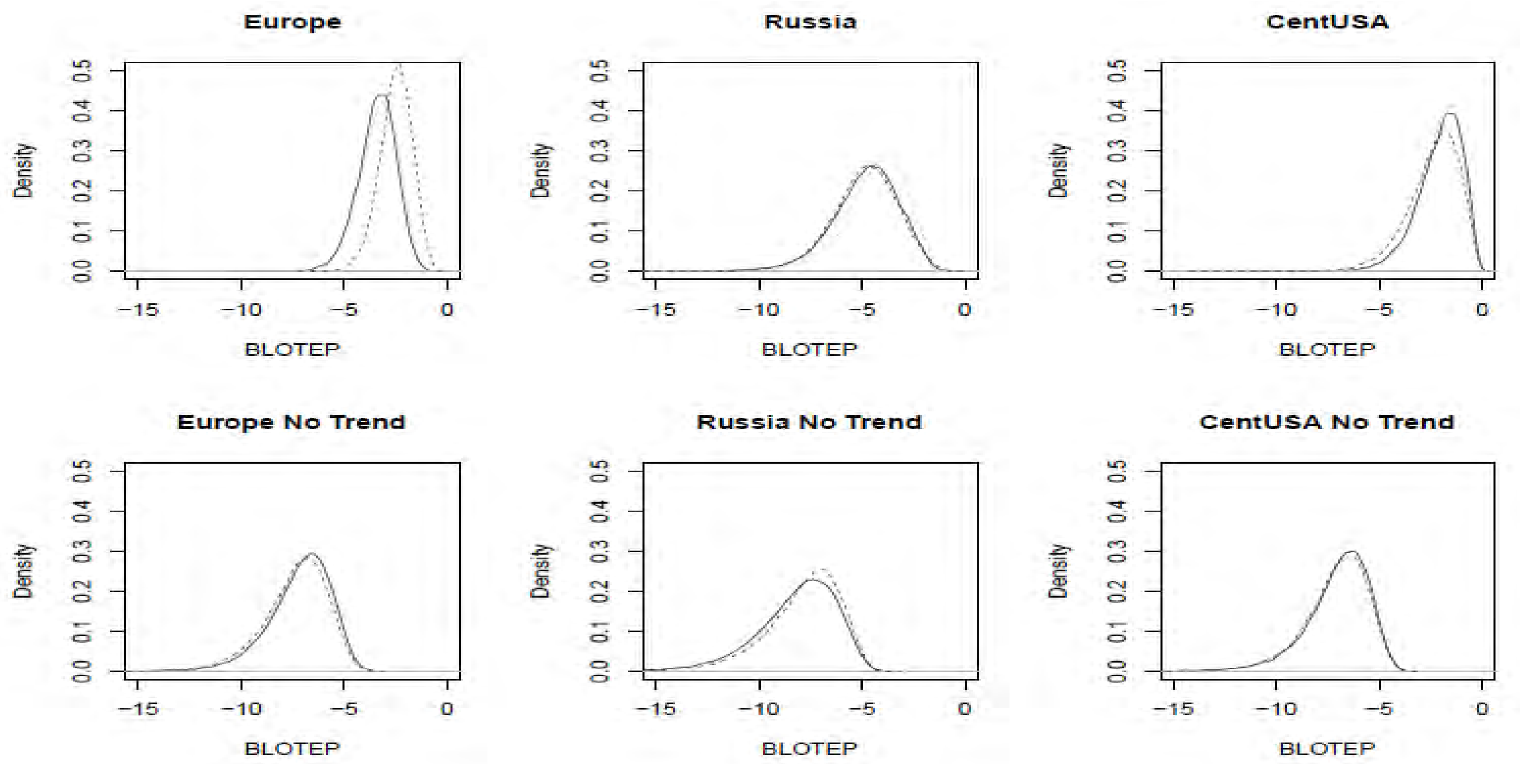


Central USA Summer Mean Temperatures With Trend



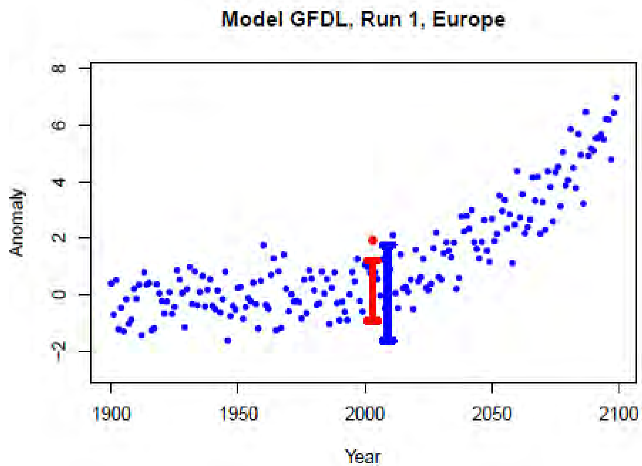
Bayesian Calculations

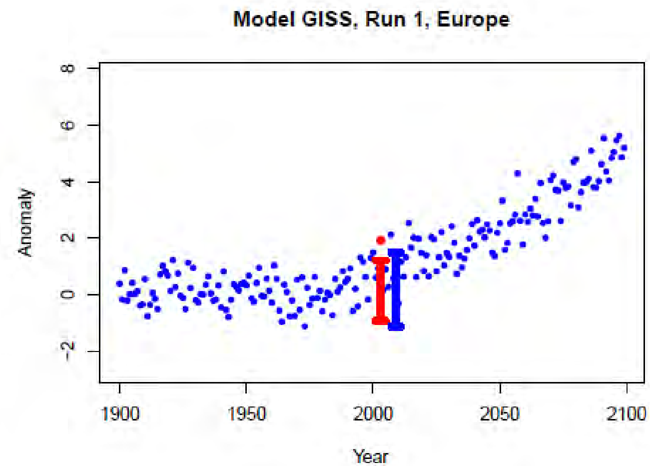
- Focus on posterior distribution of binary log of threshold exceedance probability (BLOTEP)
- Use models both with and without trends
- Use 80th (solid curve), 75th (dashed) and 85th (dot-dashed) percentiles for thresholds

