INFLUENCE OF CLIMATE CHANGE ON EXTREME WEATHER EVENTS

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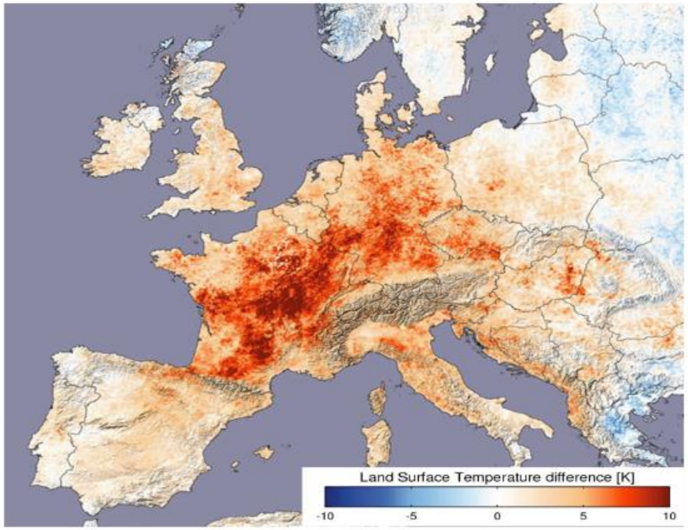
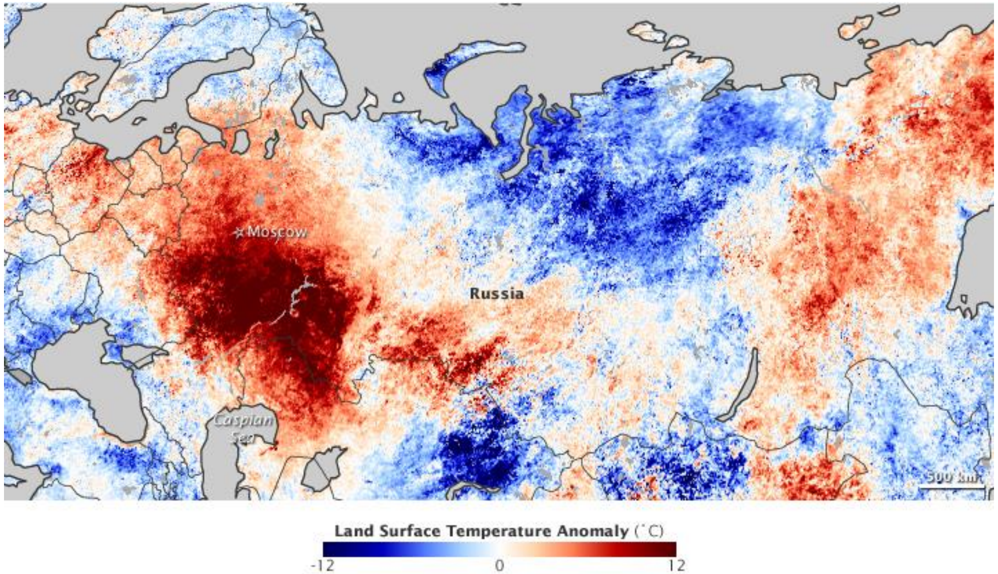
Extreme Weather Events are of Increasing Concern

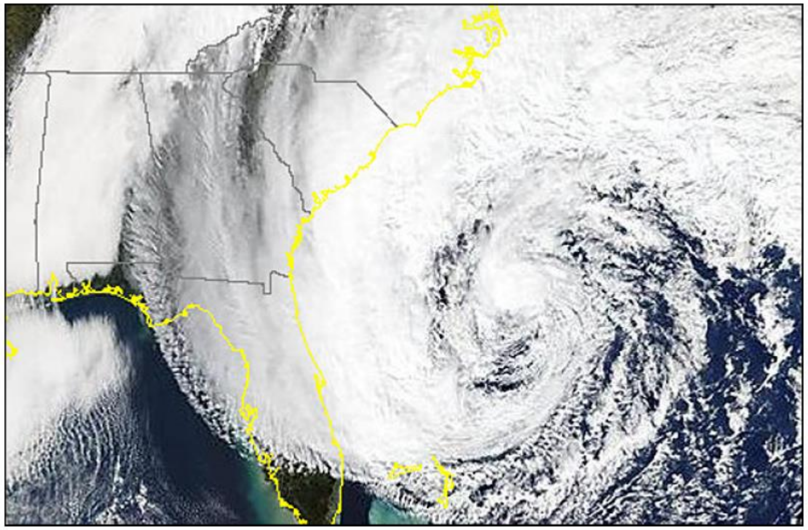


European temperatures in early August 2003, relative to 2001-2004 average

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



Russian Heatwave 2010



Superstorm Sandy 2012

How Should We Characterize the Influence of Anthropogenic Climate Change on Probabilities of Extreme Events?

- Focus of discussion is *how probabilities of extreme events are changing*
- Stott, Stone and Allen (2004) defined *fraction of attributable risk* (FAR) as a measure of human influence on extreme events
- Estimate the probabilities P_0, P_1 of the extreme event of interest under natural forcings and anthropogenic forcings respectively (derived from climate models). Then $FAR=1-P_0/P_1$.
- Example: for the Europe 2003 event they estimated the probability under anthropogenic conditions to be 1 in 250 (P_1), but the probability under natural conditions to be 1 in 1000 (P_0).
- Based on this they stated the FAR was 1-250/1000=0.75.
- According to them, 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.

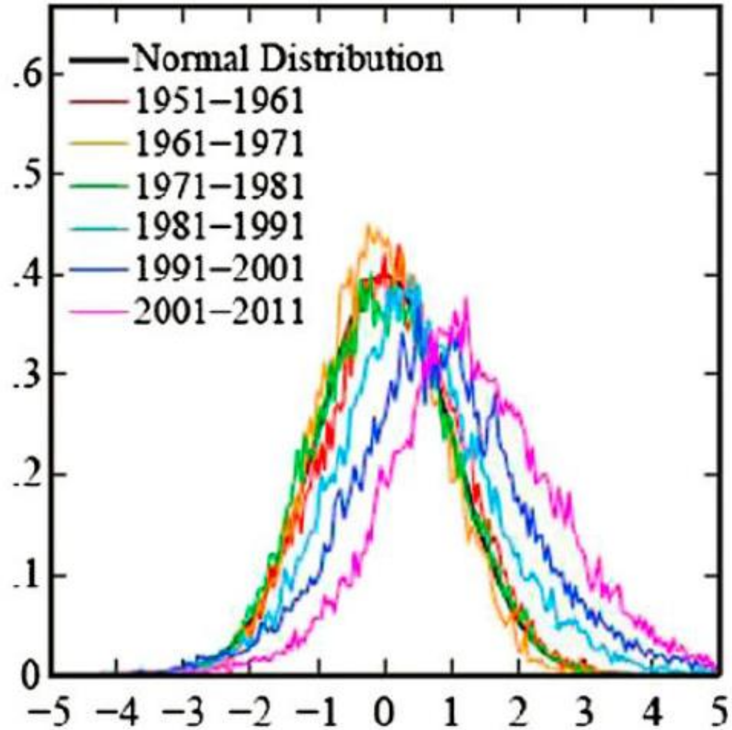
An Alternative Viewpoint - The NRC Report on "Climate and Social Stress"

- Focus on increased probability of extreme event probabilities over the next ten years – not directly concerned with attribution problem
- The committee did not find published literature that would lead to numerical answers
- But there is widespread agreement that extreme event probabilities are increasing
- Their conclusion: *Expect surprises*

Current Literature

- Initial approach given by Stott *et al*. (2004) - used extreme value theory
- Various methods based on normal distributions (Beniston and Diaz 2004, Schär *et al*. 2004, Jaeger *et al*. 2008)
- Nonparametric method (Hoerling *et al*. 2007)
- Recently Hansen *et al*. (2012) empirically examined a very large number of observational time series but did not consider climate models, so no attribution or forward projections
- Not everyone agrees extreme events represent climate change – Dole *et al*. (2011) argued Russia 2010 heatwave was the result of a natural blocking event, and Hoerling *et al*. (2013) make a similar argument for the Texas heatwave of 2011

Hansen, Saito and Ruedy (2012)



The Method of Pall et al. (Nature, 2011)

- Pall et al. proposed a simpler method based on counting of extreme events in a large ensemble of "several thousand model runs" (climateprediction.net)
- The method seems effective if you have a large ensemble and the probabilities are not too small
- However, power calculations show that the method could become extremely data intensive if the estimated probabilities are truly small

Power Calculation:

Sample size required to distinguish two event probabilities in a test of size 0.05 at power 0.8.

Null Probability	Ratio of Probabilities 2	4	6	8	10
0.05	422	71	31	18	11
0.025	880	144	67	41	28
0.01	2,239	384	170	104	73
0.001	about 23,000	3,863	1,728	1,057	743

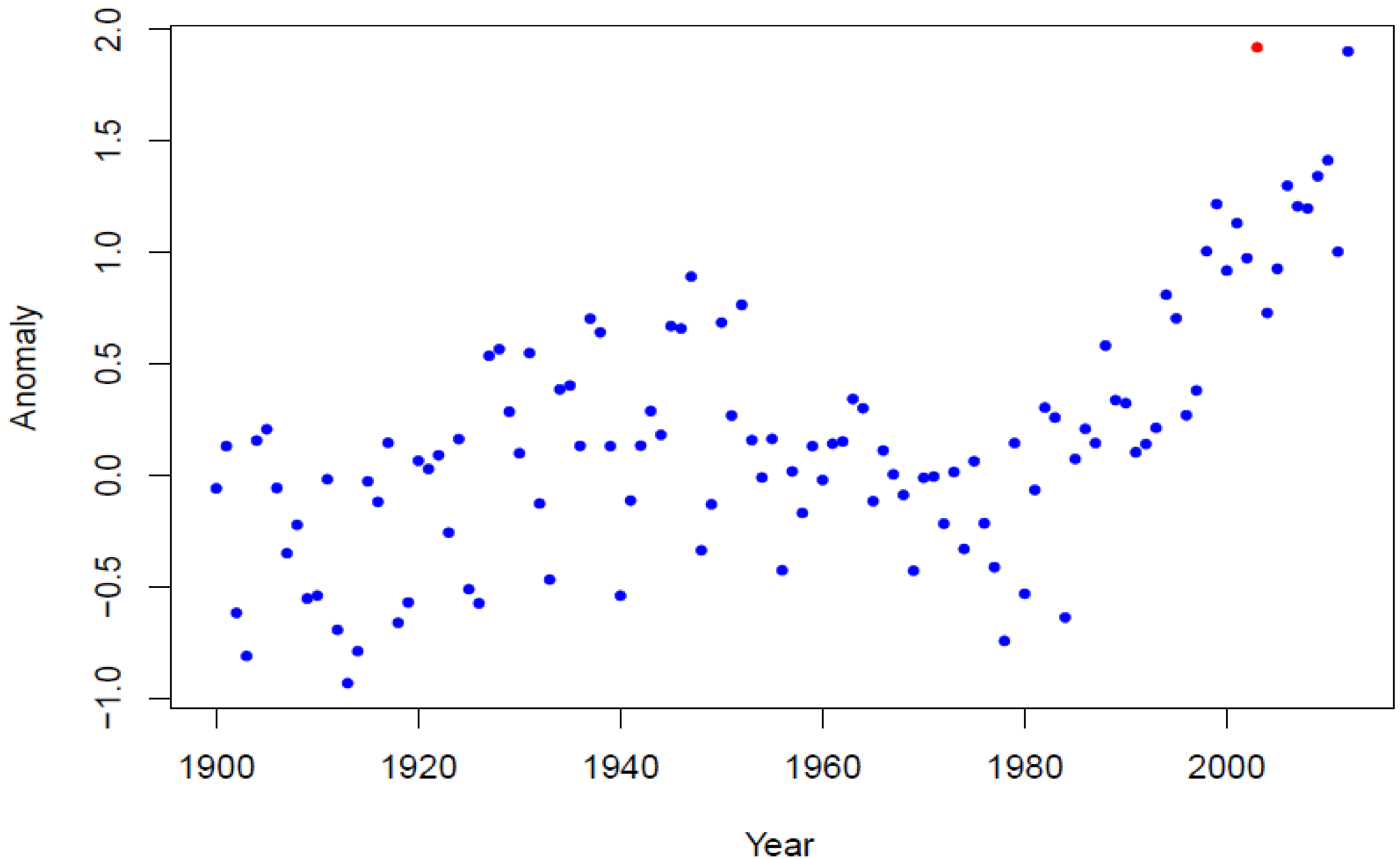
Highlighted cases correspond to two versions of the analysis by Pall *et al.*, and the probability values given in Stott, Stone and Allen (2004)

