Spatial trend analysis of gridded temperature data sets at varying spatial scales

- work in progress

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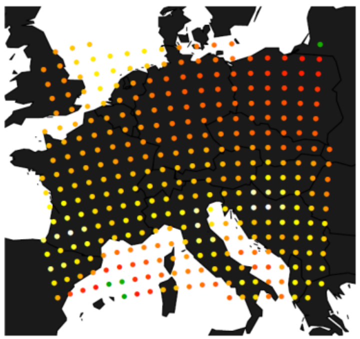
Motivation

- Where is there a significant temperature trend?
- At which spatial resolutions of the underlying data do trends show consistent spatial structures?

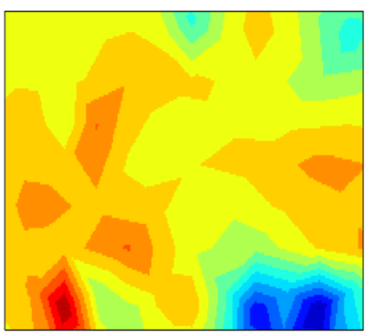
Input data resolution

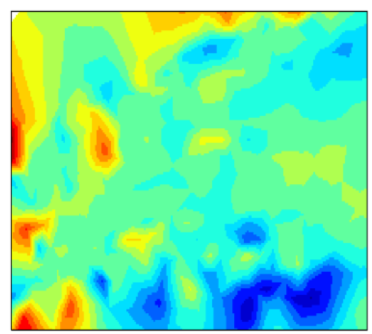


Finer scales of underlying data

Statistical model

Measure of significance





Are consistent spatial structures obtained…?

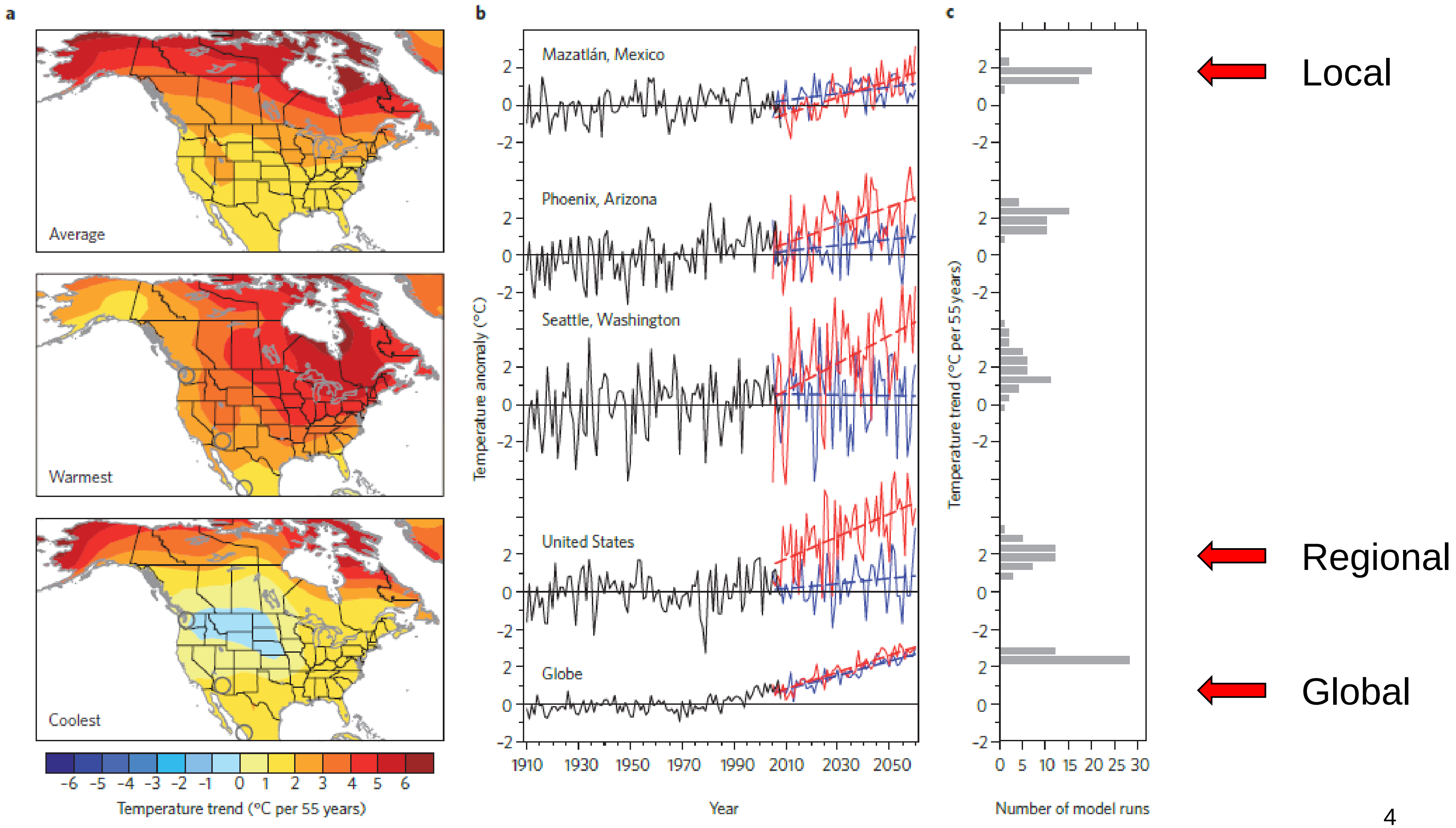
Relies on the statistical model being able to identify potential trends