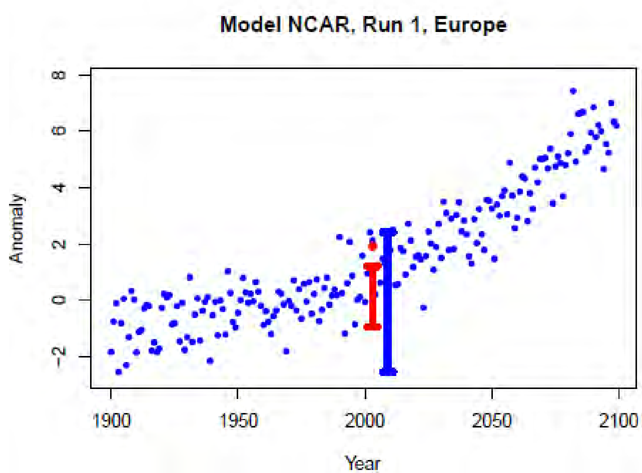


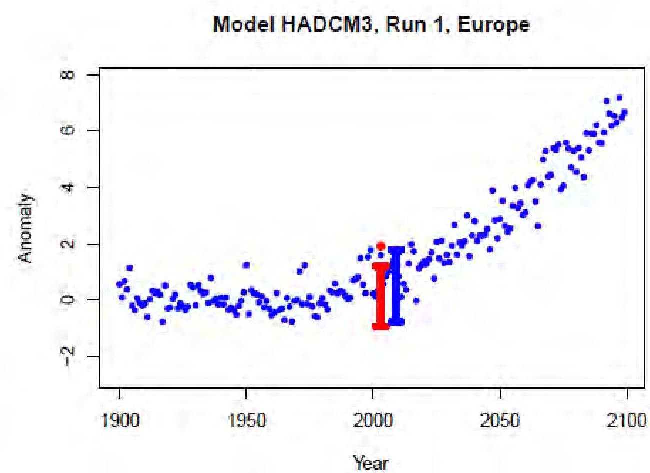
What’s Next?

- Obvious strategy at this point is to rerun the GEV calculation on the model data
- But this runs into the *scale mismatch problem*: data plots shows that the models and observations are on different scales, so we should expect the extreme value parameters to be different as well
- Requires a more subtle approach – *hierarchical modeling*

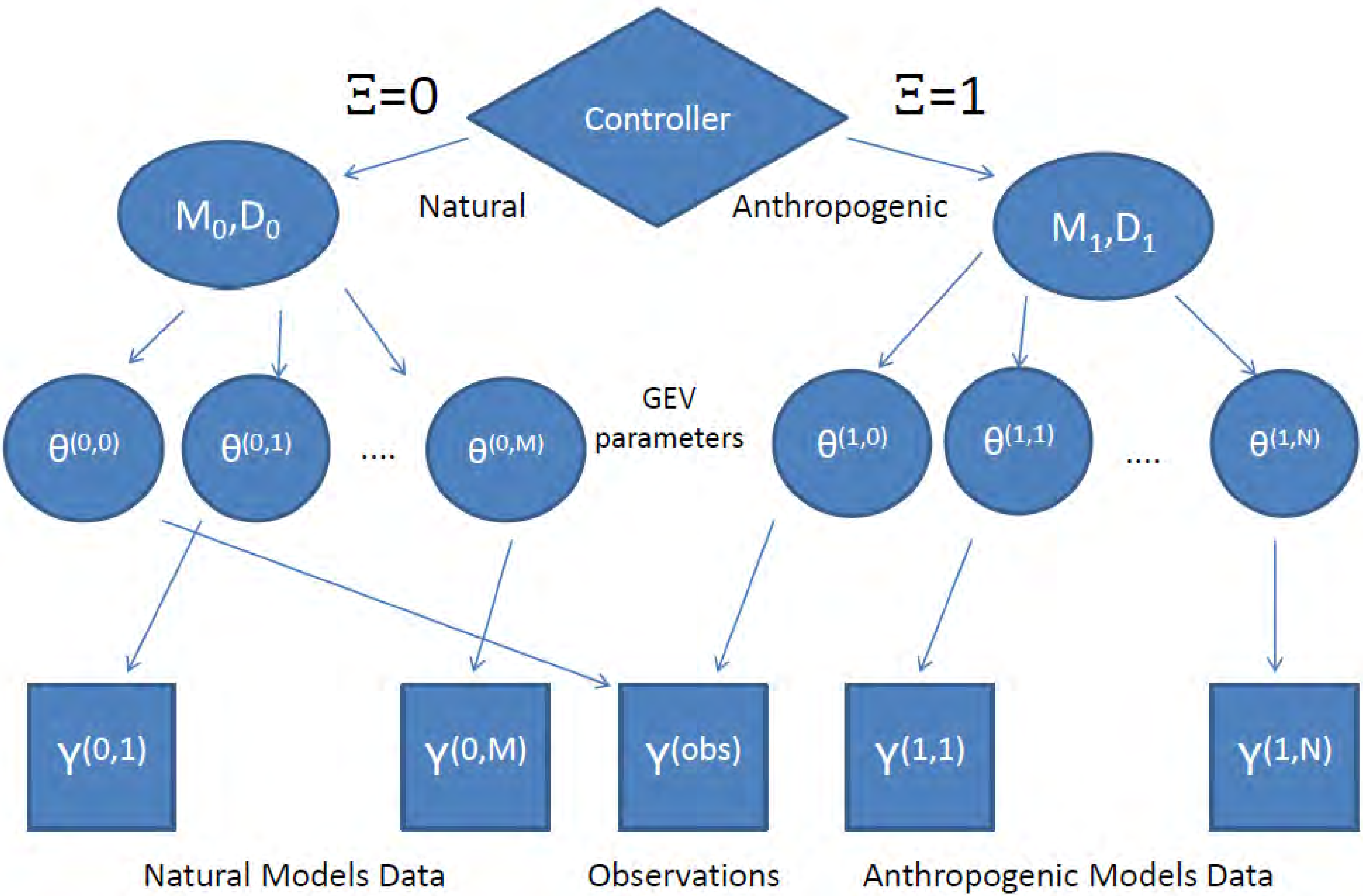








Proposed Hierarchical Model



Bayesian Statistics Details

Model Specification

- $(M_1, D_1) \sim WN_q(A, m, M^*, F)$, Wishart-Normal prior with density $\propto |D_1|^{(m-q)/2} \exp\left[-\frac{1}{2}\text{tr}\left\{D_1\left(A + F(M_1 - M^*)(M_1 - M^*)^T\right)\right\}\right]$.
- Given M_1, D_1, $\theta^{(1,0)}, ..., \theta^{(1,N)}$ are IID $\sim N_q(M_1, D_1^{-1})$.
- Given $\theta^{(1,j)}$, $\mathbf{Y}^{(1,j)}$ generated by GEV with parameters $\theta^{(1,j)}$ ($\mathbf{Y}^{(\text{obs})}$ for $j = 0$, if $\Xi = 1$)
- Similar structure for M_0, D_0 etc.
- We can expand this model by defining $\theta^{(1,0)} \sim N_q(M_1, (\psi D_1)^{-1})$ where ψ represents departure from exchangeability ($\psi = 1$ is exchangeable). However, ψ is not identifiable — we can only try different values as a sensitivity check.