Conclusion: the method could become *extremely* data intensive

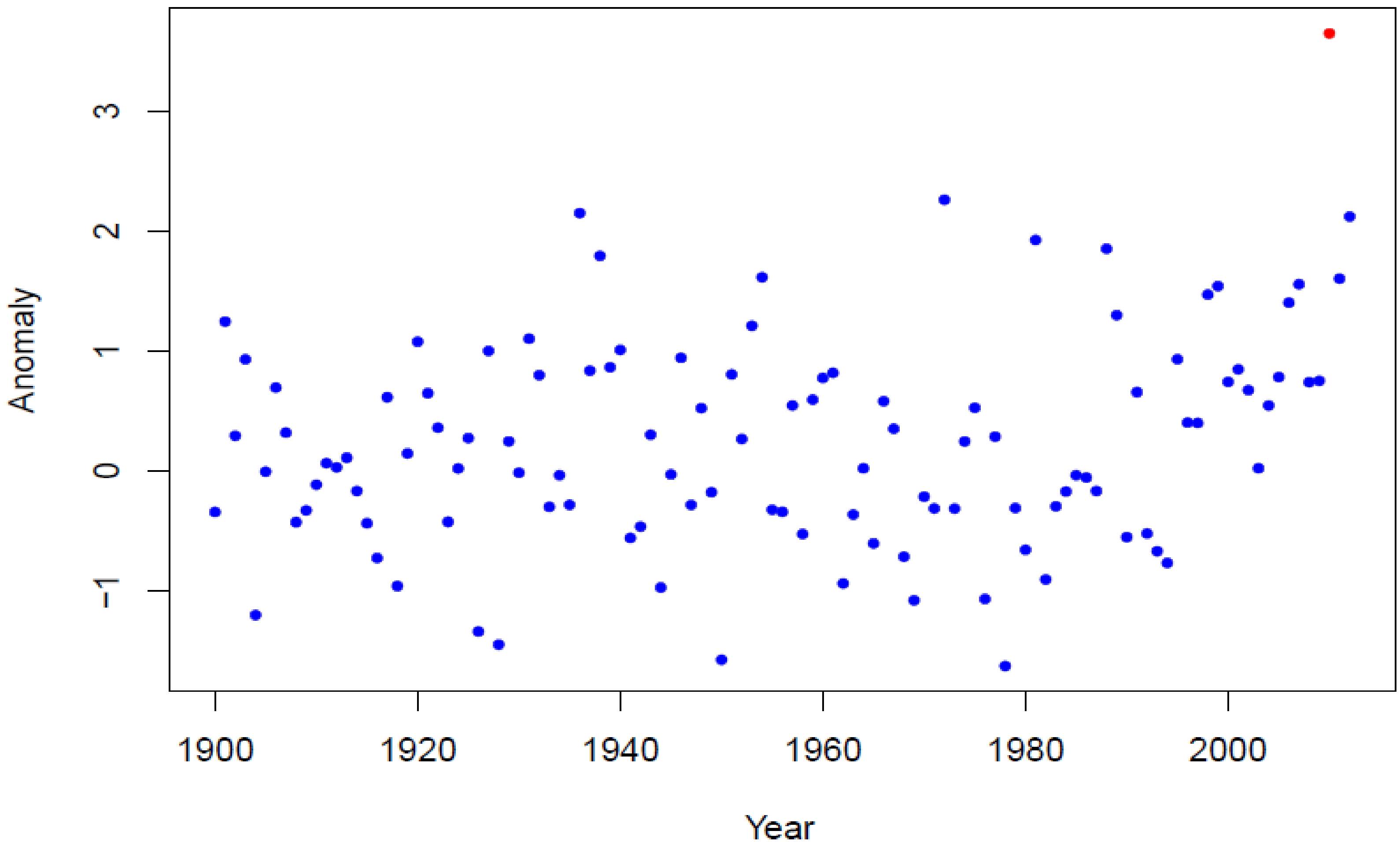
Data

- 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

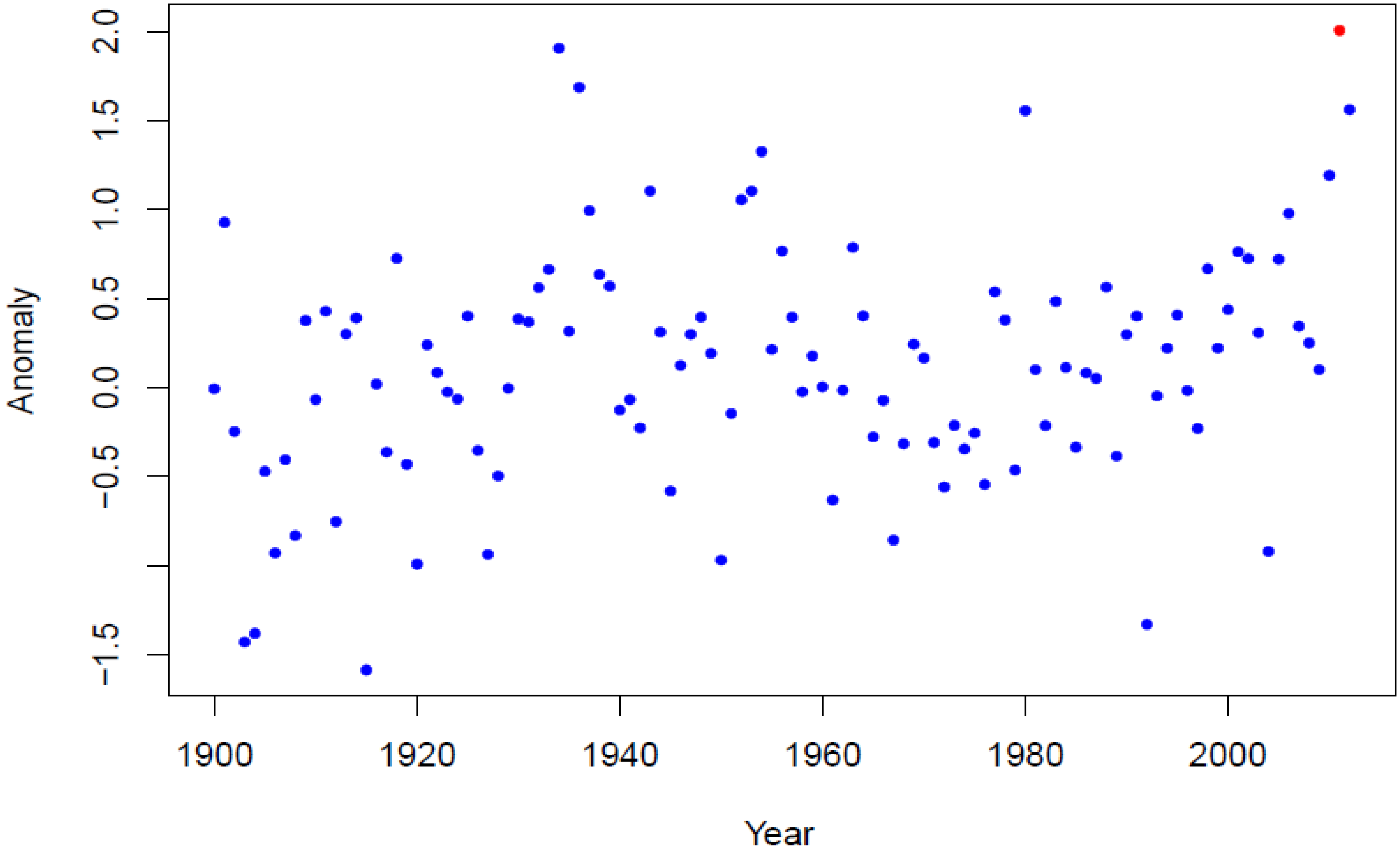
Europe Summer Mean Temperatures



Russia Summer Mean Temperatures



Central USA Summer Mean Temperatures



Introduction To Extreme Value Theory

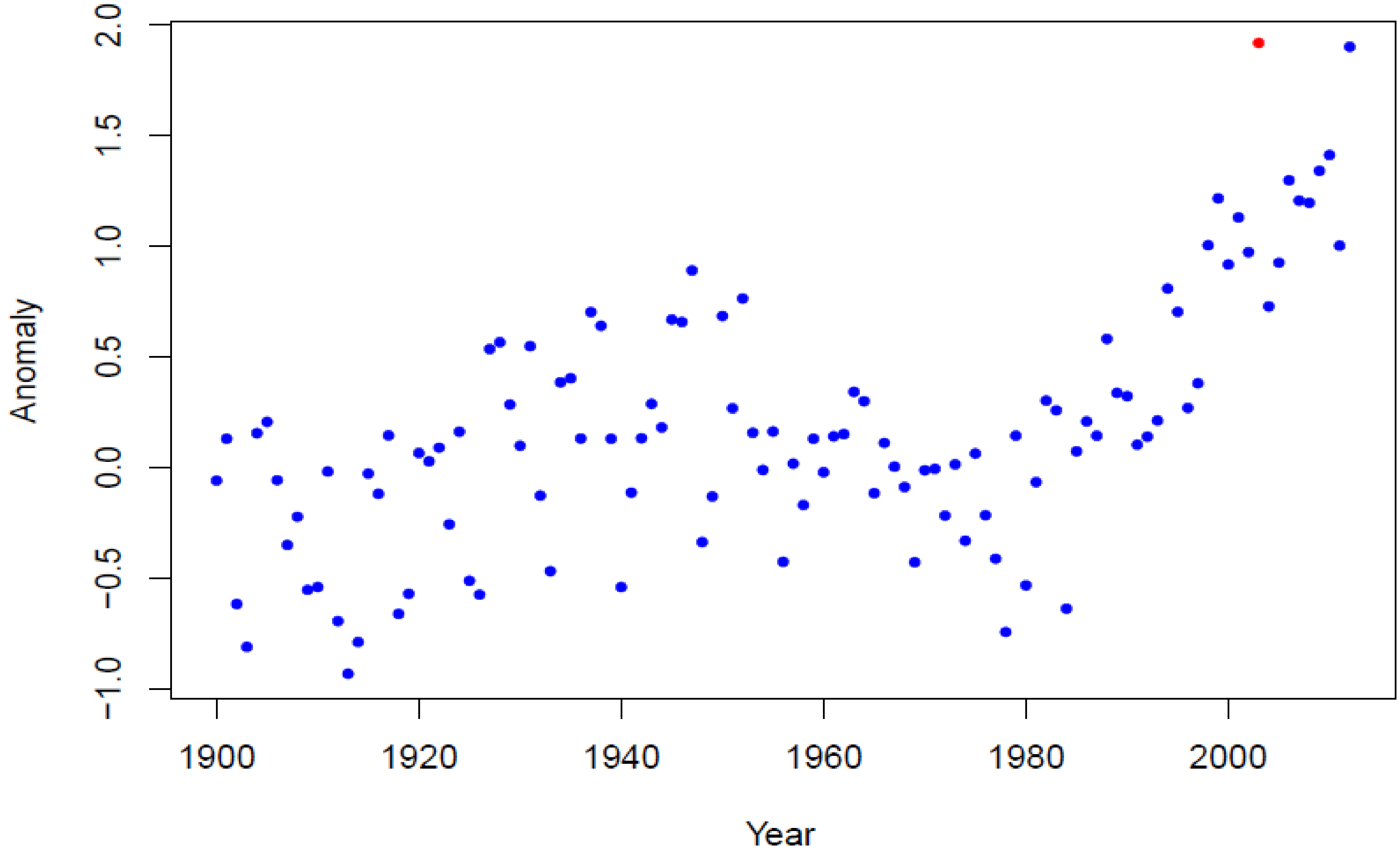
Key tool: *Generalized Extreme Value* Distribution (GEV)