Contents

- Background
- Data
- Models
- Results
- Significance – excursion sets

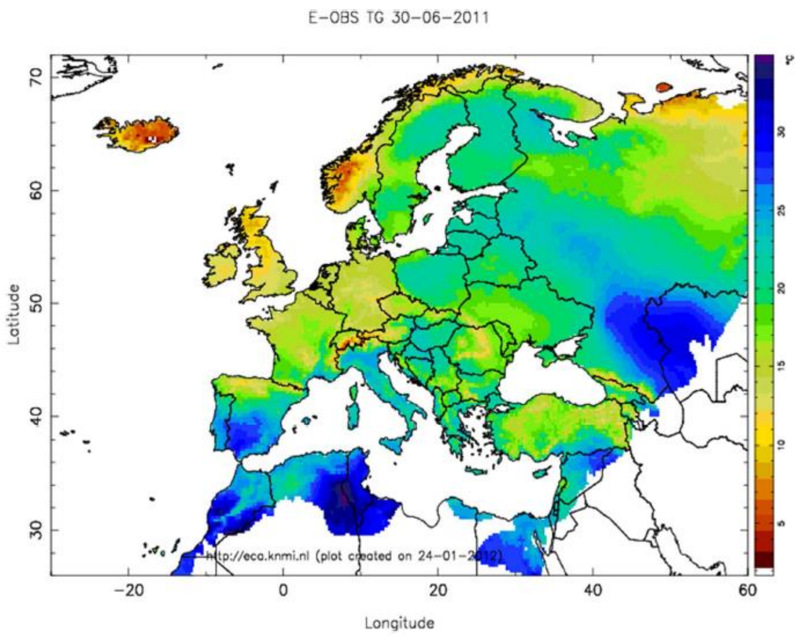
Background

Deser et al, NCC (2012):
Communication of the role of natural variability in future North American climate



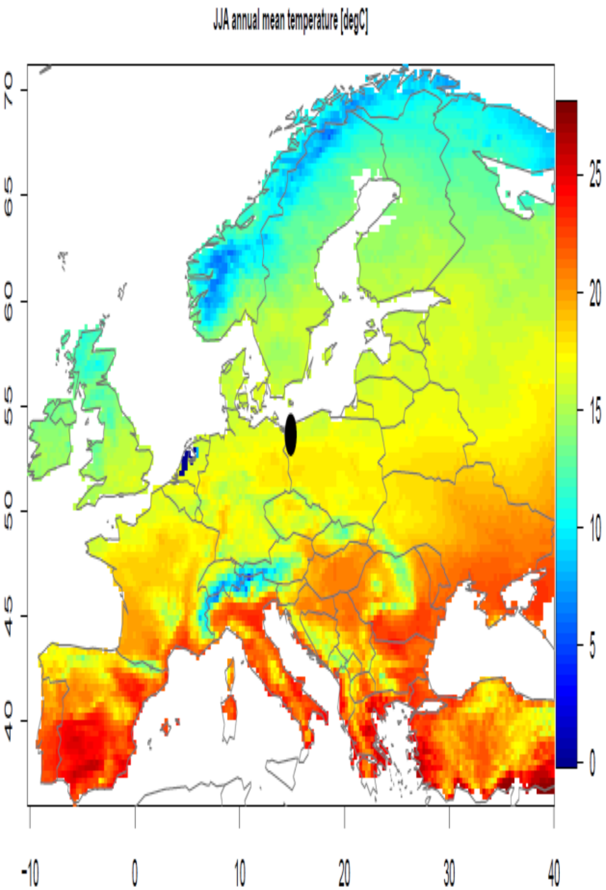
Data

- E-OBS temperature data for Europe
  - Regular grid: 0.25° x 0.25° (~15,000 locations)
  - Monthly means 1950-2014

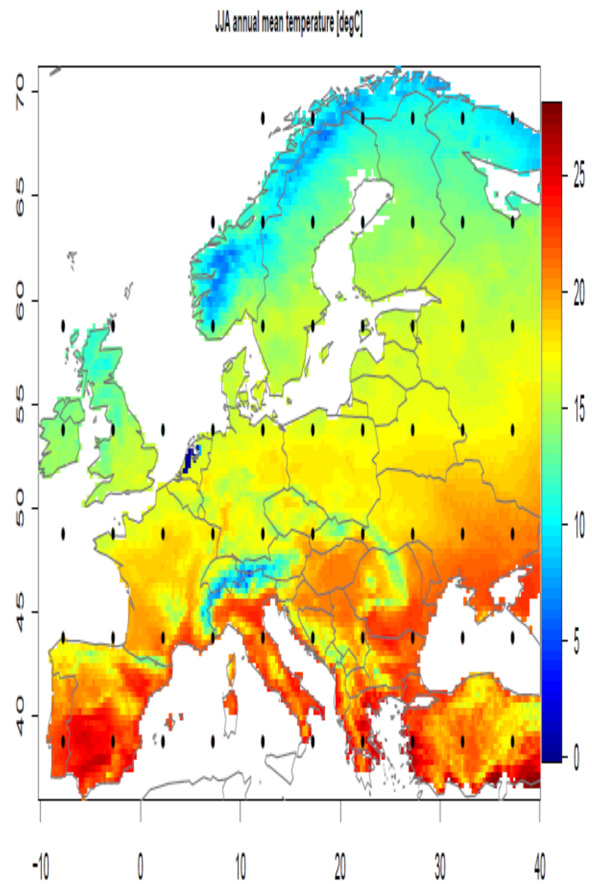


- In our analyses, we consider:
  - Aggregated resolutions:
    - 1° x 1°, 5° x 5° and 1 point (European mean)
  - Seasonal summer (JJA) and winter (DJF) means
    - Time series of 65 values in each location
  - Centered and scaled temperature anomalies (for each location)