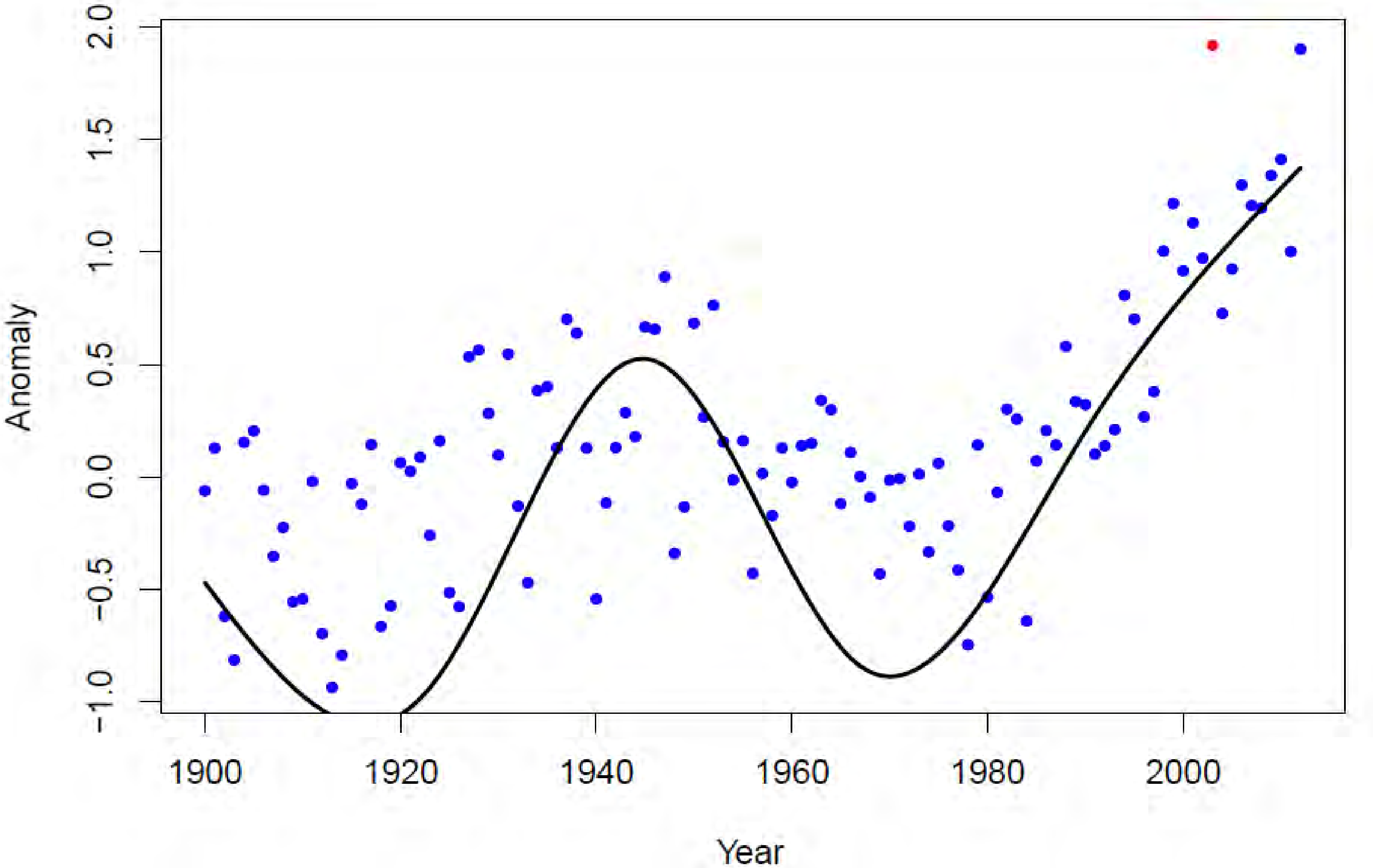
Computation

- $(M_1, D_1) \mid \theta^{(1,1)}, ..., \theta^{(1,N)} \sim WN_q(\tilde{A}, \tilde{m}, \tilde{M}^*, \tilde{F})$, where $\tilde{m} = m + N, \tilde{F} = F + N, \tilde{M}^* = \left(FM^* + \sum_{j=1}^N \theta^{(1,j)}\right)/\tilde{F}, \tilde{A} = A + FM^*M^{*T} + \sum_{j=1}^N \theta^{(j)}\theta^{(j)T} - \tilde{F}\tilde{M}^*\tilde{M}^{*T}$.
- Metropolis update for $\theta^{(1,1)}, ..., \theta^{(1,N)}$ given M_1, D_1 and $\mathbf{Y}$'s
- Metropolis update for $\theta^{(1,0)}$ based on conditional density