- 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

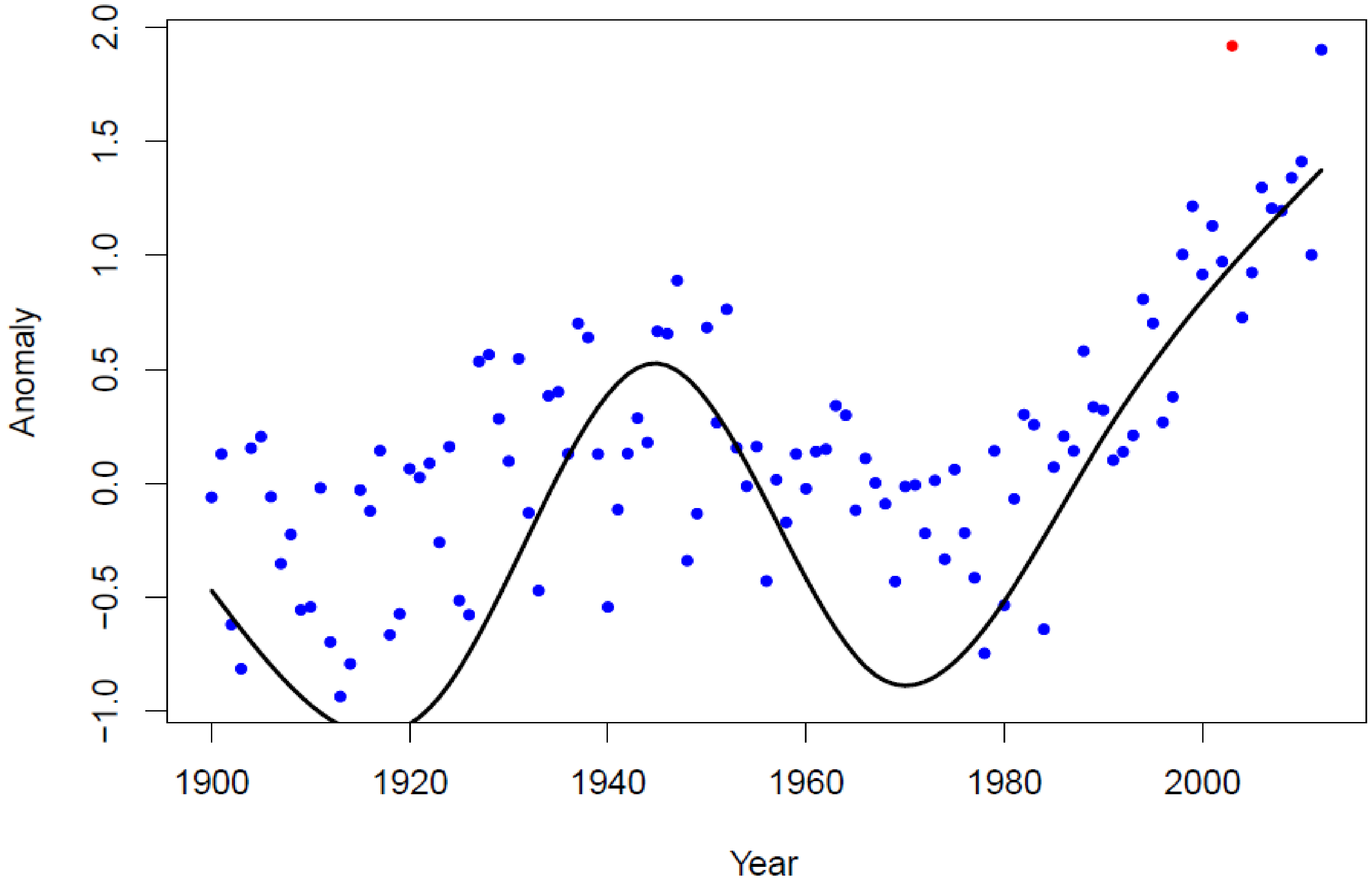
$$\Pr\{Y \le y\} \;=\; \exp\left[-\left\{1+\xi\left(\frac{y-\mu}{\sigma}\right)\right\}_{+}^{-1/\xi}\right].$$

- *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

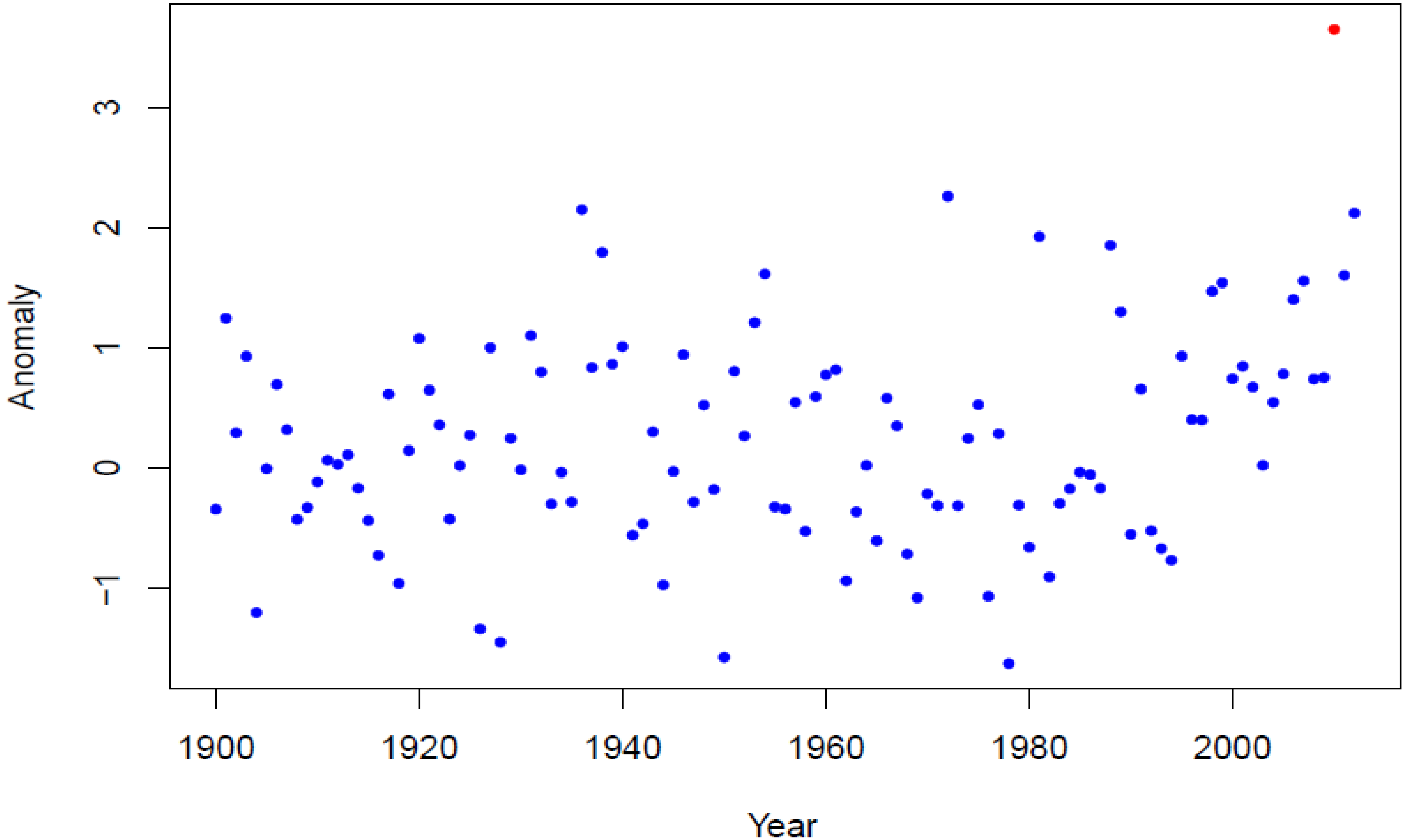
Europe Summer Mean Temperatures



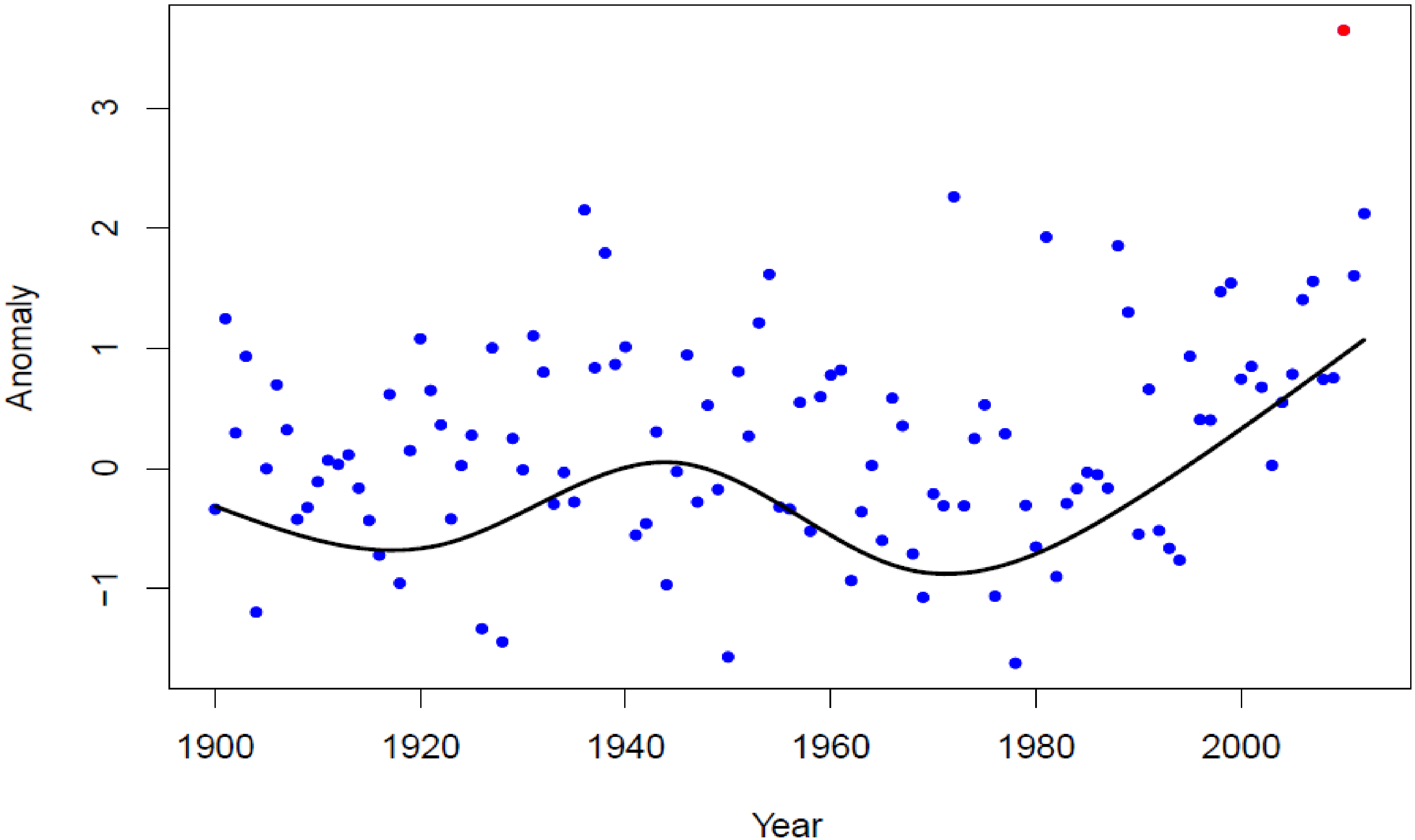
Europe Summer Mean Temperatures With Trend