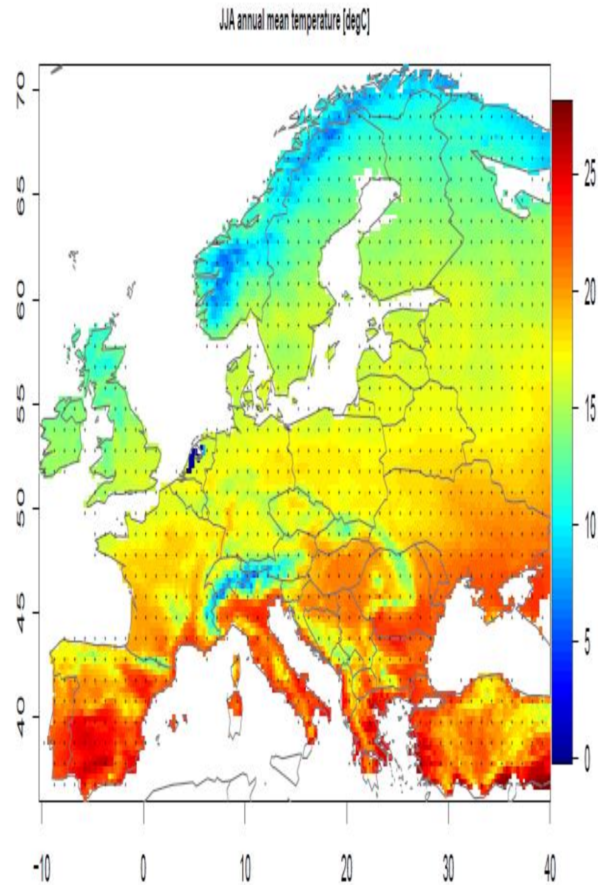
Spatial grids



1 data point



5° x 5°: 70 data points



1° x 1°: 1207 data points

Statistical model

- General representation for the anomalies:

$$Y_{st} = g_s(t) + \varepsilon_{st} \qquad \text{where } s = 1, \dots, S$$
$$t = 1, \dots, T$$

  and where $g_s(t)$ describes the trend, and ε_{st} is Gaussian measurement noise, uncorrelated in space and time

  In the current setting ***S* = 1, 70 or 1207**, and ***T* = 65**

- Independent regression analysis for each grid point ignores the spatial correlation. What effect (if any) does this have?
  - Try models with and without spatial structure

Models

- Spatially uncorrelated models
  - A: $g_s(t) = \alpha_1 t$
  - B: $g_s(t) = \alpha_1 t + \tau_{ts}$ where $\tau_{ts} = a\tau_{(t-1)s}$ *ie* AR(1) in time

- Models with spatial structure
  - C: $g_s(t) = (\alpha_1 + \alpha_{1s})\, t$

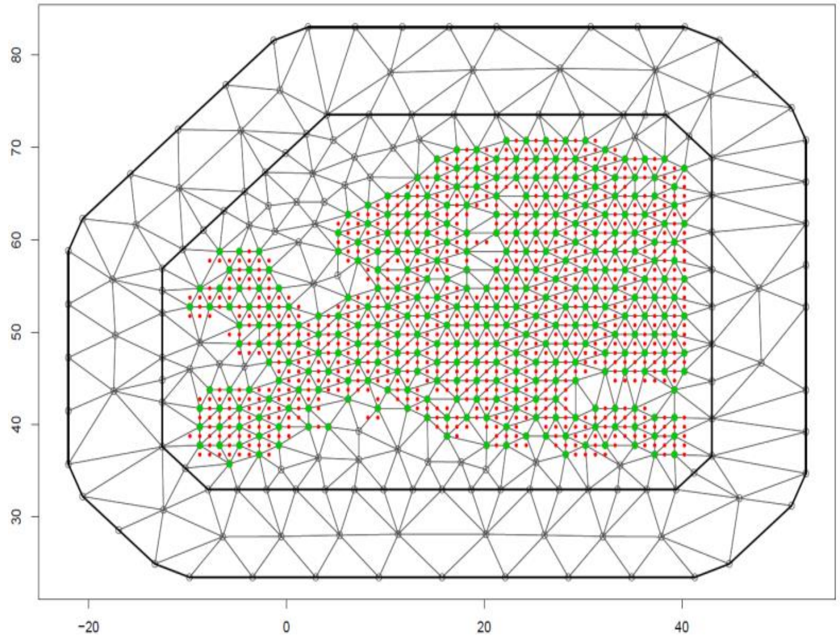
    $\boldsymbol{\alpha_1} \sim$ zero-mean GRF with spatial Matérn covariance
  - D: $g_s(t) = (\alpha_1 + \alpha_{1s})\, t + \tau_{ts}$

    $\tau_{ts} = a\tau_{(t-1)s} + \xi_{ts}$ *ie* AR(1) in time

    $\boldsymbol{\alpha_1}$, $\boldsymbol{\xi} \sim$ zero-mean temporally independent GRFs with spatial Matérn covariances