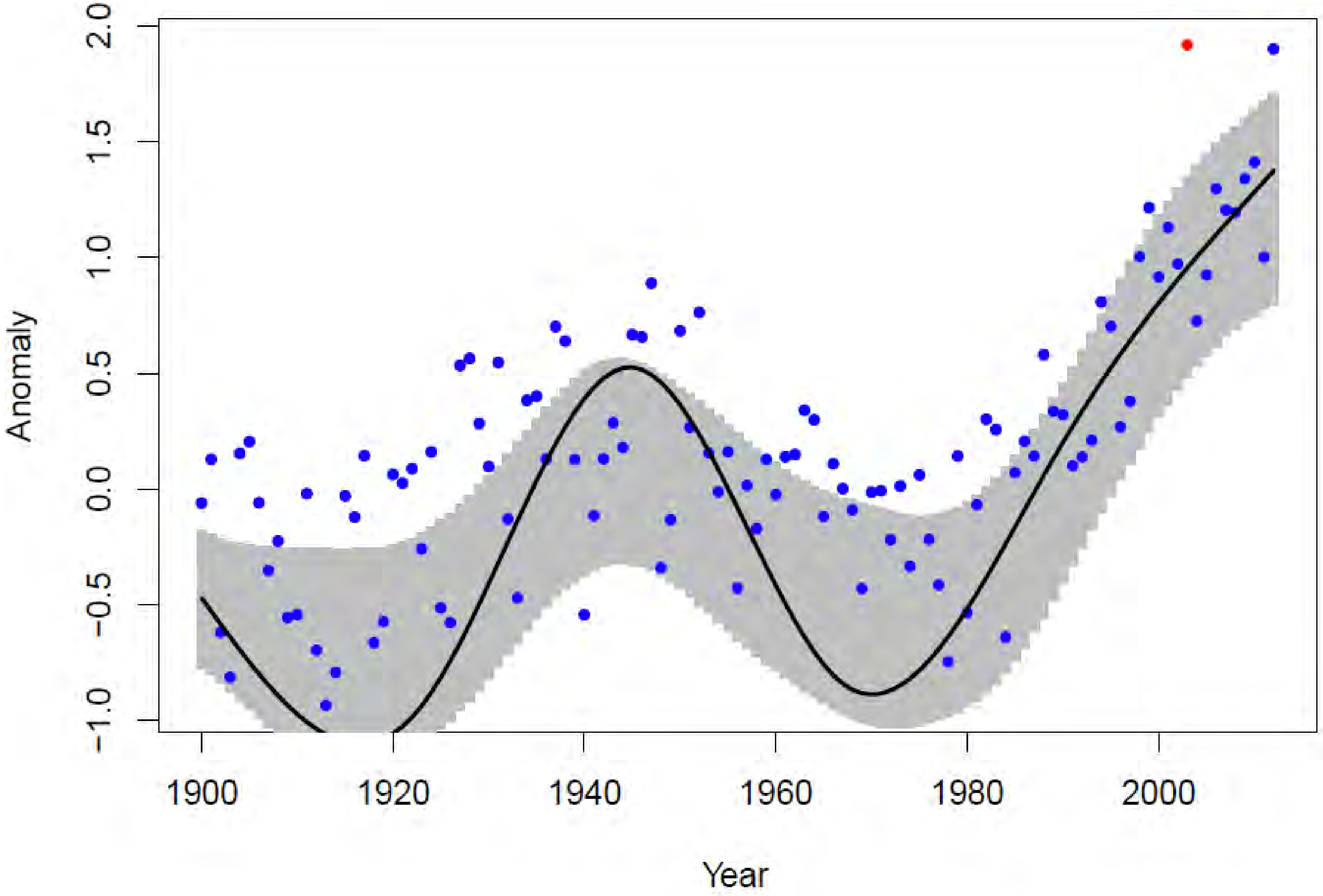
$$\exp\left\{-\frac{\psi}{2}\left(\theta^{(1,0)} - M_1\right)^T D_1\left(\theta^{(1,0)} - M_1\right)\right\} \cdot L\left(\theta^{(1,0)}; \mathbf{Y}^{(\text{obs})}\right)$$

  where L is likelihood for $\theta^{(1,0)}$ given data $\mathbf{Y}^{(\text{obs})}$ and $\Xi = 1$
- Similar updates for $\Xi = 0$ side of picture; up to 1,000,000 iterations

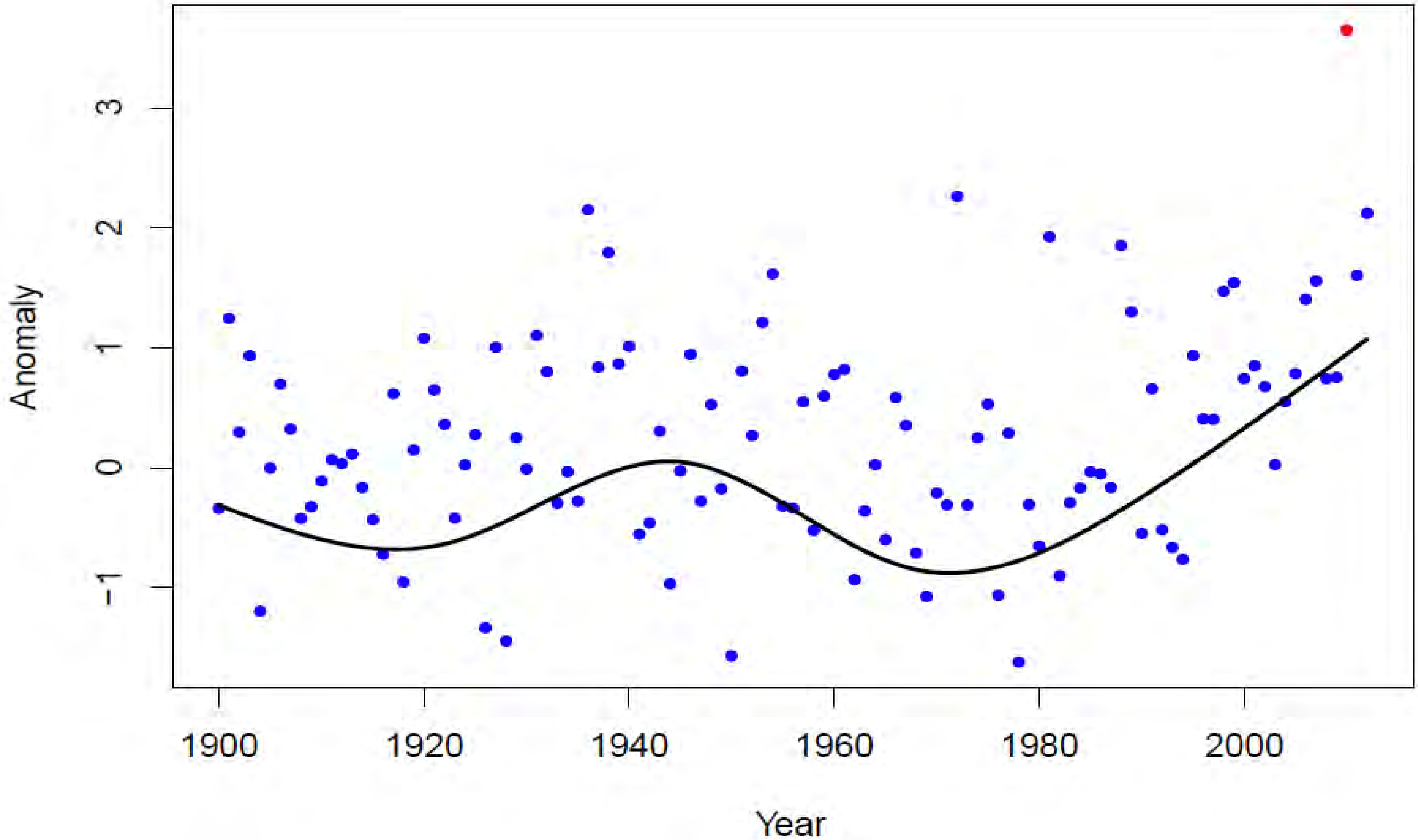
Europe Summer Mean Temperatures With Trend