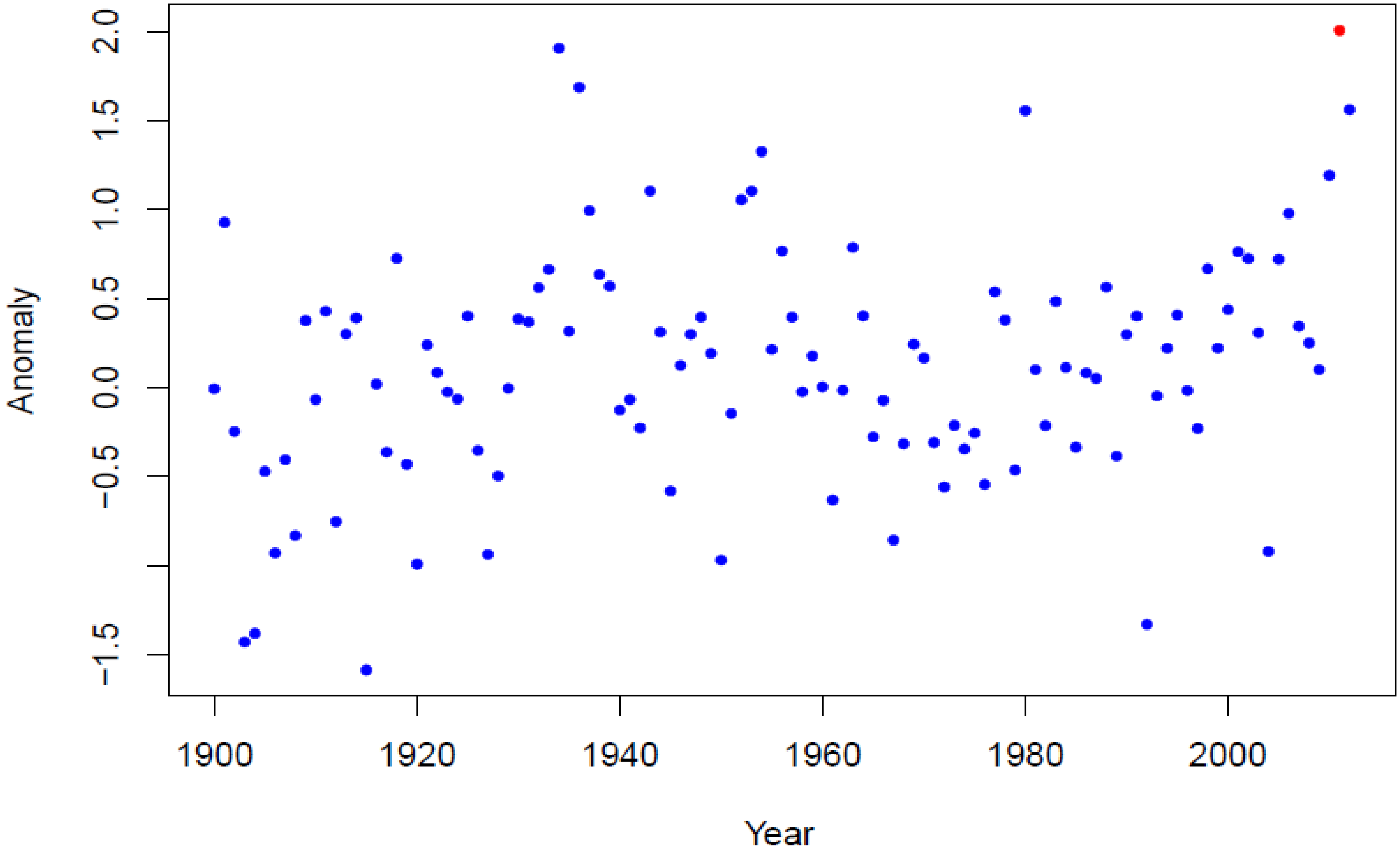
Russia Summer Mean Temperatures



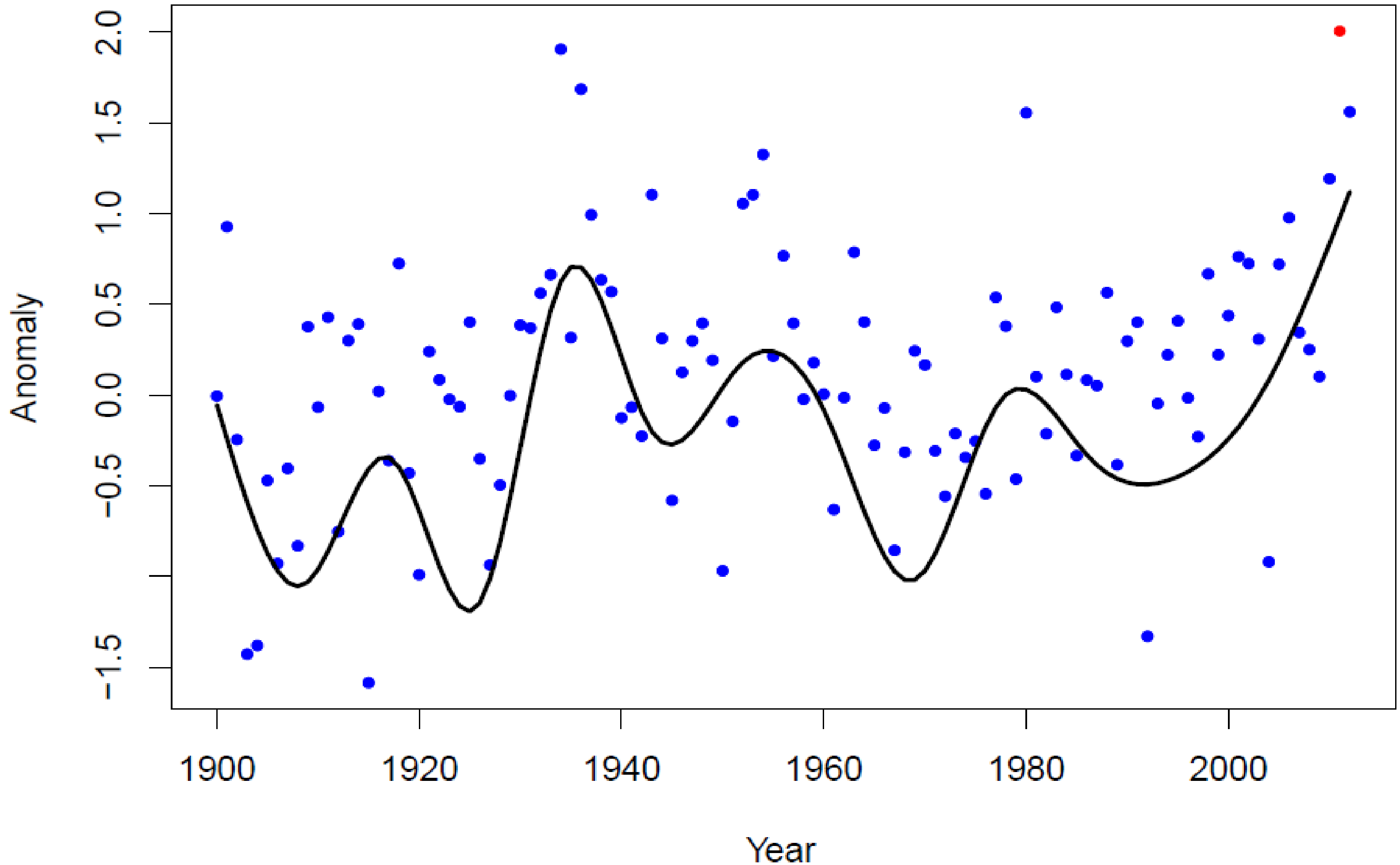
Russia Summer Mean Temperatures With Trend