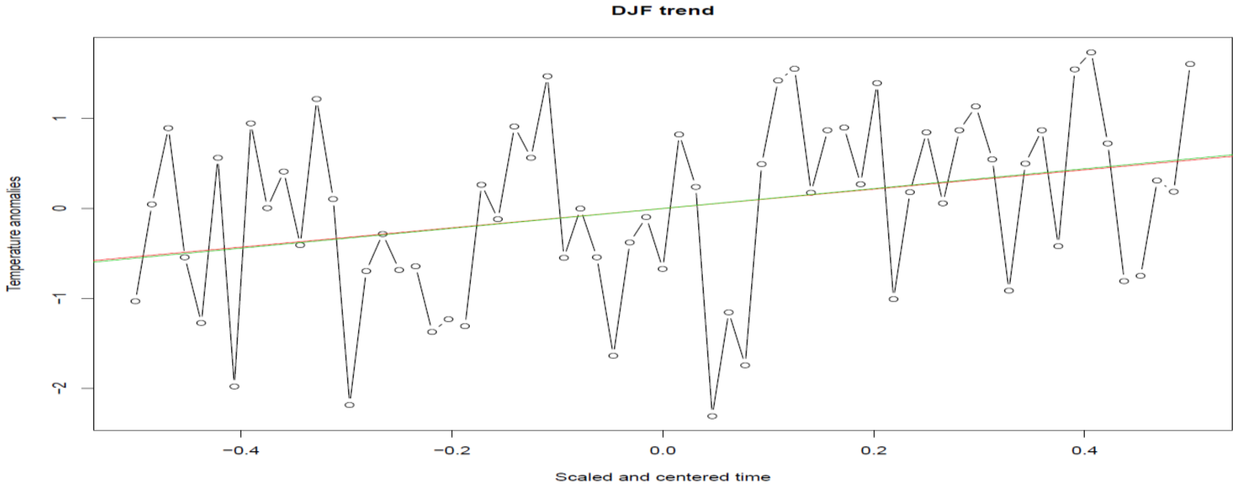
Model parameter estimation

- ► Non-spatial models are fitted for each location via OLS
- ► Spatial models are fitted via R-INLA/SPDE
  - ▪ Bayesian inference via INLA is computationally effective and thus well suited for certain kinds of big data problems

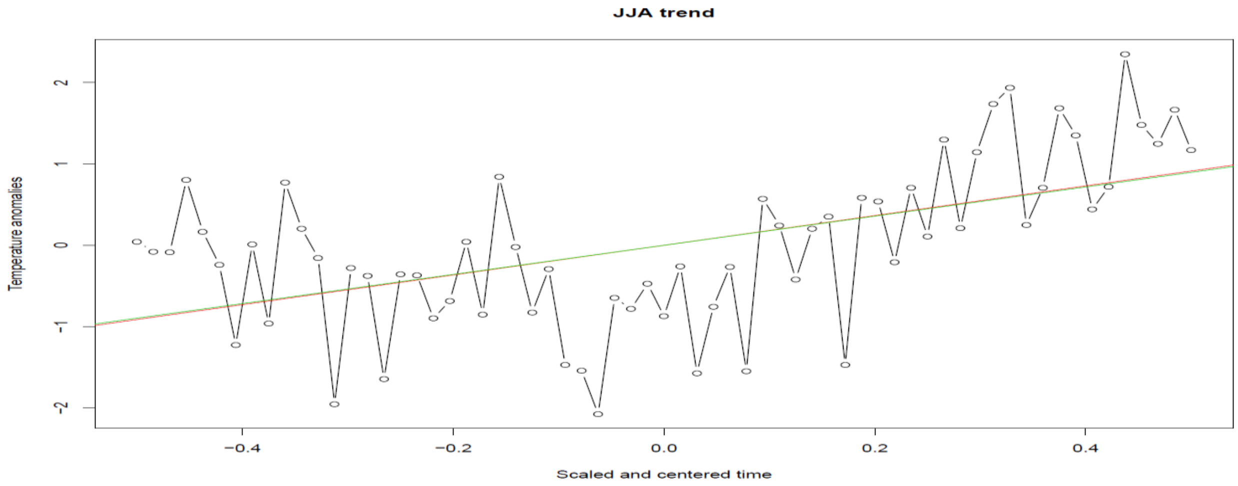


References:
- http://www.r-inla.org/
- Rue et al *Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations*. JRSS-B (2009).
- Lindgren et al *An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach.* JRSS-B (2011).

Europe: 1 point

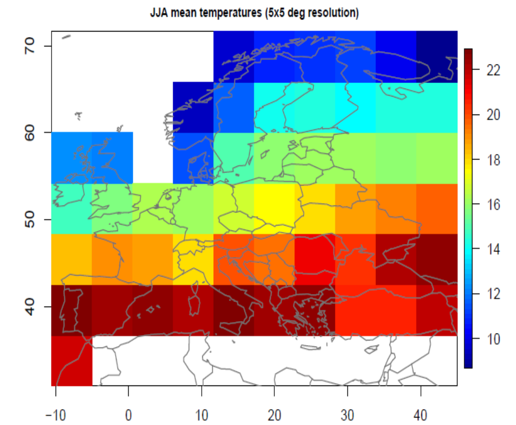


DJF	Trend	StErr	AR(1)
OLS iid	0.16	0.06	-
OLS AR(1)	0.17	0.07	0.18

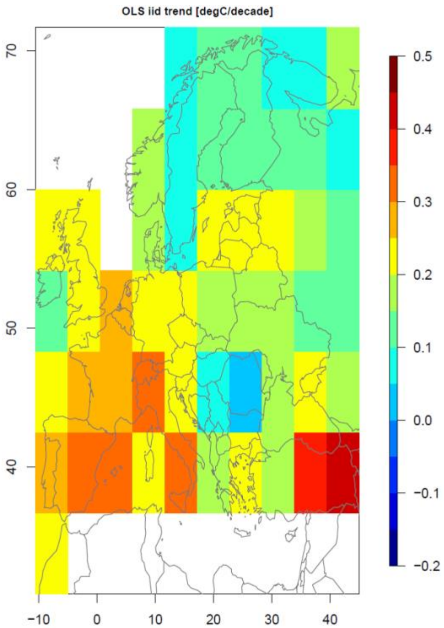


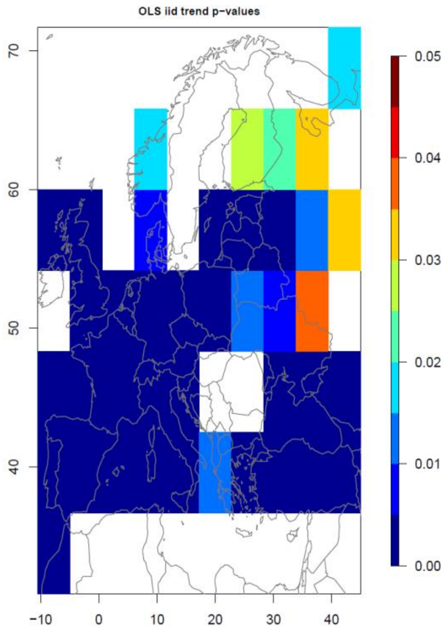
JJA	Trend	StErr	AR(1)
OLS iid	0.28	0.06	-
OLS AR(1)	0.28	0.08	0.35