Europe Summer Mean Temperatures With Trend and Central 50% of Hierarchical Model Distribution



Russia Summer Mean Temperatures With Trend



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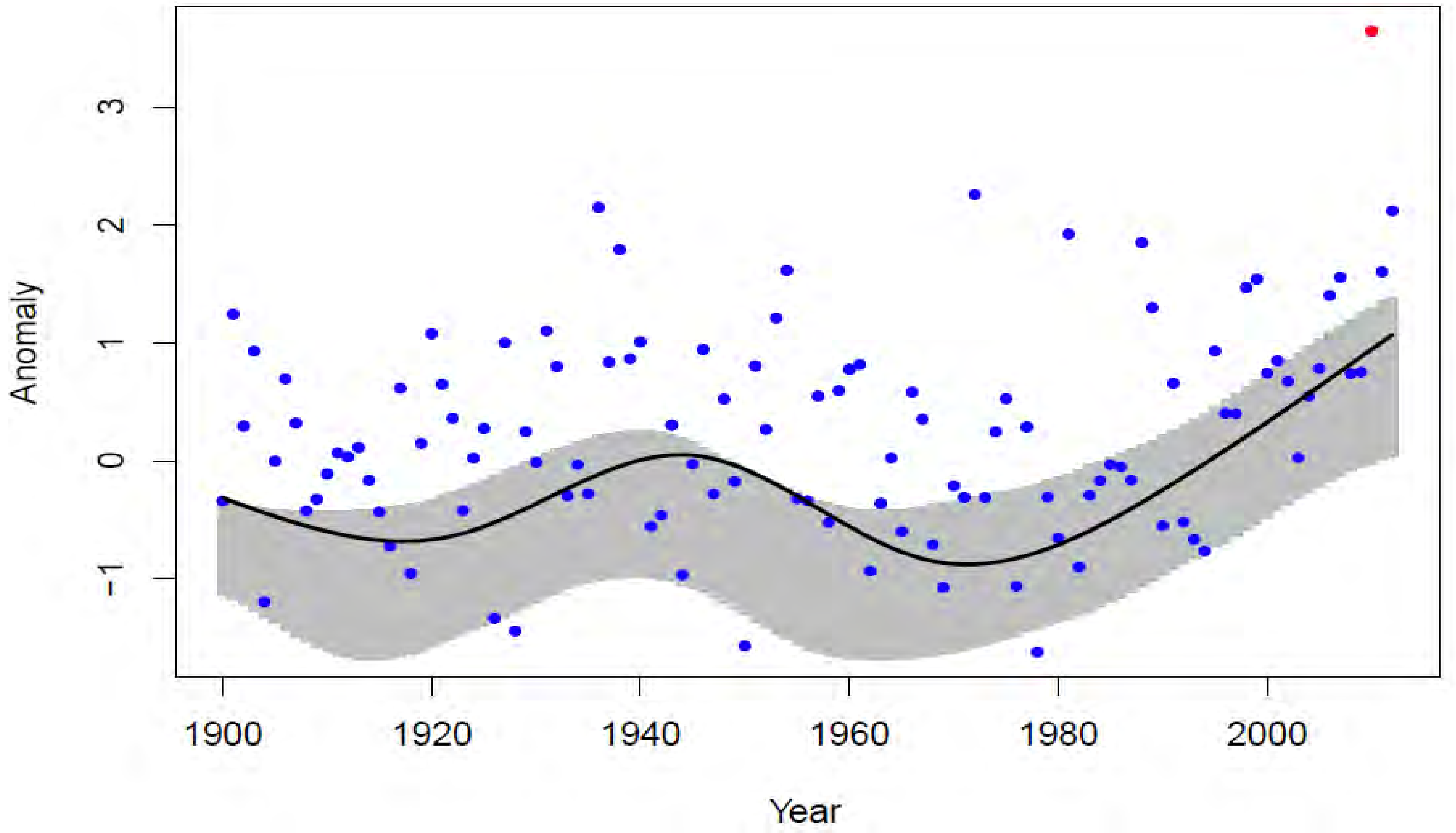
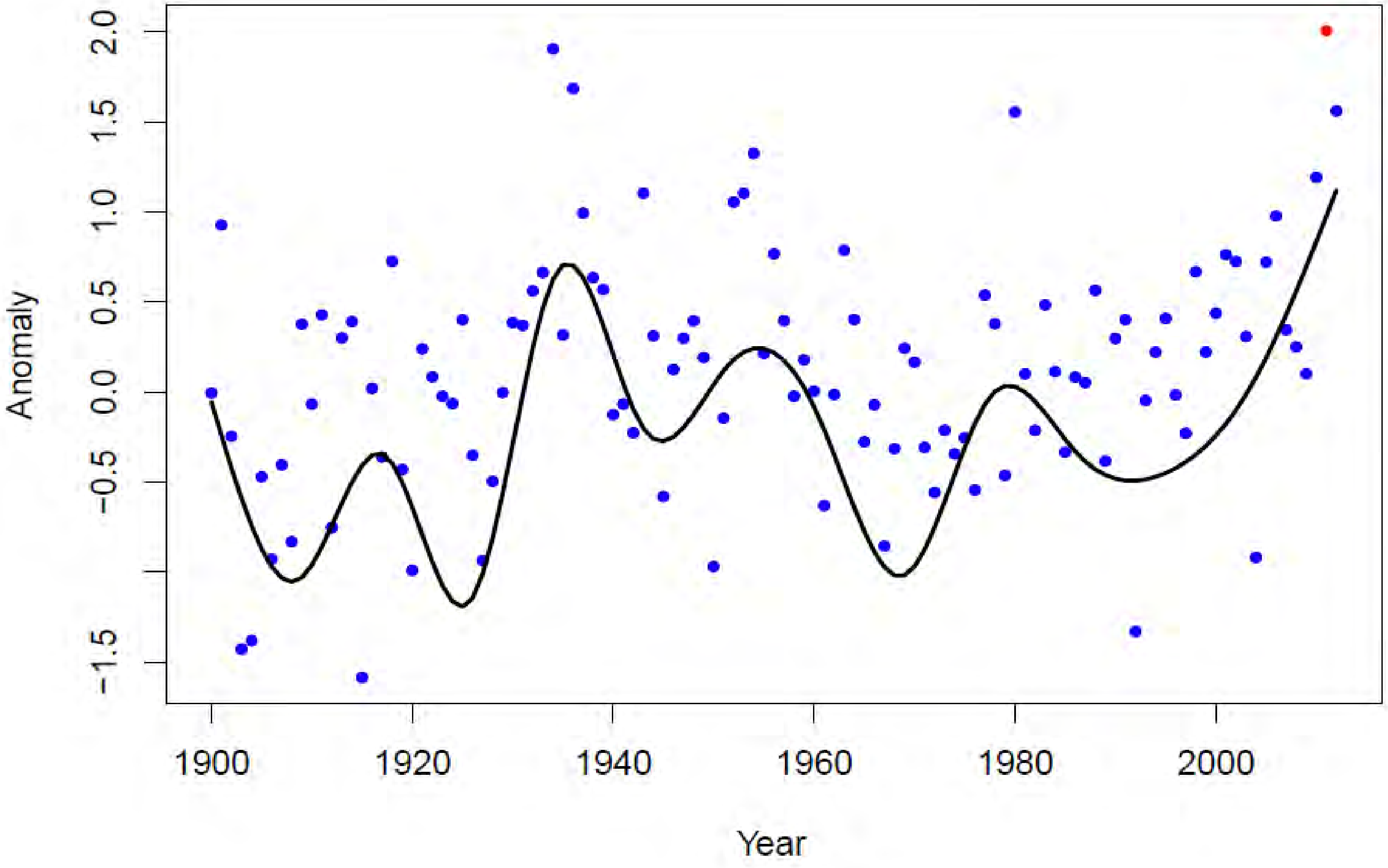


