Large scale spatial statistics

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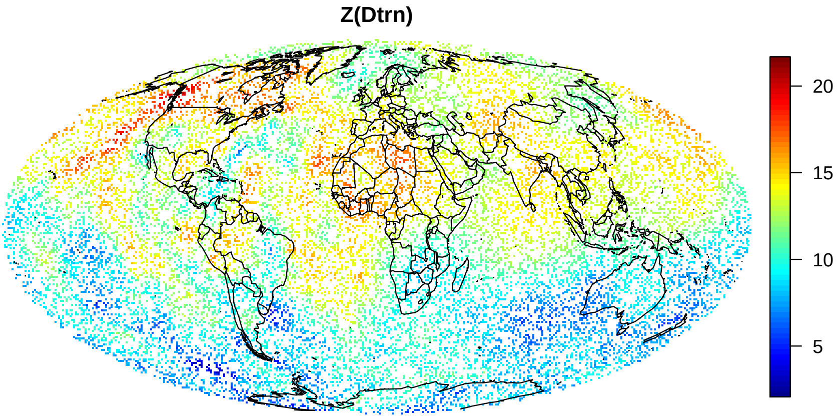
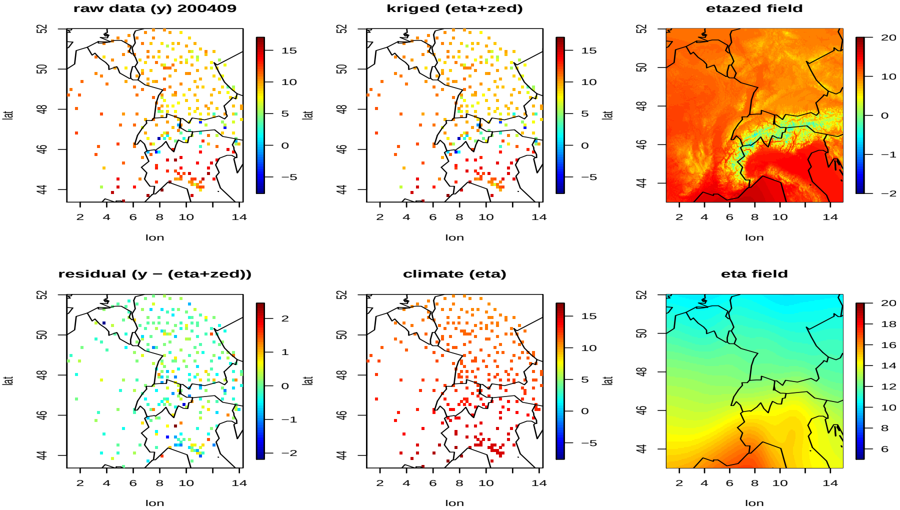
"Big" data



Synthetic data mimicking satellite based CO_2 measurements.
Iregular data locations, uneven coverage, and all scales need to be handled.

Sparse spatial coverage of temperature measurements



Regional observations: ≈ 20,000,000 from daily timeseries over 160 years

Note: This is a small *subset* of the full data!

Spatio-temporal modelling framework

Spatial statistics framework

- Spatial domain Ω, or space-time domain $\Omega \times \mathbb{T}$, $\mathbb{T} \subset \mathbb{R}$.
- Random field $u(\boldsymbol{s})$, $\boldsymbol{s} \in \Omega$, or $u(\boldsymbol{s}, t)$, $(\boldsymbol{s}, t) \in \Omega \times \mathbb{T}$.
- Observations y_i. In the simplest setting, $y_i = u(\boldsymbol{s}_i) + \epsilon_i$, but more generally $y_i \sim$ GLMM, with $u(\cdot)$ as a structured random effect.
- Needed: models capturing stochastic dependence on multiple scales
- Partial solution: Basis function expansions, with large scale functions and covariates to capture static and slow structures, and small scale functions for more local variability

Two basic model and method components

- Stochastic models for $u(\cdot)$.
- Computationally efficient (i.e. avoid MCMC whenever possible) inference methods for the posterior distribution of $u(\cdot)$ given data $\boldsymbol{y}$.