JJA: 5deg resolution

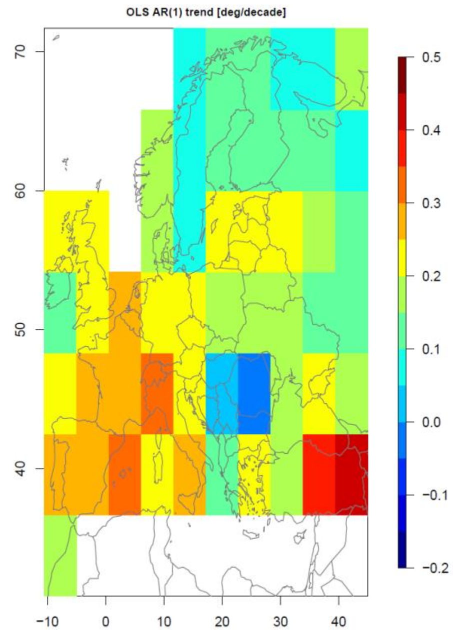


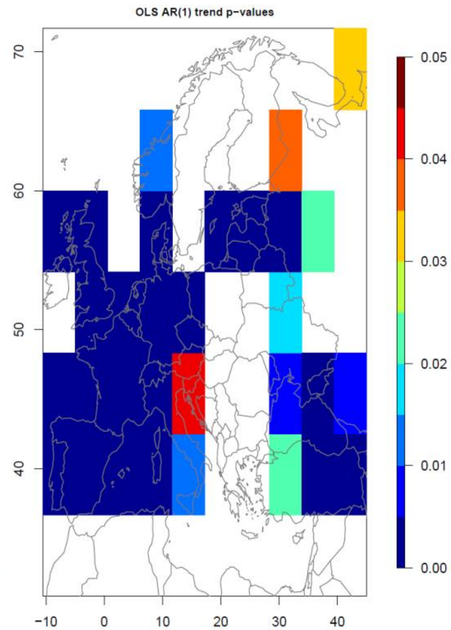
JJA mean temperatures





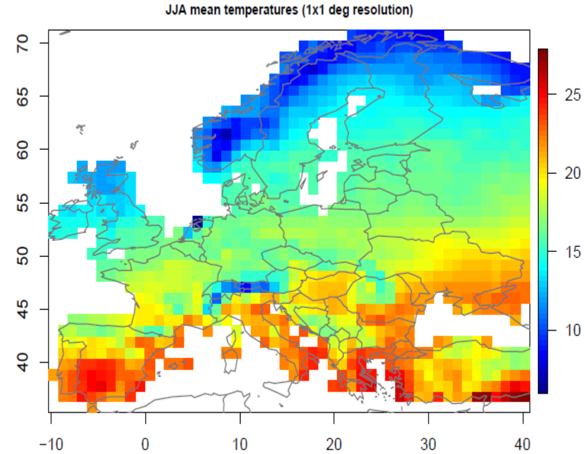
Model A: IID



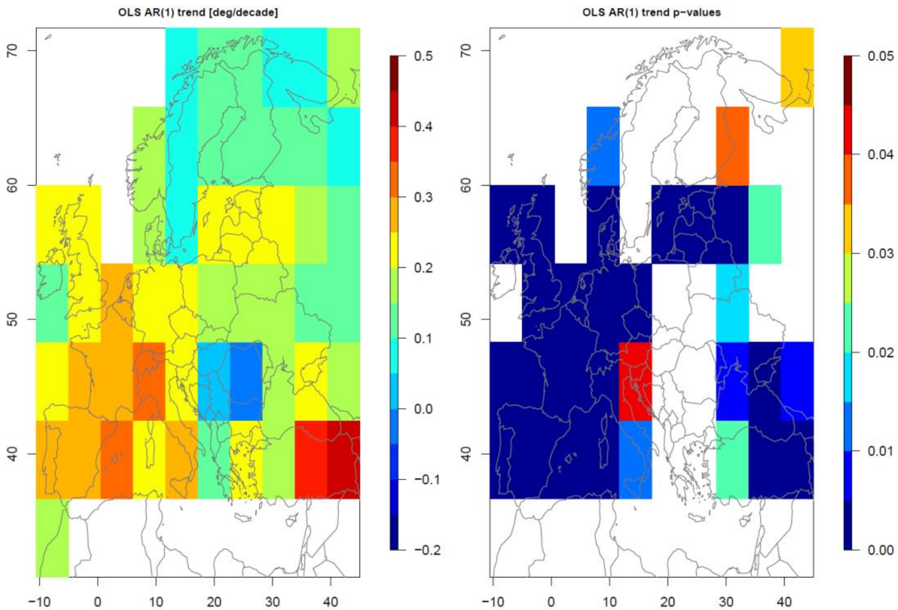


Model B: AR(1)