Central USA Summer Mean Temperatures With Trend



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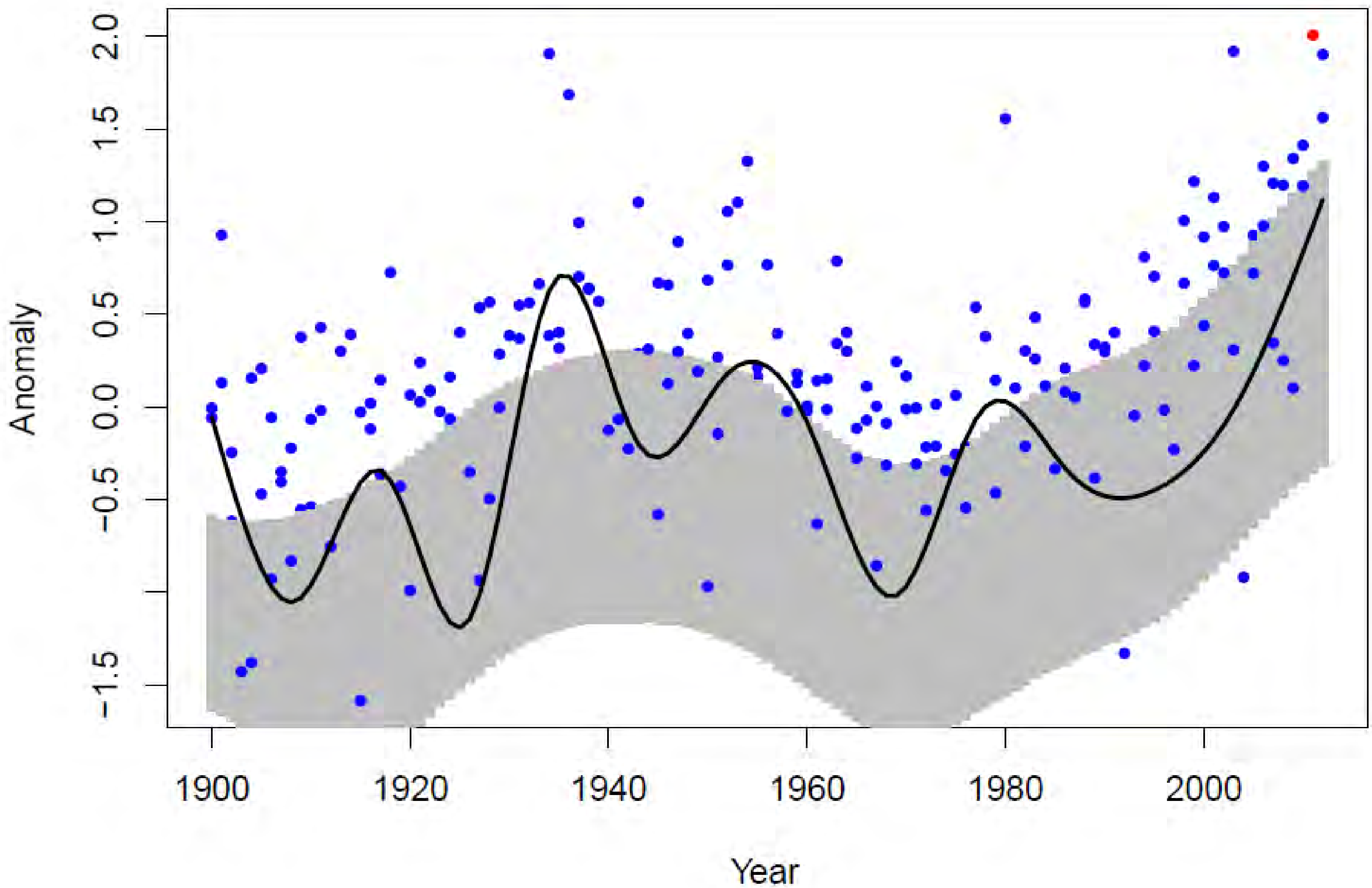
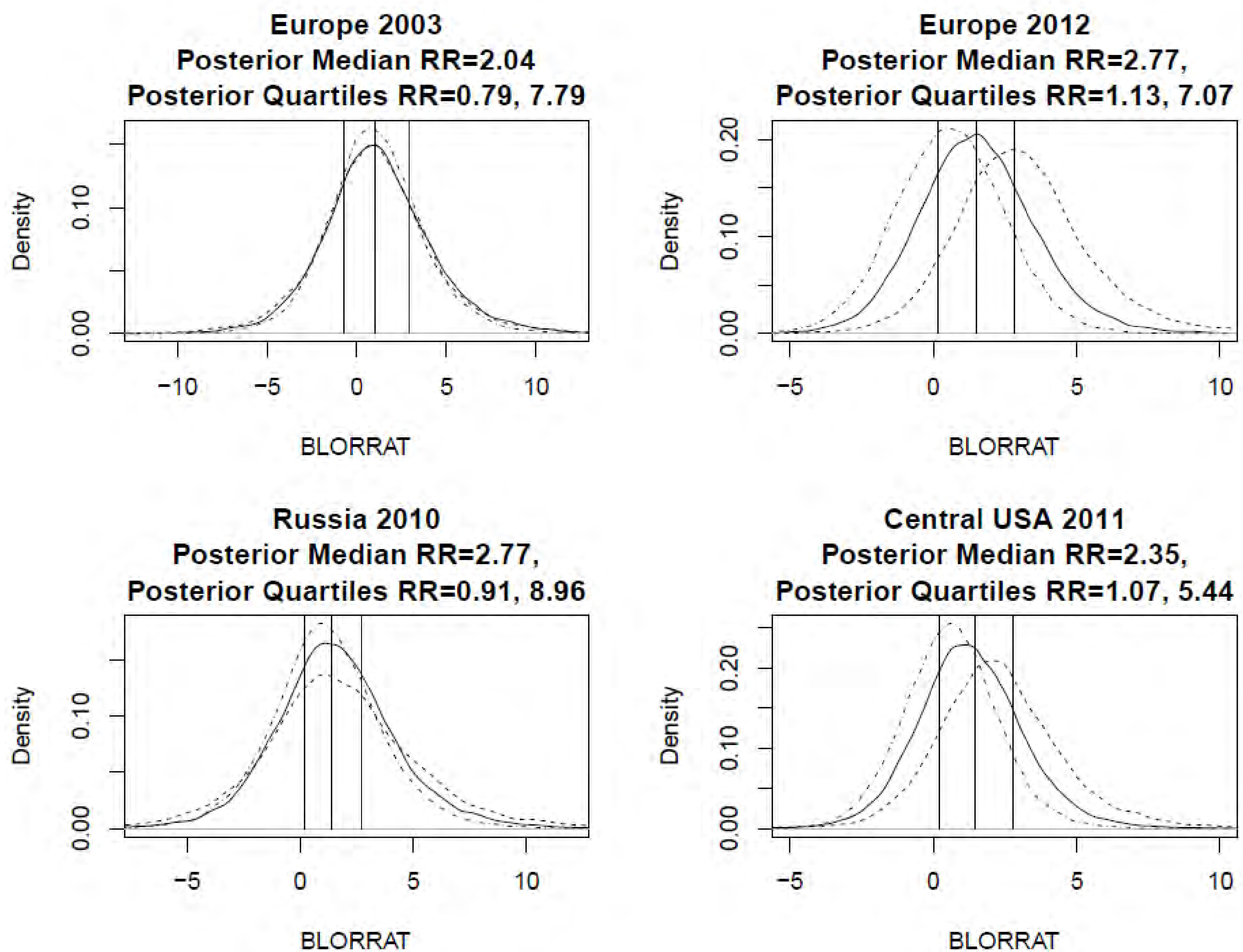
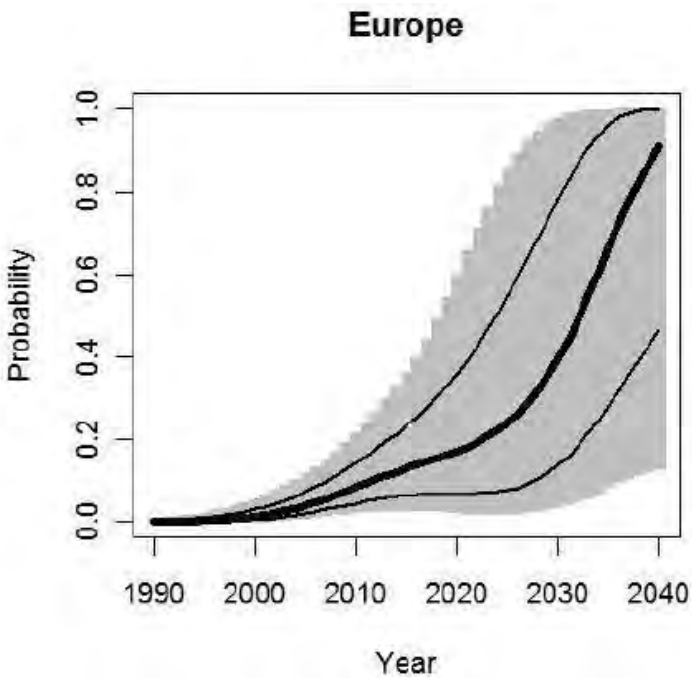