Central USA Summer Mean Temperatures

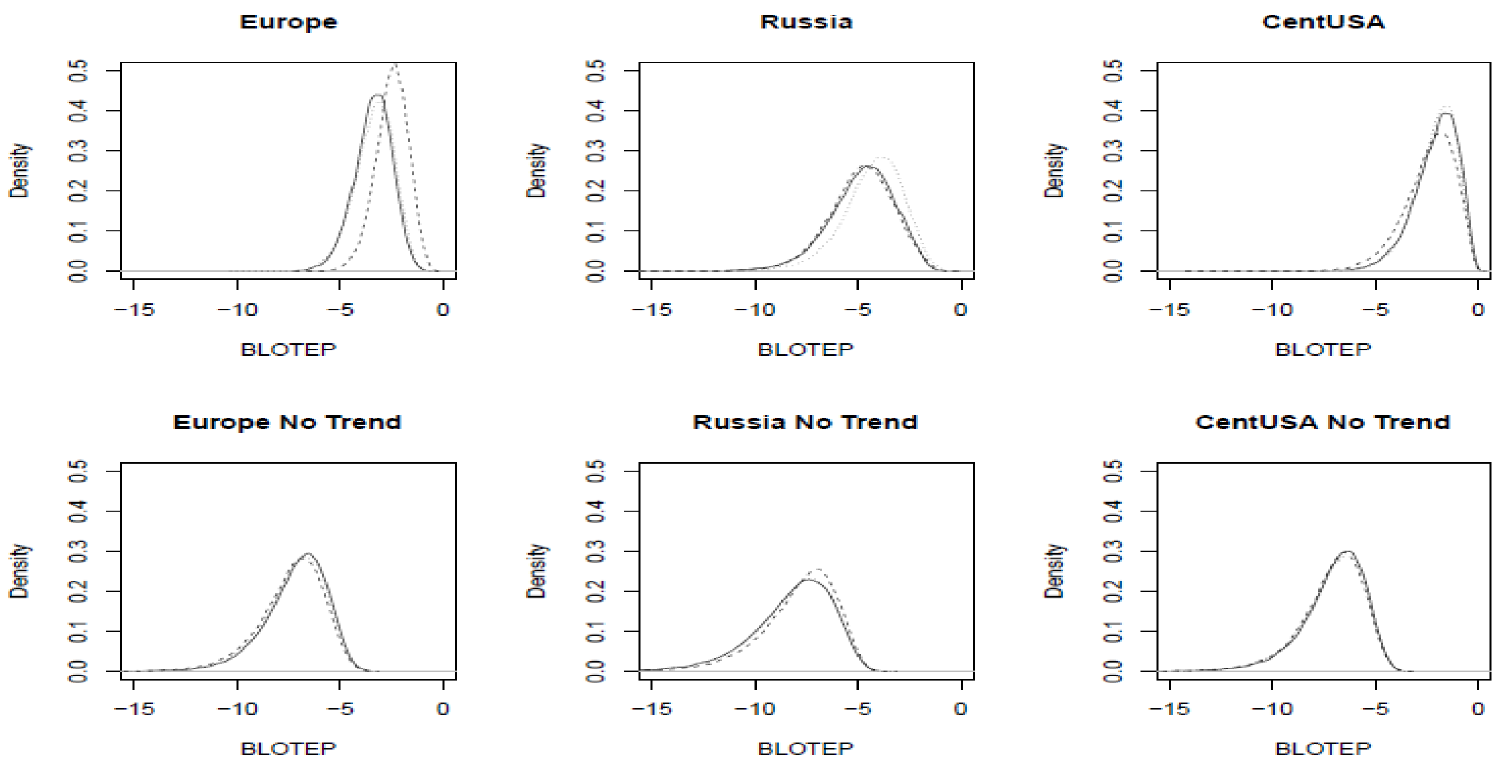


Central USA Summer Mean Temperatures With Trend



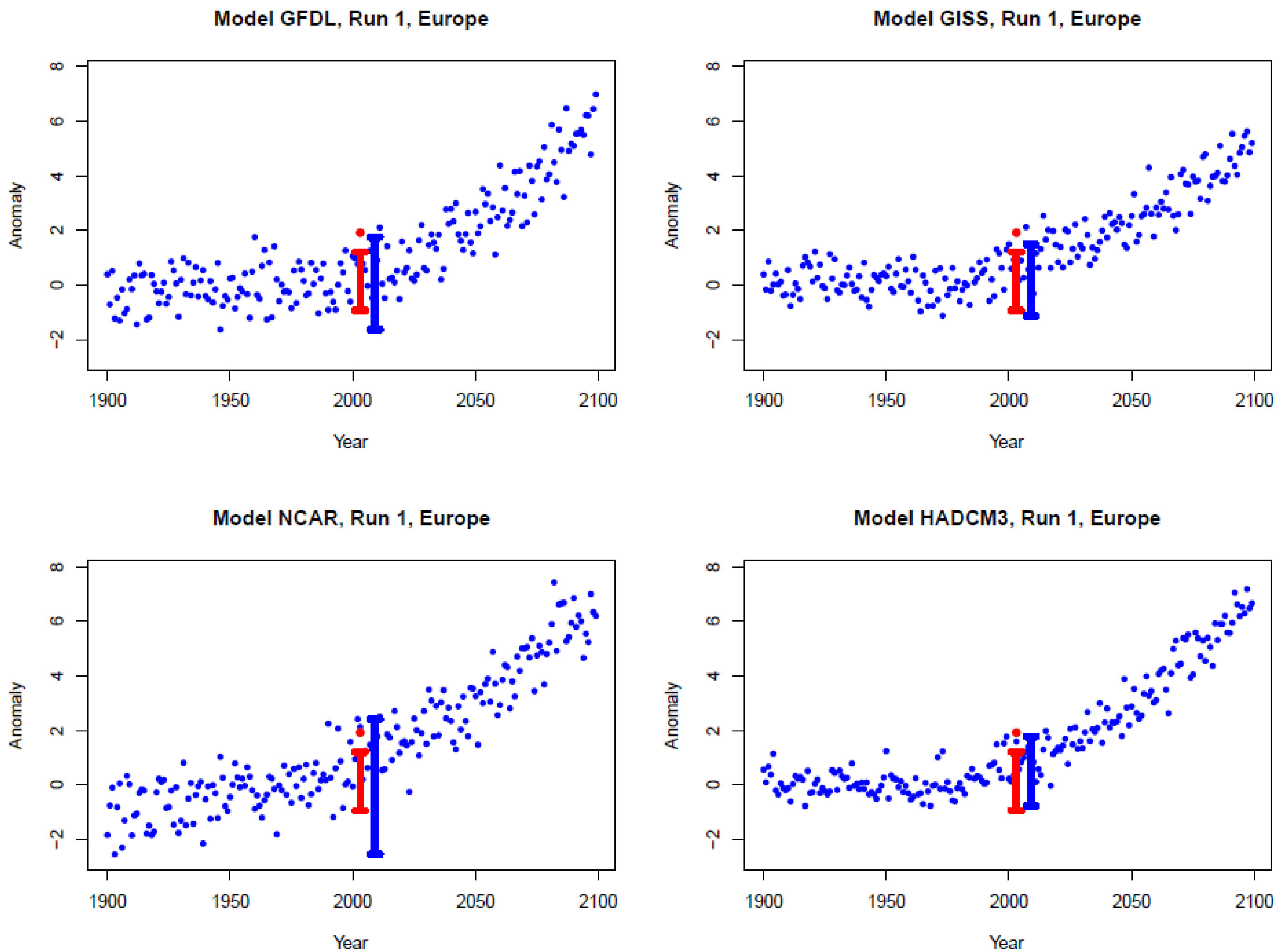
Bayesian Calculations

- 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

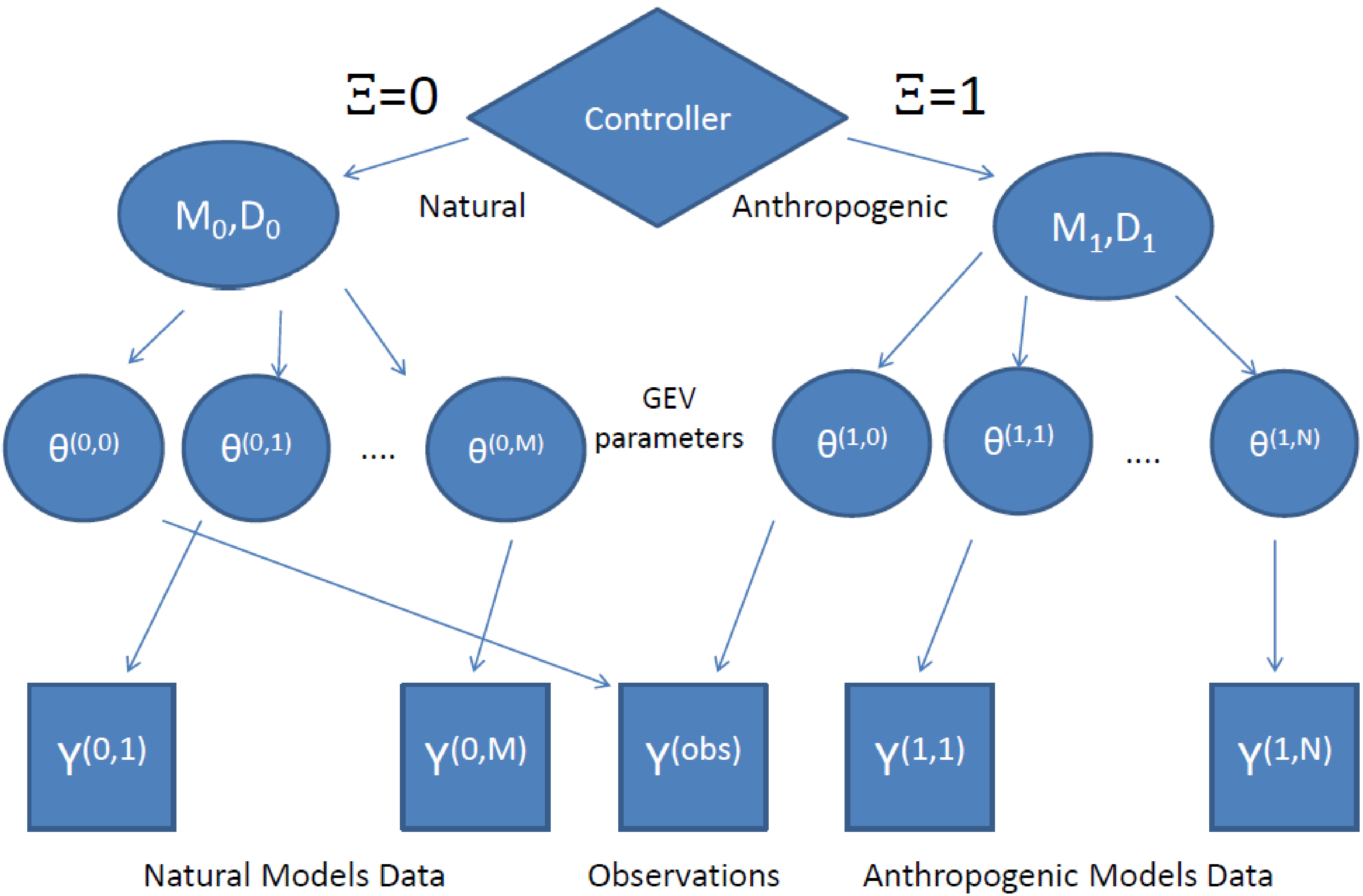


What's Next?

- 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 $\propto |D_1|^{(m-q)/2} \exp\left[-\frac{1}{2}\mathrm{tr}\left\{D_1\left(A + F(M_1 - M^*)(M_1 - M^*)^T\right)\right\}\right]$.
- 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 $\theta^{(1,j)}$ ($\mathbf{Y}^{(\mathrm{obs})}$ 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.