Covariance functions and stochastic PDEs

The Matérn covariance family on $\mathbb{R}^d$

$$\mathsf{Cov}(u(\mathbf{0}), u(\boldsymbol{s})) = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} (\kappa\|\boldsymbol{s}\|)^\nu K_\nu(\kappa\|\boldsymbol{s}\|)$$

Scale $\kappa > 0$, smoothness $\nu > 0$, variance $\sigma^2 > 0$

Whittle (1954, 1963): Matérn as SPDE solution

Matérn fields are the stationary solutions to the SPDE

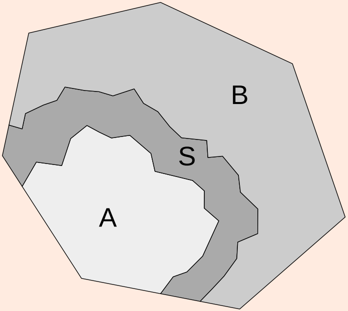
$$\left(\kappa^2 - \nabla \cdot \nabla\right)^{\alpha/2} u(\boldsymbol{s}) = \mathcal{W}(\boldsymbol{s}), \quad \alpha = \nu + d/2$$

$\mathcal{W}(\cdot)$ white noise, $\nabla \cdot \nabla = \sum_{i=1}^d \frac{\partial^2}{\partial s_i^2}$, $\sigma^2 = \frac{\Gamma(\nu)}{\Gamma(\alpha)\kappa^{2\nu}(4\pi)^{d/2}}$
(Continuous domain white noise, $\mathsf{E}(\mathcal{W}(A)) = 0$, and $\mathsf{Cov}(\mathcal{W}(A), \mathcal{W}(B)) = |A \cap B|$, for all measurable $A, B \subseteq \mathbb{R}^d$. Not to be confused with pointwise independent noise.)

Continuous and discrete Markov properties

Markov properties

S is a separating set for A and B: $u(A) \perp u(B) \mid u(S)$



Solutions to

$$\left(\kappa^2 - \nabla \cdot \nabla\right)^{\alpha/2} u(\boldsymbol{s}) = \mathcal{W}(\boldsymbol{s})$$

are Markov when α is an integer. (Rozanov, 1977)

Discrete representations ($\boldsymbol{Q} = \boldsymbol{\Sigma}^{-1}$):

$$\boldsymbol{Q}_{AB} = \boldsymbol{0}$$

$$\boldsymbol{Q}_{A|S,B} = \boldsymbol{Q}_{AA}$$

$$\boldsymbol{\mu}_{A|S,B} = \boldsymbol{\mu}_A - \boldsymbol{Q}_{AA}^{-1}\boldsymbol{Q}_{AS}(\boldsymbol{u}_S - \boldsymbol{\mu}_S)$$

Continuous domain Markov approximations

Continuous Markovian spatial models (Lindgren et al, 2011)

Local basis: $u(\boldsymbol{s}) = \sum_k \psi_k(\boldsymbol{s}) u_k$, (compact, piecewise linear)

Basis weights: $\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}^{-1})$, sparse $\boldsymbol{Q}$ based on an SPDE

Special case: $(\kappa^2 - \nabla \cdot \nabla) u(\boldsymbol{s}) = \mathcal{W}(\boldsymbol{s})$, $\boldsymbol{s} \in \Omega$

Precision: $\boldsymbol{Q} = \kappa^4 \boldsymbol{C} + 2\kappa^2 \boldsymbol{G} + \boldsymbol{G}_2$ $(\kappa^4 + 2\kappa^2 |\boldsymbol{\omega}|^2 + |\boldsymbol{\omega}|^4)$

Conditional distribution in a Gaussian model

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{\mu}_u, \boldsymbol{Q}_u^{-1}), \quad \boldsymbol{y}|\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{A}\boldsymbol{u}, \boldsymbol{Q}_{y|u}^{-1}) \qquad (A_{ij} = \psi_j(\boldsymbol{s}_i))$$

$$\boldsymbol{u}|\boldsymbol{y} \sim \mathcal{N}(\boldsymbol{\mu}_{u|y}, \boldsymbol{Q}_{u|y}^{-1})$$

$$\boldsymbol{Q}_{u|y} = \boldsymbol{Q}_u + \boldsymbol{A}^T \boldsymbol{Q}_{y|u} \boldsymbol{A}$$ (∼"Sparse iff ψ_k have compact support")

$$\boldsymbol{\mu}_{u|y} = \boldsymbol{\mu}_u + \boldsymbol{Q}_{u|y}^{-1} \boldsymbol{A}^T \boldsymbol{Q}_{y|u} (\boldsymbol{y} - \boldsymbol{A}\boldsymbol{\mu}_u)$$