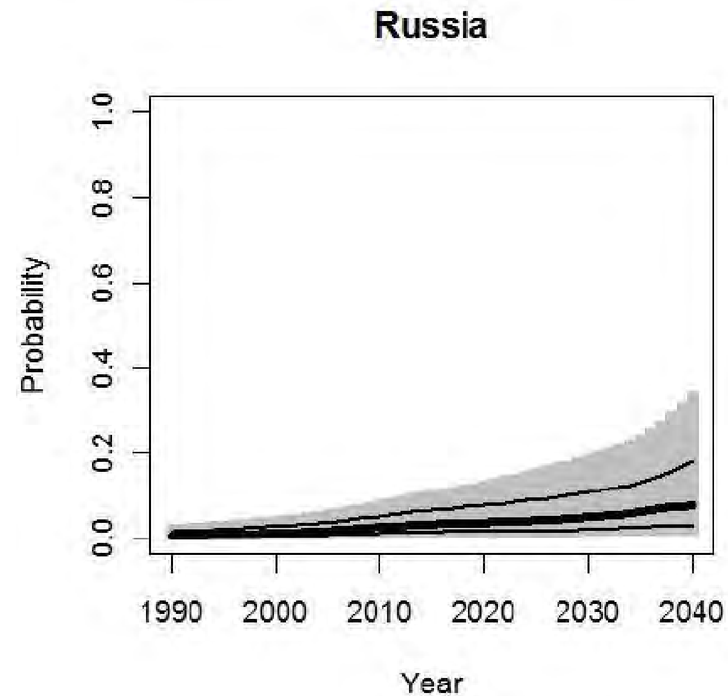
Posterior Densities for the BLORRAT

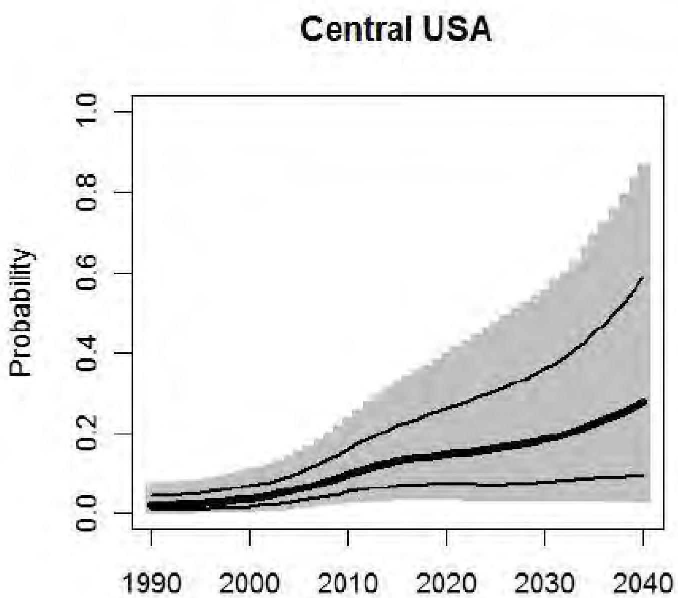
(numbers are for solid curves and equal weights; dashed curves allow for different weights between climate models and observations)



Changes in Projected Extreme Event Probabilities Over Time







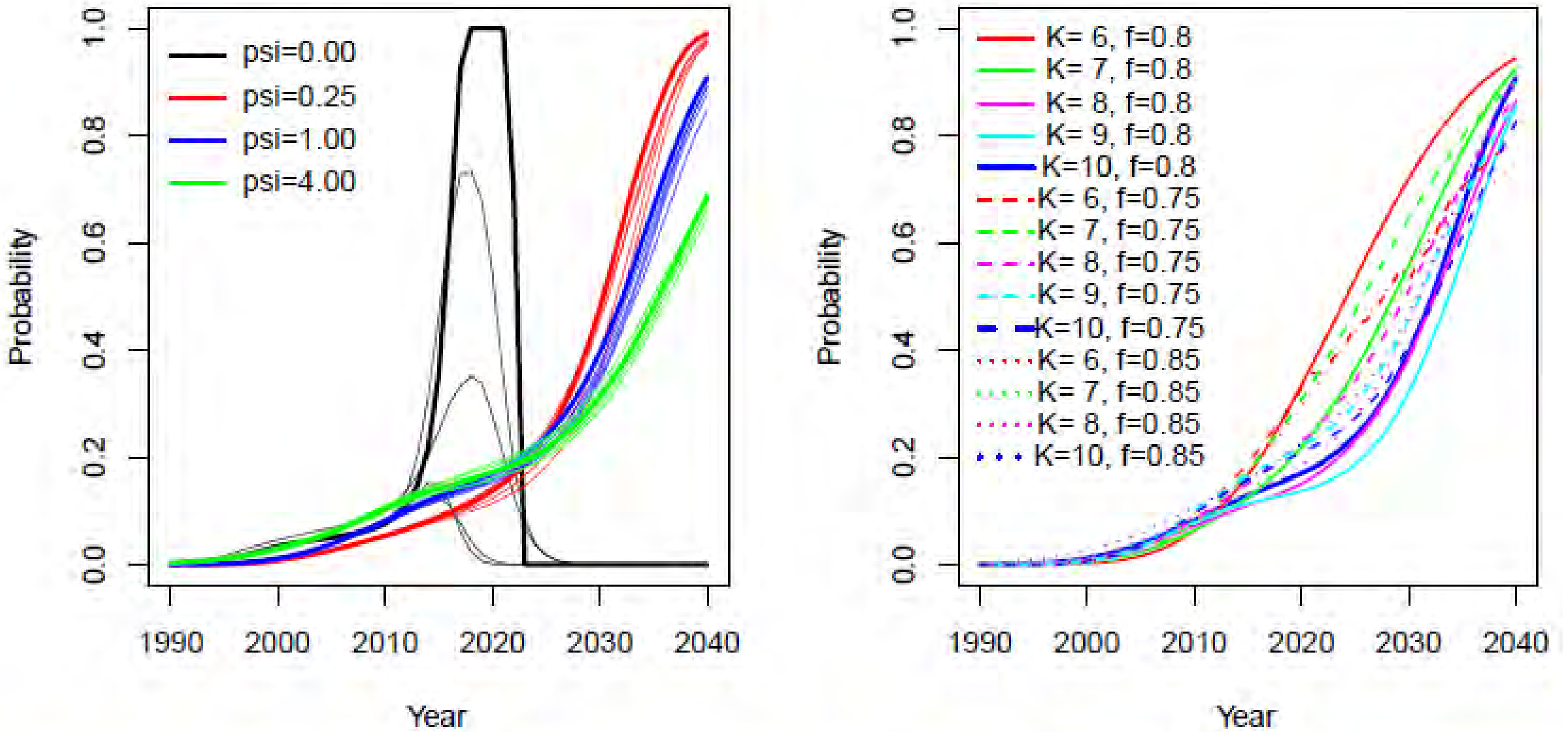
Central Solid Curve: Posterior Median

Thin Outer Curves: Posterior Quartiles

Outer Limits of Shaded Region:

Posterior 10^{th} and 90^{th} percentiles

Sensitivity Plots



Sensitivity plots for Europe. Left-hand figure: Plots of the posterior median probability of the extreme event for various weightings between models and observations, represented by psi, and with the Monte Carlo procedure repreated several times. Right-hand figure: Plots of the posterior median probability of the extreme event with various choices of the smoothness of the trend and the threshold of the distribution fit.

Conclusions

- Extreme value theory provides a viable method for estimating extreme event probabilities in the presence of a trend
- For combining observations with climate models, we propose a hierarchical model that allows for systematic discrepancies between models and observations
- For each of Russia 2010, Central USA 2011 and Europe 2012 events, estimated risk ratio is at least 2.3, and it's *likely* (probability at least .66) that the risk ratio is >1.5.
- We also computed future projections of extreme event probabilities; sharp increase for Europe; much less so for the other two regions studied
- Paper to be submitted shortly; data and programs will be available