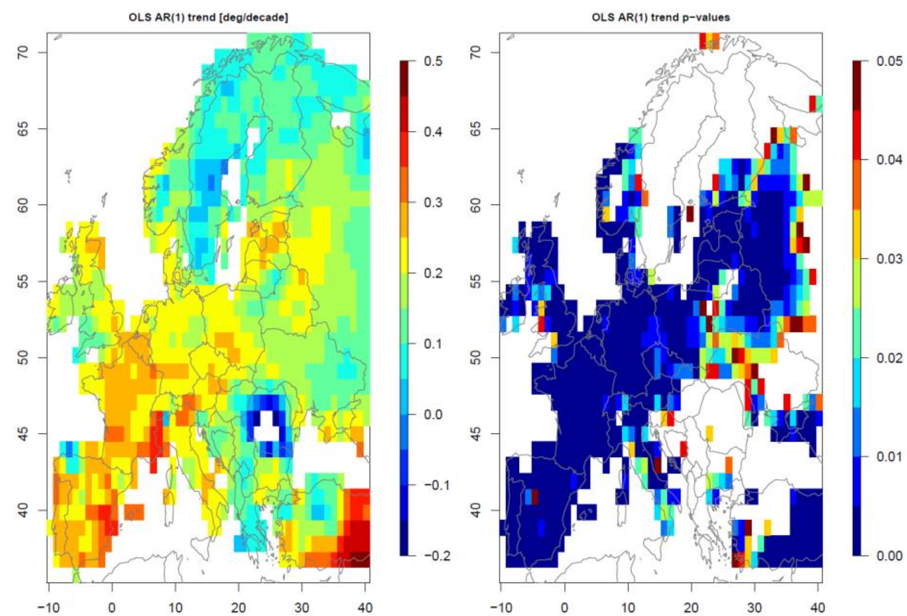
JJA: 5deg vs 1deg



JJA mean temperatures

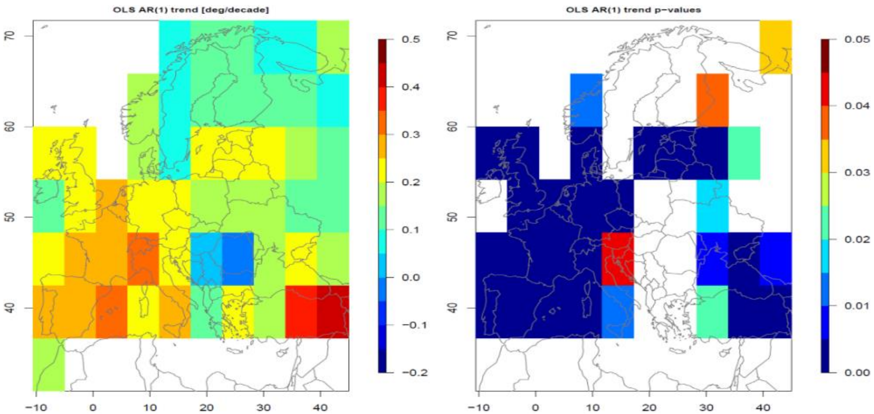


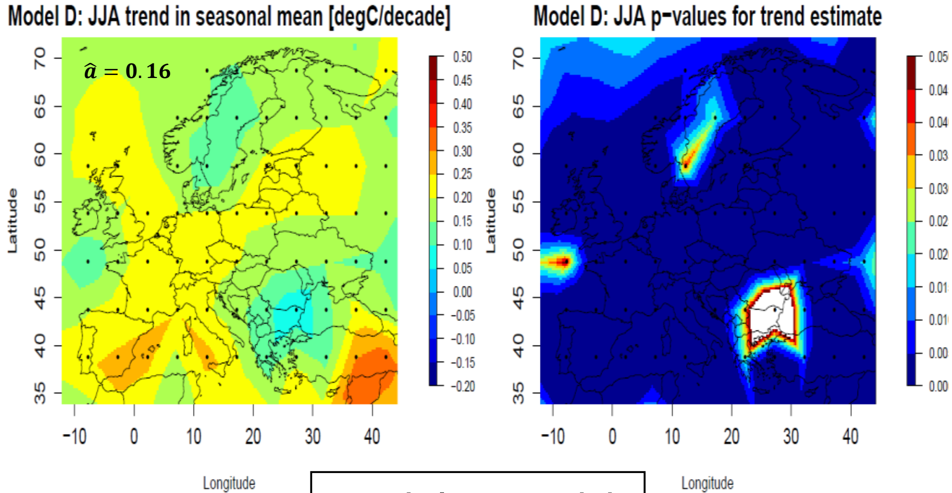
Model B: AR(1)



Model B: AR(1)

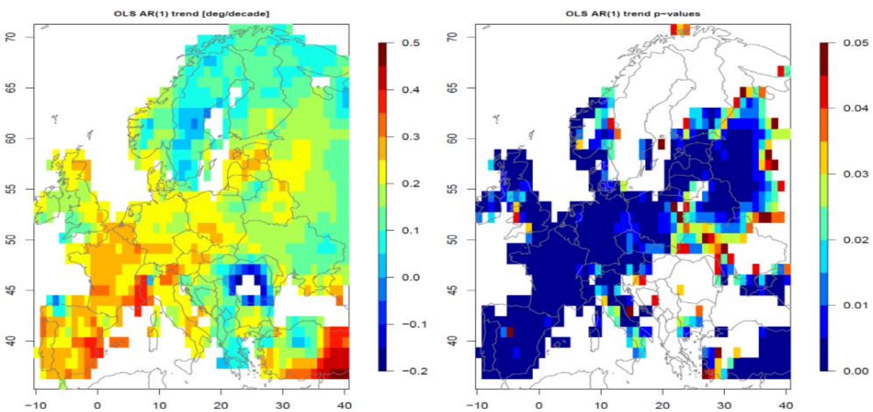
JJA: Add spatial structure (5deg, 1deg)