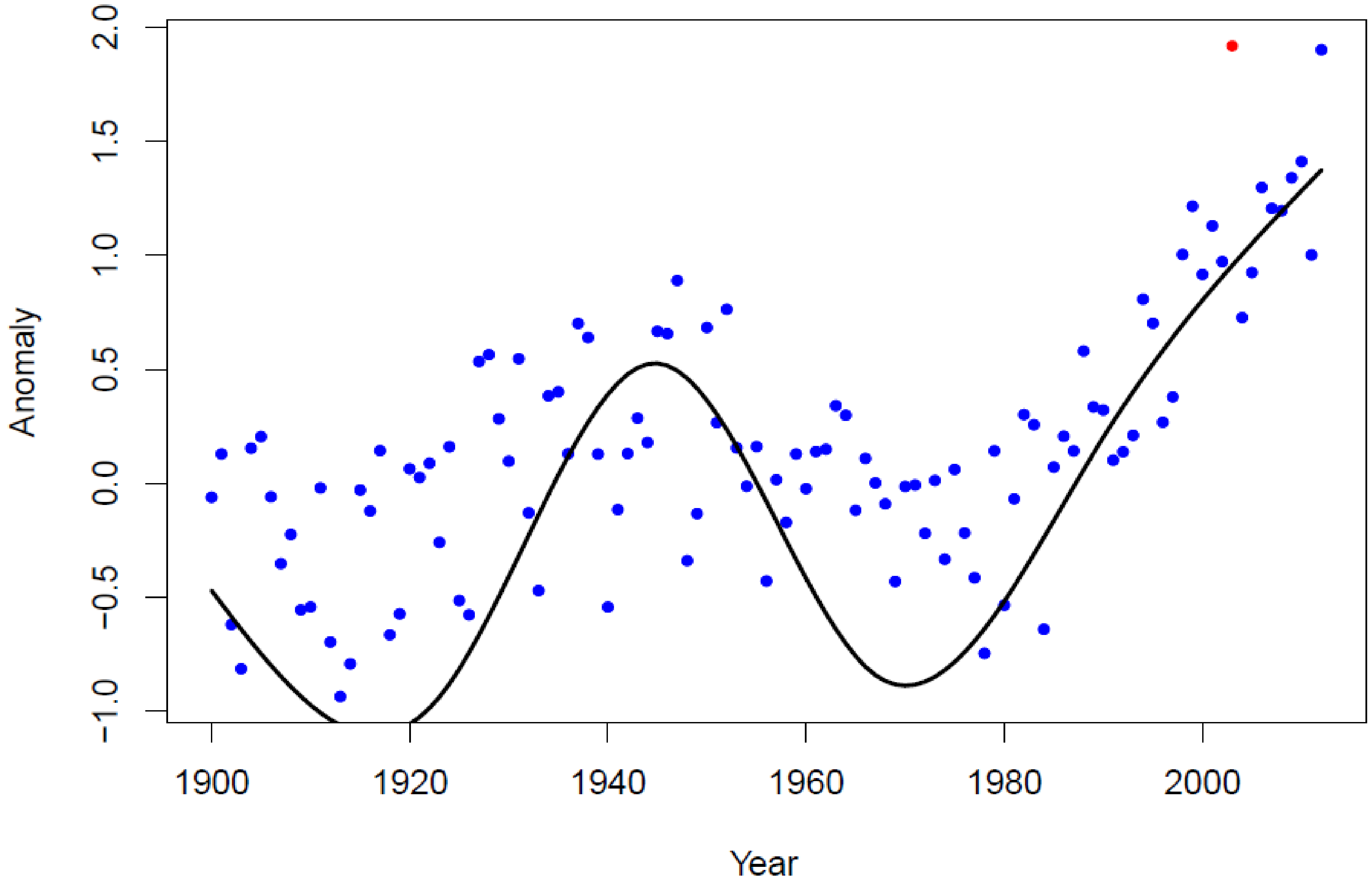
Computation

- $(M_1, D_1) \mid \theta^{(1,1)}, ..., \theta^{(1,N)} \sim WN_q(\tilde{A}, \tilde{m}, \tilde{M}^*, \tilde{F})$, 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

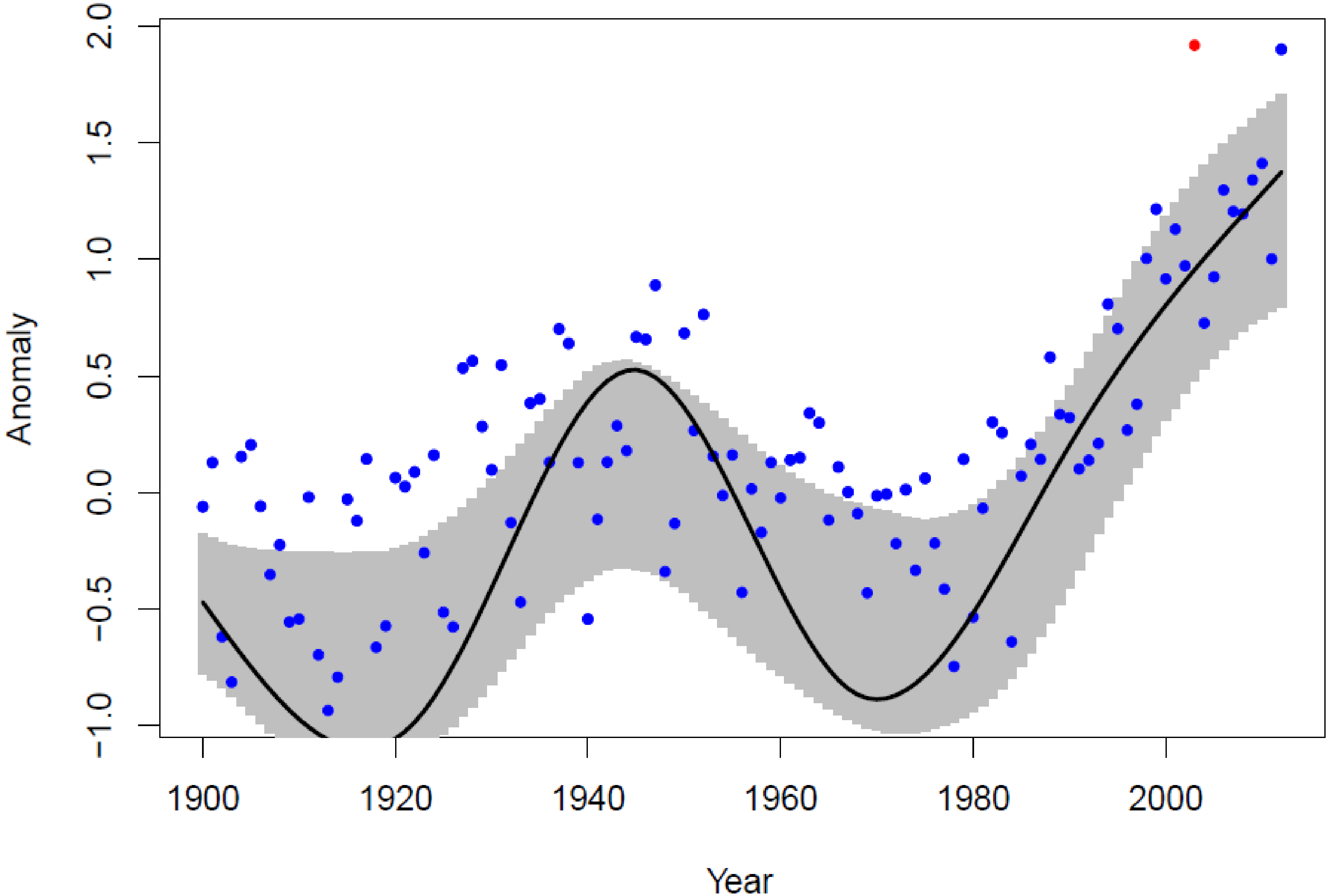
$$\exp\left\{-\frac{\psi}{2}\left(\theta^{(1,0)} - M_1\right)^T D_1 \left(\theta^{(1,0)} - M_1\right)\right\} \cdot L\left(\theta^{(1,0)}; \mathbf{Y}^{(\mathrm{obs})}\right)$$

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

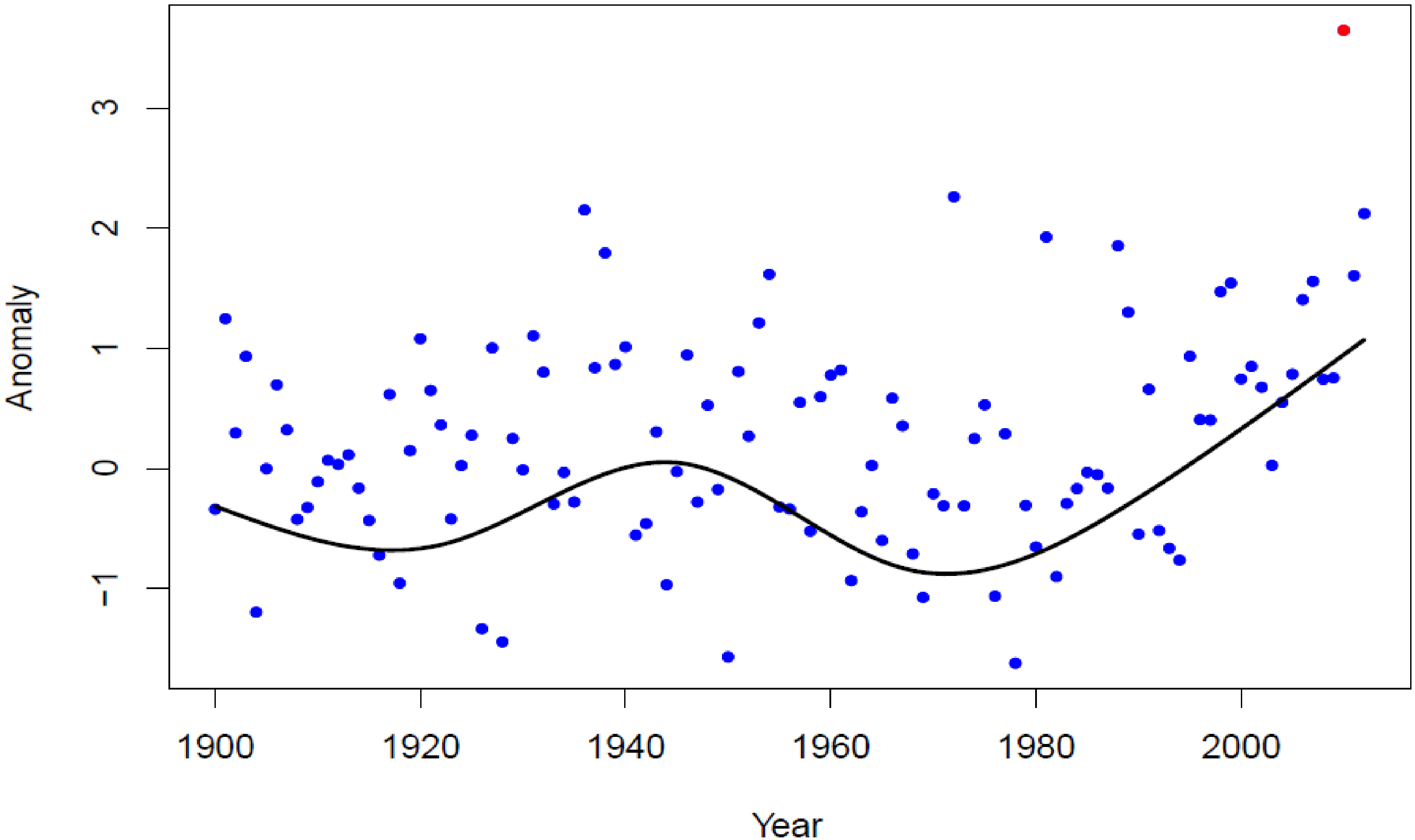
Europe Summer Mean Temperatures With Trend