We've translated the spatial inference problem into sparse numerical linear algebra similar to finite element PDE solvers

The computational GMRF work-horse

Cholesky decomposition (Cholesky, 1924)

$\boldsymbol{Q} = \boldsymbol{L}\boldsymbol{L}^\top$, $\boldsymbol{L}$ lower triangular ($\sim \mathcal{O}(n^{(d+1)/2})$ for $d = 1, 2, 3$)

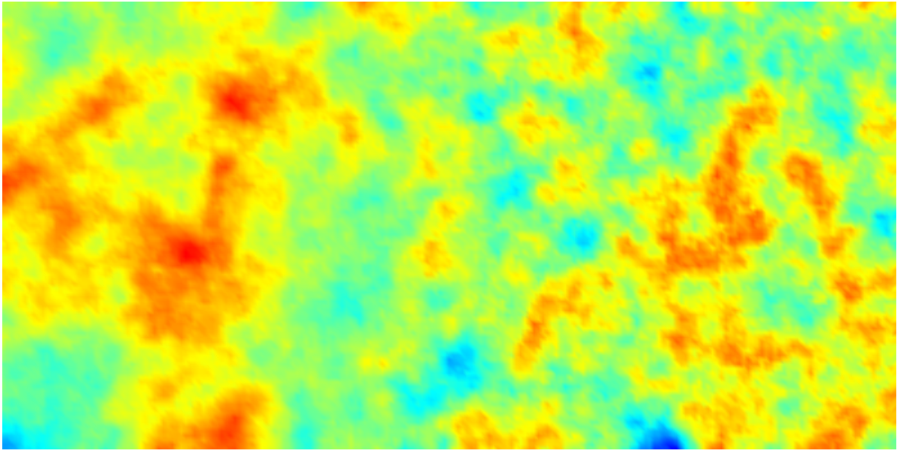
$\boldsymbol{Q}^{-1}\boldsymbol{x} = \boldsymbol{L}^{-\top}\boldsymbol{L}^{-1}\boldsymbol{x}$, via forward/backward substitution

$$\log\det\boldsymbol{Q} = 2\log\det\boldsymbol{L} = 2\sum_i \log L_{ii}$$

André-Louis Cholesky (1875–1918)

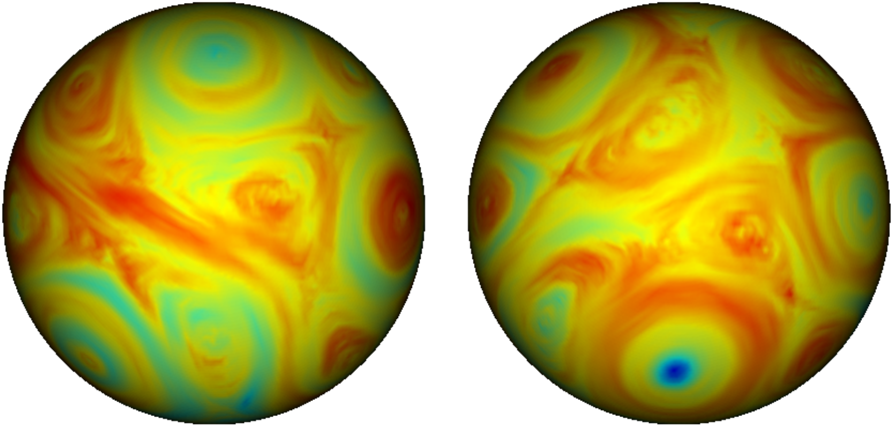
"He invented, for the solution of the condition equations in the method of least squares, a very ingenious computational procedure which immediately proved extremely useful, and which most assuredly would have great benefits for all geodesists, if it were published some day." (Euology by Commandant Benoit, 1922)