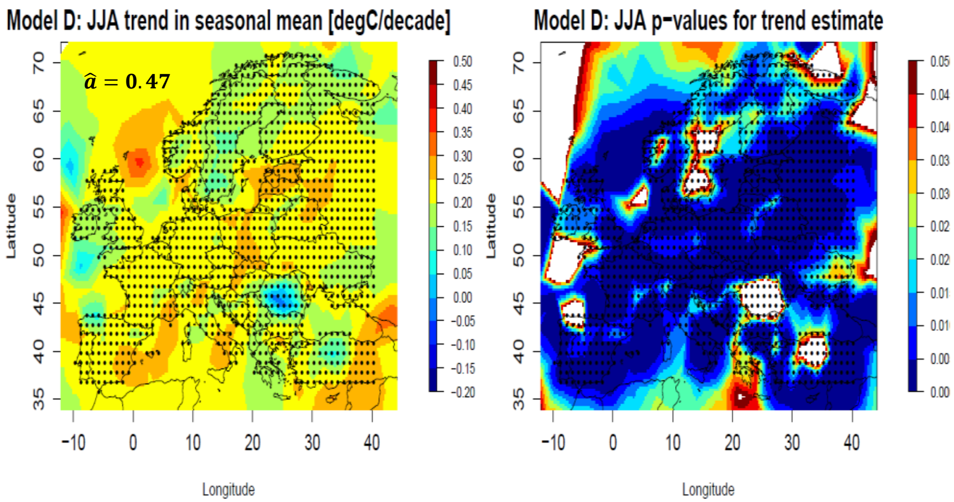




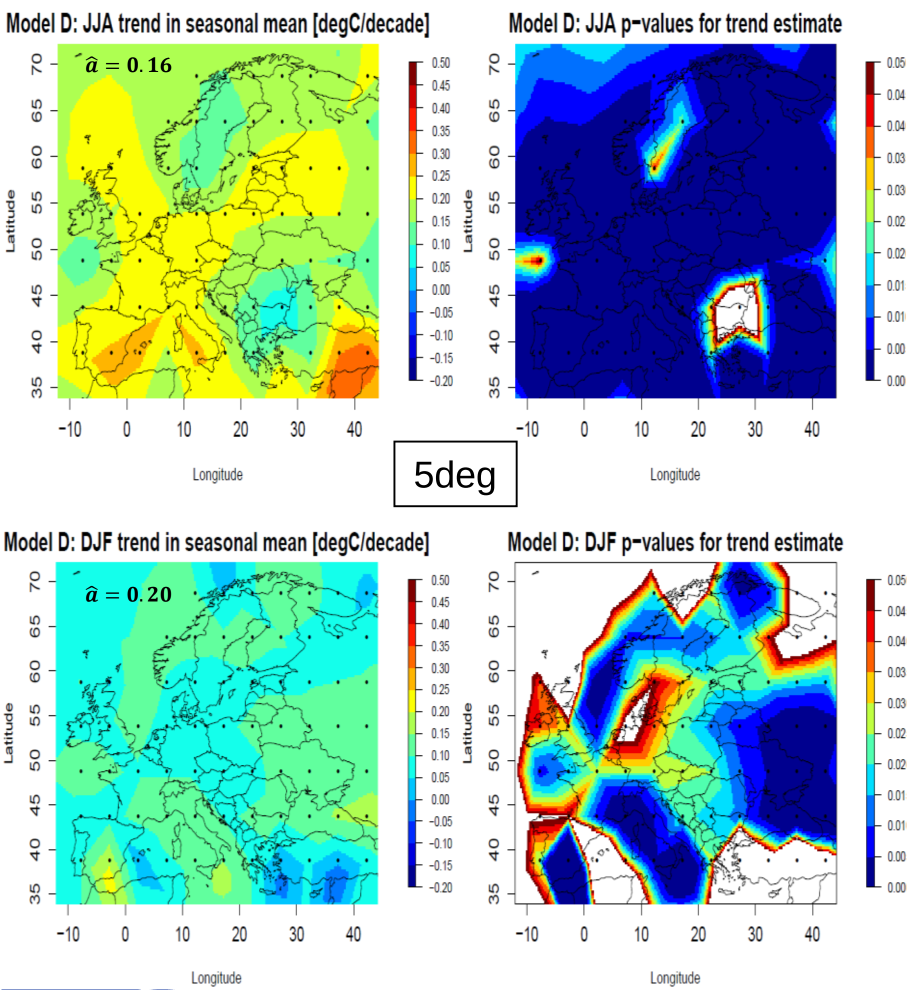
Model B: AR(1)