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



Russia Summer Mean Temperatures With Trend



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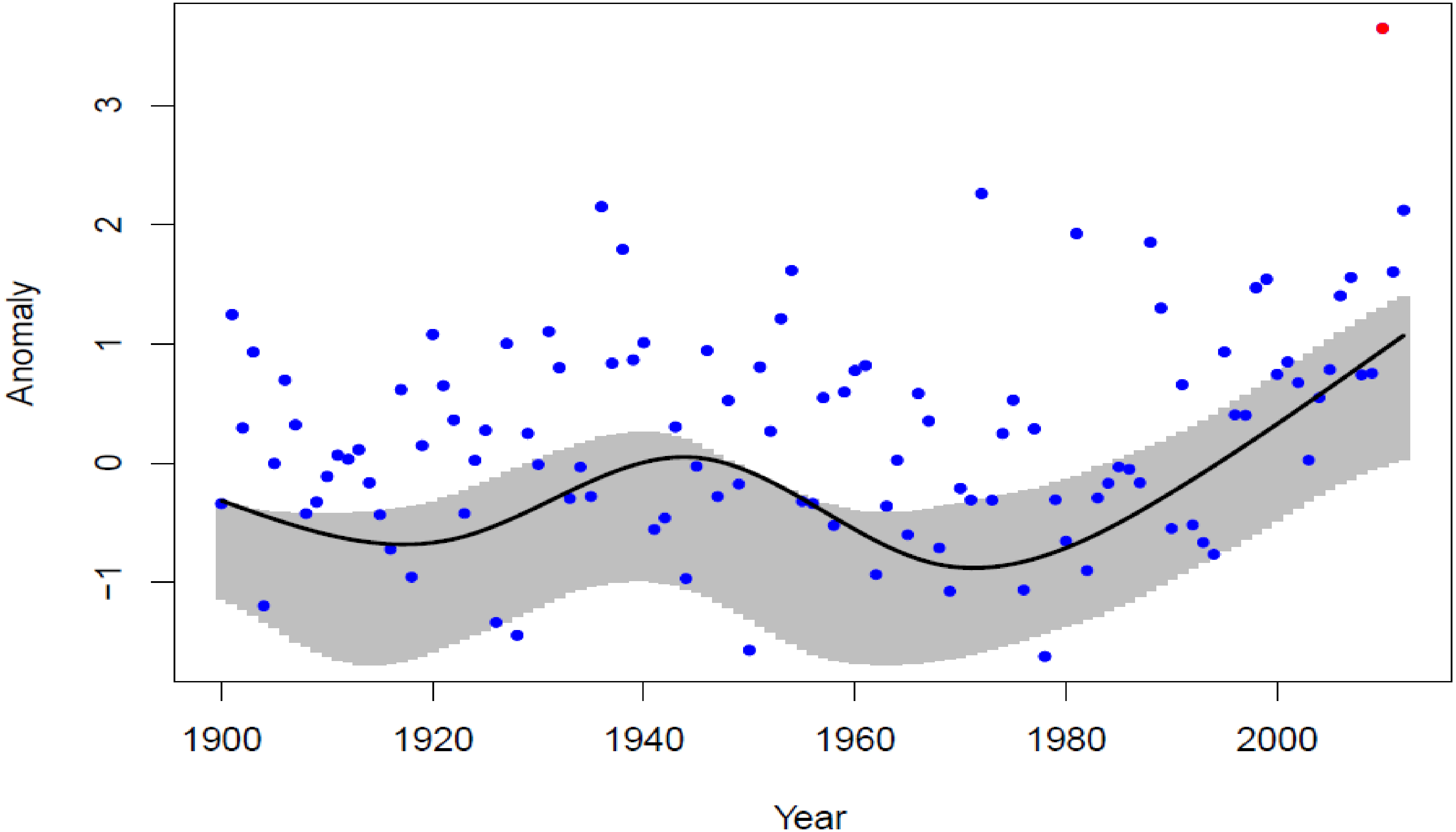
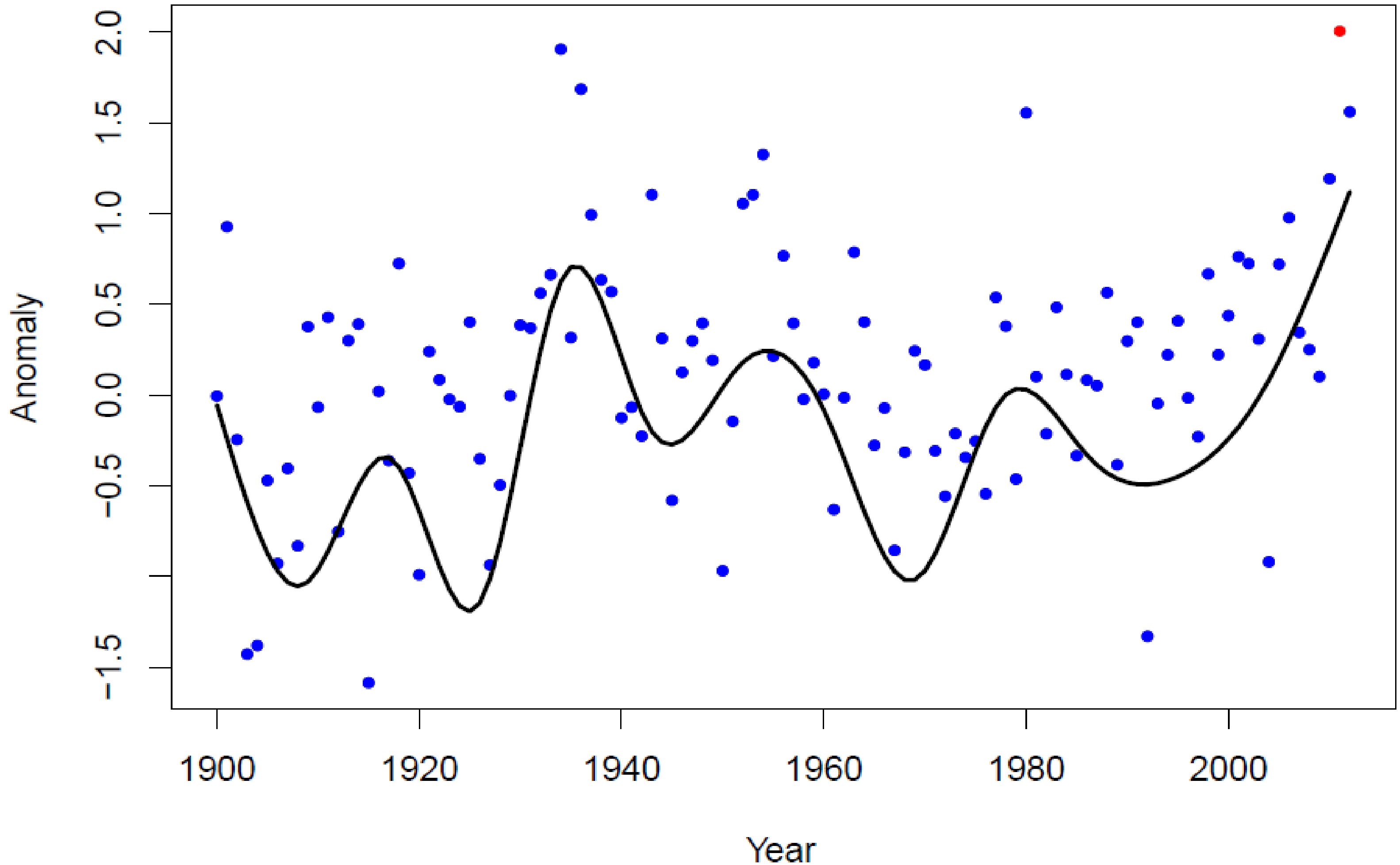


Central USA Summer Mean Temperatures With Trend



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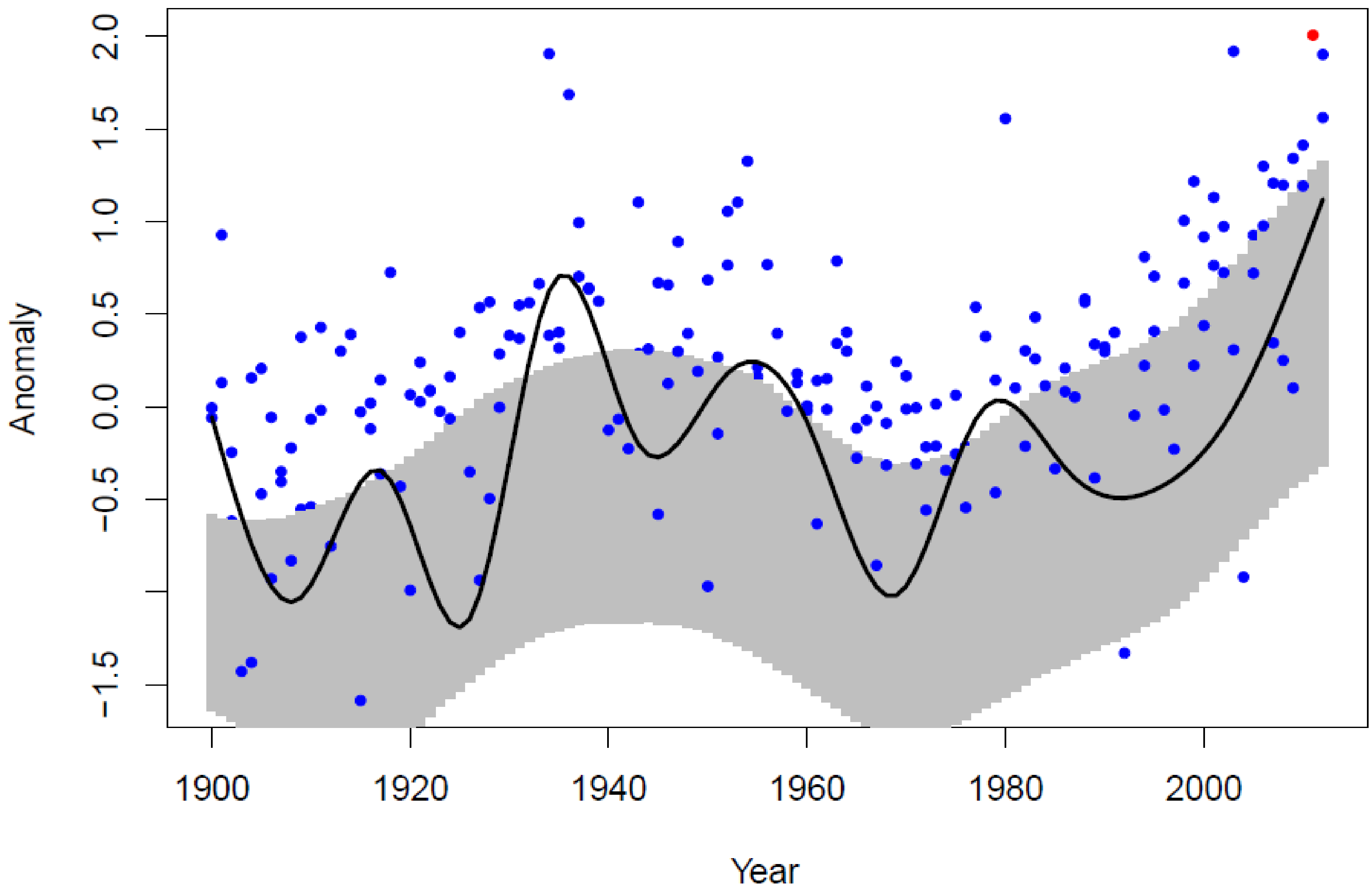
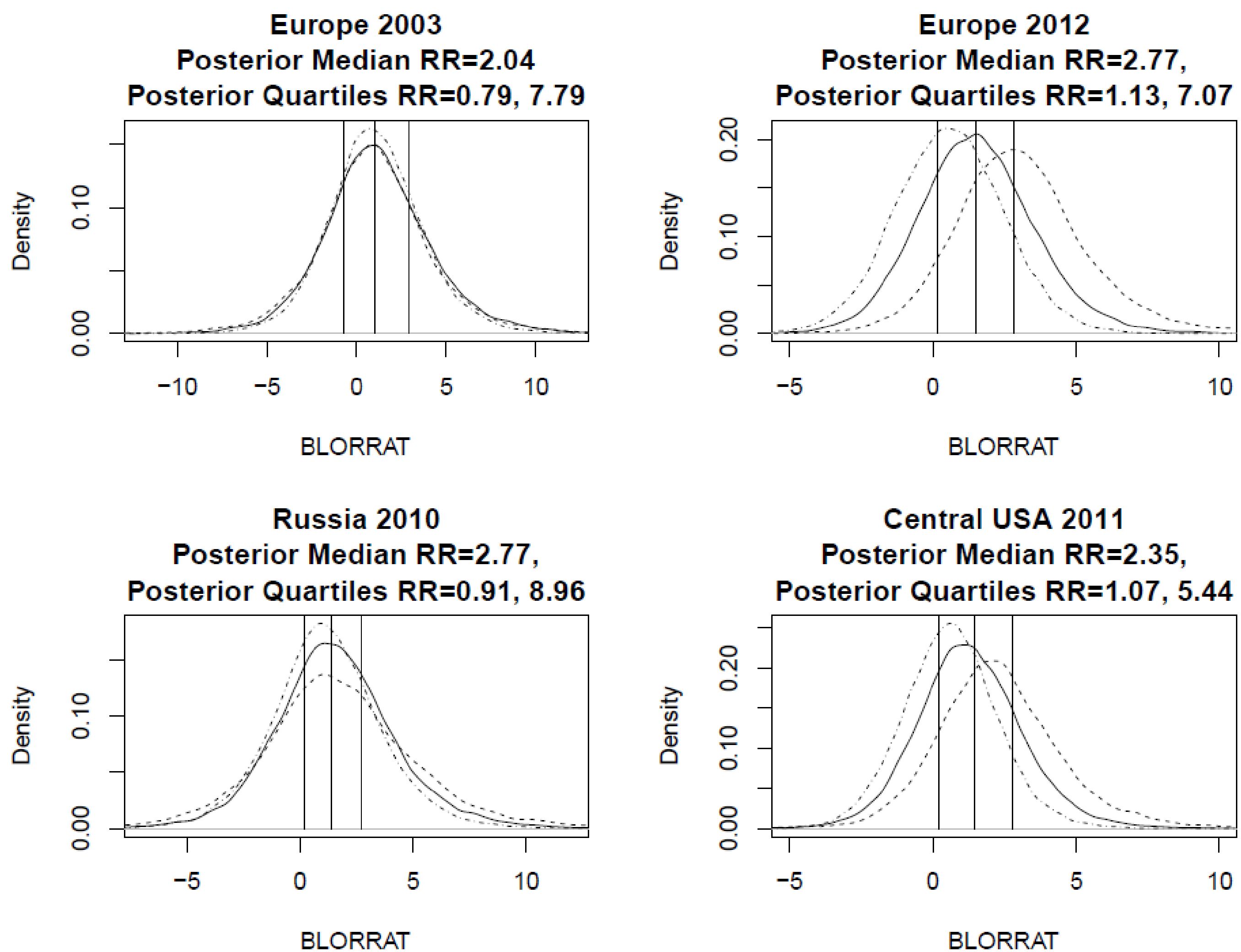
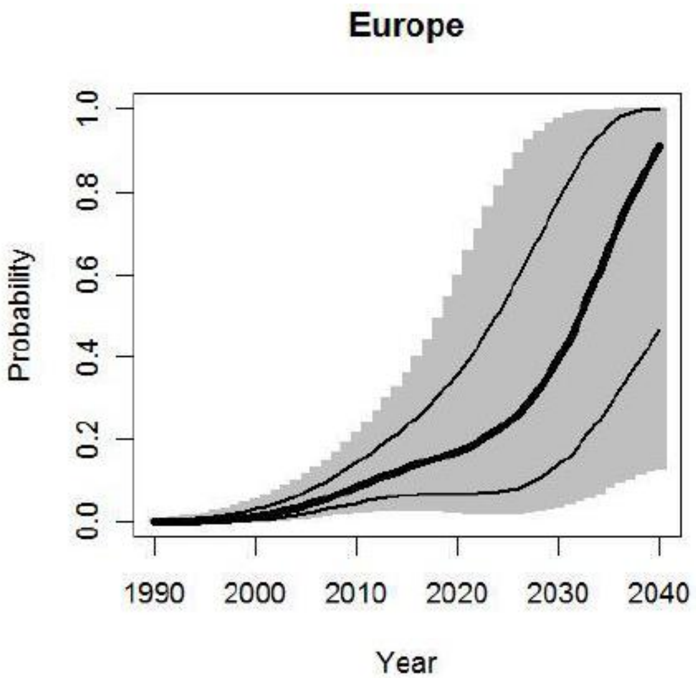