Non-stationary field



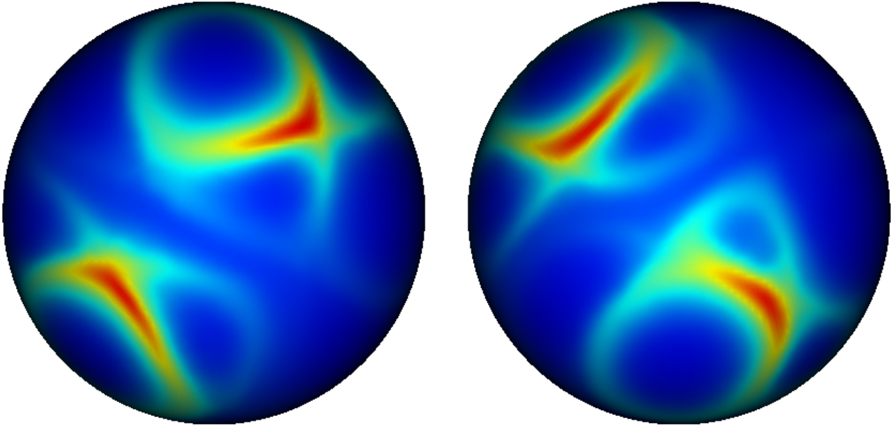
$$(\kappa(\boldsymbol{s})^2 - \nabla \cdot \nabla) u(\boldsymbol{s}) = \kappa(\boldsymbol{s}) \mathcal{W}(\boldsymbol{s}), \quad \boldsymbol{s} \in \Omega$$

Anisotropic field on a globe via vector parameter field



$$(\kappa(\boldsymbol{s})^2 - \nabla \cdot \boldsymbol{H}(\boldsymbol{s})\nabla) u(\boldsymbol{s}) = \kappa(\boldsymbol{s})\mathcal{W}(\boldsymbol{s}), \quad \boldsymbol{s} \in \Omega$$

Covariances for four reference points



Climate and weather model (simplified)

- Climate process, simplified stochastic heat equation

$$\frac{\partial}{\partial t} z(\boldsymbol{s}, t) - \nabla \cdot \nabla z(\boldsymbol{s}, t) = \mathcal{E}(\boldsymbol{s}, t)$$
$$(1 - \gamma_{\mathcal{E}} \nabla \cdot \nabla)\mathcal{E}(\boldsymbol{s}, t) = \mathcal{W}_{\mathcal{E}}(\boldsymbol{s}, t)$$

- Weather anomaly, non-stationary spatial SPDE/GMRF
  $(\kappa(\boldsymbol{s})^2 - \nabla \cdot \nabla)(\tau(\boldsymbol{s}) a(\boldsymbol{s}, t)) = \mathcal{W}_a(\boldsymbol{s}, t)$
- Temperature measurements from one or several sources
  $y_i = a(\boldsymbol{s}_i, t_i) + z(\boldsymbol{s}_i, t_i) + \epsilon_i$, discretised into
  $\boldsymbol{y} = \boldsymbol{A}(\boldsymbol{a} + (\boldsymbol{B} \otimes \boldsymbol{I})\boldsymbol{z}) + \boldsymbol{\epsilon}$, $\boldsymbol{\epsilon} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}_{\epsilon}^{-1})$

The posterior precision can be formulated for $(a + z, z)|y$:

$$\boldsymbol{Q}_{(a+z,z)|y} = \begin{bmatrix} \boldsymbol{I} \otimes \boldsymbol{Q}_a + \boldsymbol{A}^\top \boldsymbol{Q}_\epsilon \boldsymbol{A} & -\boldsymbol{B} \otimes \boldsymbol{Q}_a \\ -\boldsymbol{B}^\top \otimes \boldsymbol{Q}_a & \boldsymbol{Q}_z + \boldsymbol{B}^\top \boldsymbol{B} \otimes \boldsymbol{Q}_a \end{bmatrix}$$

Locally isotropic non-stationary precision construction

Finite element construction of basis weight precision

Non-stationary SPDE:

$$\left(\kappa(\boldsymbol{s})^2 - \nabla\cdot\nabla\right)\left(\tau(\boldsymbol{s})u(\boldsymbol{s})\right) = \mathcal{W}(\boldsymbol{s})$$