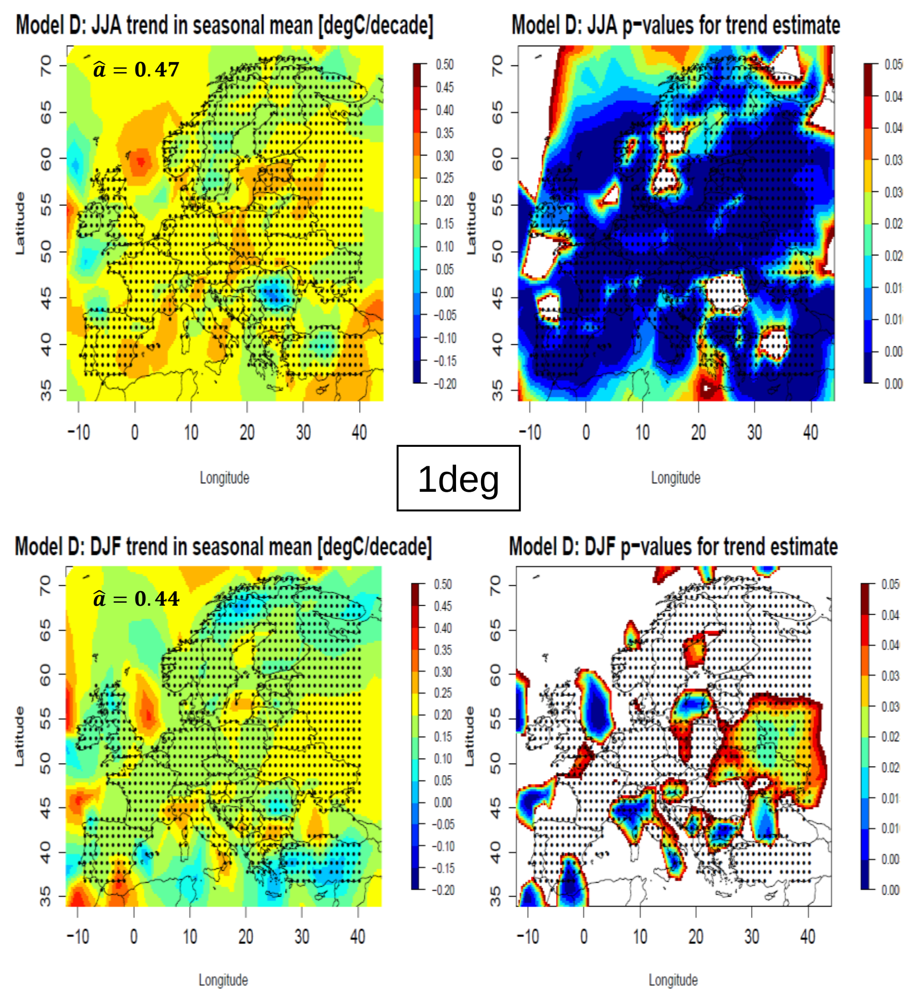
Model D: AR(1)





JJA vs DJF for spatial model





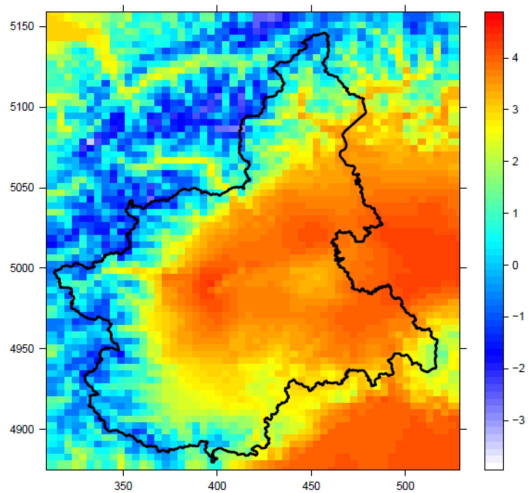
Excursion sets

- Aim: Identify regions with a significant temperature increase or decrease
- So far: Marginal p-values providing information about trend significance in every single grid point of a region *separately*
- Rather: Consider significance for the region as a whole
  - Excursion sets – contour avoiding regions
    - Concept that helps us identify the largest area so that, with some (high) probability 1-α, the trend is different from u=0 at *all locations* in that area
    - Closely linked to multiple testing

Reference:

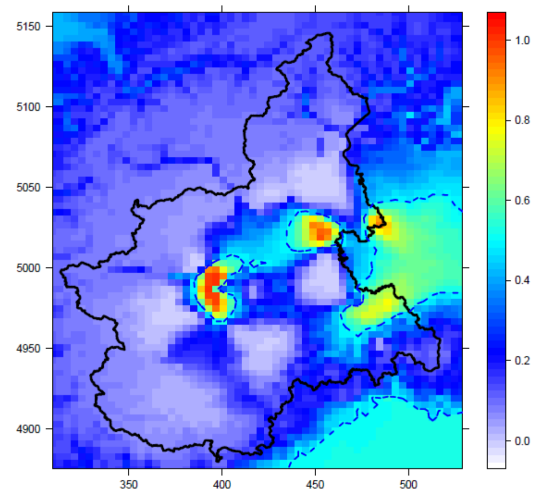
- Bolin and Lindgren *Excursion and contour uncertainty regions for latent Gaussian models* JRSS-B (2015)

Avoidance contour maps/Significance maps by excursion sets

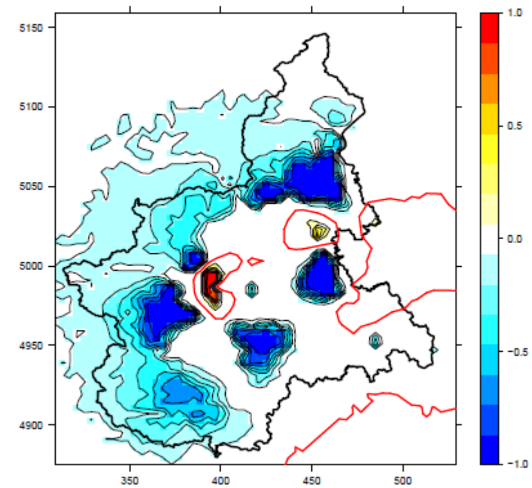


Posterior mean logPM10 on a certain day

Example: Air pollution (PM10)



Marginal probabilities



Signed avoidance contours

From a presentation by David Bolin, Chalmers University of Technology, Sweden

Summary

- Preliminary conclusions from marginal analysis
  - Significant summer temperature trends are indentified for most of Europe at all grid scales
  - Trends are stronger in summer than in winter for scales down to 5deg
  - 1deg winter trends are higher than those for 5deg, but the finer scale estimates are hardly significant. Indication of minimum skillful scale reached?
- Excursion sets will add strength to our results by referring to simultaneous significance for all locations in a region

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