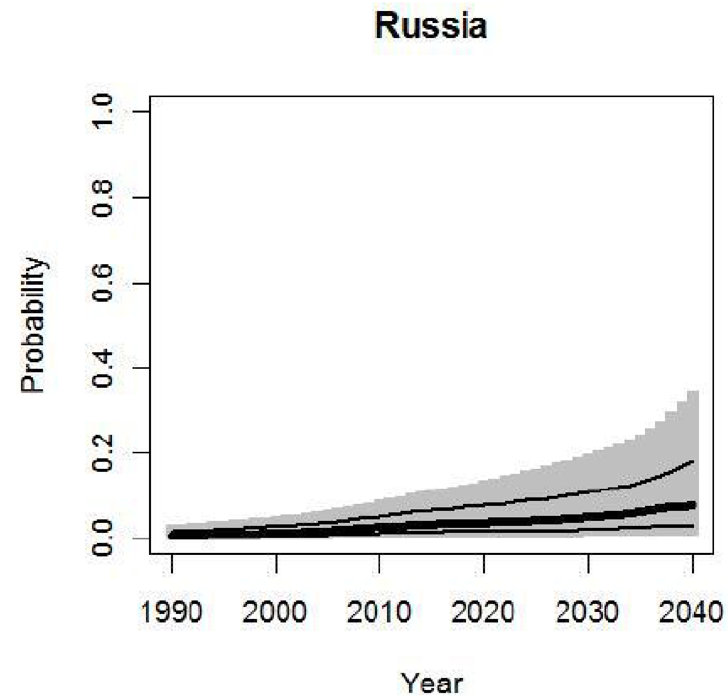
Posterior Densities for the BLORRAT

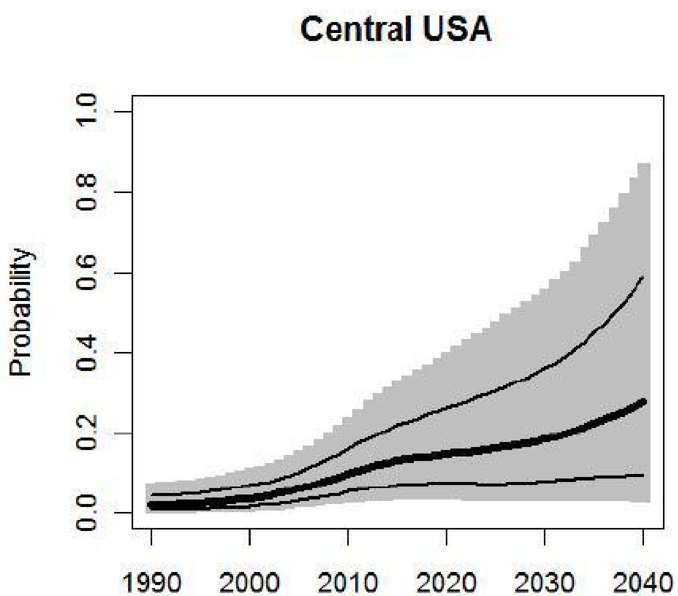
(numbers are for solid curves and equal weights; dashed curves allow for different weights between climate models and observations)



Changes in Projected Extreme Event Probabilities Over Time

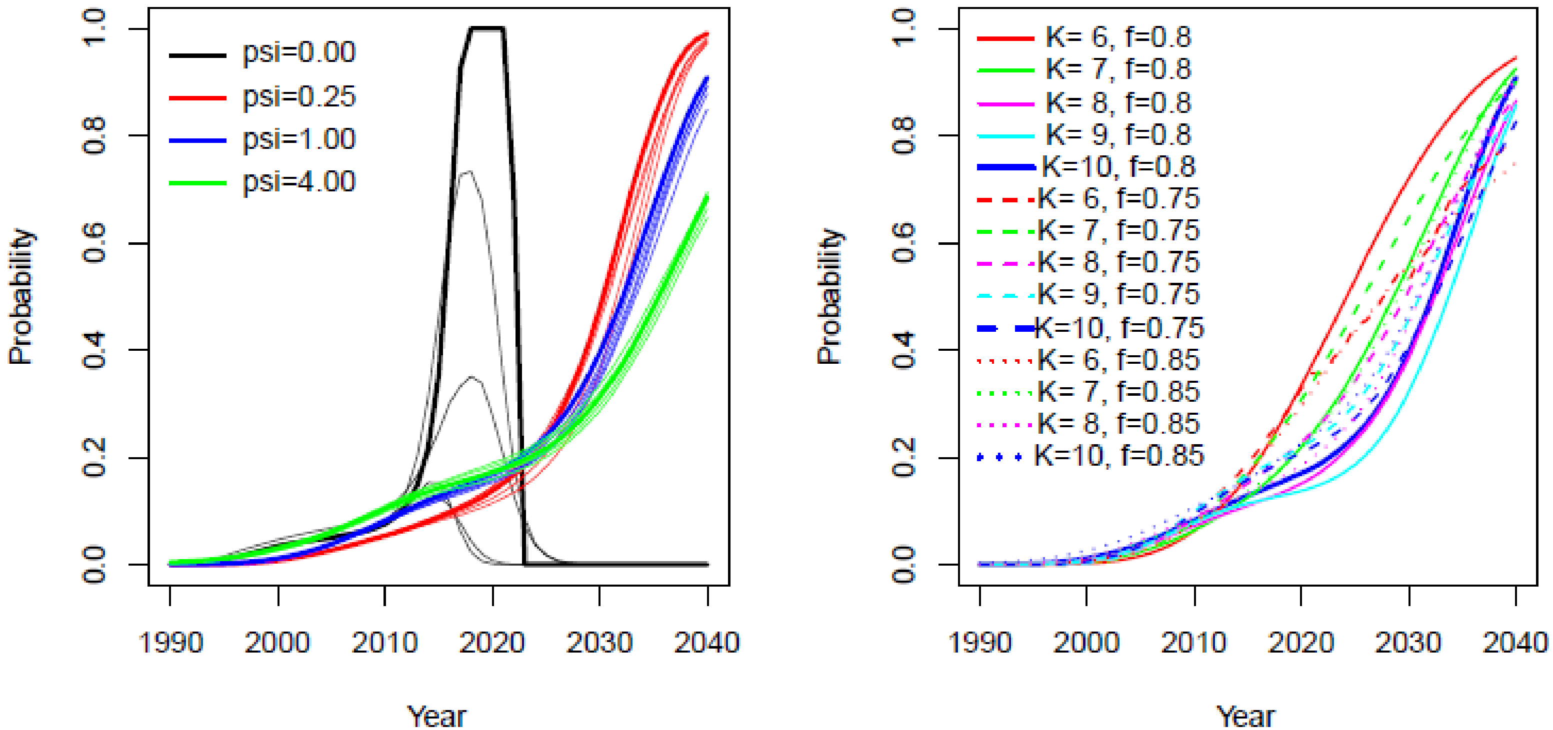






Central Solid Curve: Posterior Median
Thin Outer Curves: Posterior Quartiles
Outer Limits of Shaded Region:
Posterior 10^{th} and 90^{th} percentiles

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.

What Next?

- We plan to repeat the analyses using newer datasets and other meteorological variables (especially precipitation, maximum windspeed in hurricanes)
- High-impact events that depend on more than one meteorological variable, e.g.
  - Texas 2011: high temperatures and a drought in the same year. One extreme event caused by a combination of two meteorological variables
  - The Russian heatwave and the Pakistani floods of 2011 may have been related: two different events but possible statistical dependence
- Spatial analysis – the actual scale of interest may be different from the one at which data were originally compiled – need for downscaling
- Account for multiple comparisons

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