The SPDE parameters are constructed via spatial covariates:

$$\log\tau(\boldsymbol{s}) = b_0^\tau(\boldsymbol{s}) + \sum_{j=1}^p b_j^\tau(\boldsymbol{s})\theta_j, \quad \log\kappa(\boldsymbol{s}) = b_0^\kappa(\boldsymbol{s}) + \sum_{j=1}^p b_j^\kappa(\boldsymbol{s})\theta_j$$

Finite element calculations give

$$\boldsymbol{T} = \mathrm{diag}(\tau(\boldsymbol{s}_i)), \quad \boldsymbol{K} = \mathrm{diag}(\kappa(\boldsymbol{s}_i))$$

$$C_{ii} = \int \psi_i(\boldsymbol{s})\,d\boldsymbol{s}, \quad G_{ij} = \int \nabla\psi_i(\boldsymbol{s})\cdot\nabla\psi_j(\boldsymbol{s})\,d\boldsymbol{s}$$

$$\boldsymbol{Q} = \boldsymbol{T}\left(\boldsymbol{K}^2\boldsymbol{C}\boldsymbol{K}^2 + \boldsymbol{K}^2\boldsymbol{G} + \boldsymbol{G}\boldsymbol{K}^2 + \boldsymbol{G}\boldsymbol{C}^{-1}\boldsymbol{G}\right)\boldsymbol{T}$$

For the temporally independent anomalies, we get $\boldsymbol{I}\otimes\boldsymbol{Q}_a$

GMRF precision for simplified stochastic heat equation

$$
\begin{aligned}
\boldsymbol{Q}_z &= \boldsymbol{M}_2^{(t)} \otimes \boldsymbol{M}_0^{(s)} + \boldsymbol{M}_1^{(t)} \otimes \boldsymbol{M}_1^{(s)} + \boldsymbol{M}_0^{(t)} \otimes \boldsymbol{M}_2^{(s)} \\
\boldsymbol{M}_0^{(s)} &= \boldsymbol{C} + \gamma_{\mathcal{E}} \boldsymbol{G} \\
\boldsymbol{M}_1^{(s)} &= \boldsymbol{G} + \gamma_{\mathcal{E}} \boldsymbol{G} \boldsymbol{C}^{-1} \boldsymbol{G} \\
\boldsymbol{M}_2^{(s)} &= \boldsymbol{G} \boldsymbol{C}^{-1} \boldsymbol{G} + \gamma_{\mathcal{E}} \boldsymbol{G} \boldsymbol{C}^{-1} \boldsymbol{G} \boldsymbol{C}^{-1} \boldsymbol{G}
\end{aligned}
$$

Ignoring the degenerate aspect of the model, the precision structure can be used to formulate sampling as

$$
\boldsymbol{Q}_z \boldsymbol{z} = \widetilde{\boldsymbol{L}}_z \boldsymbol{w}, \quad \boldsymbol{w} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})
$$

where $\widetilde{\boldsymbol{L}}_z$ is a pseudo Cholesky factor,

$$
\begin{aligned}
\widetilde{\boldsymbol{L}}_z = \Big[&\Big[\boldsymbol{L}_2^{(t)} \otimes \boldsymbol{L}_C, \quad \boldsymbol{L}_1^{(t)} \otimes \boldsymbol{L}_G, \quad \boldsymbol{L}_0^{(t)} \otimes \boldsymbol{G} \boldsymbol{L}_C^{-\top} \Big], \\
&\gamma_{\mathcal{E}}^{1/2} \Big[\boldsymbol{L}_2^{(t)} \otimes \boldsymbol{L}_G, \quad \boldsymbol{L}_1^{(t)} \otimes \boldsymbol{G} \boldsymbol{L}_C^{-\top}, \quad \boldsymbol{L}_0^{(t)} \otimes \boldsymbol{G} \boldsymbol{C}^{-1} \boldsymbol{L}_G \Big] \Big]
\end{aligned}
$$

Posterior calculations

Write $x = (a + z, z)$ for the full latent field.

$$\boldsymbol{Q}_{x|y} = \begin{bmatrix} \boldsymbol{I} \otimes \boldsymbol{Q}_a + \boldsymbol{A}^\top \boldsymbol{Q}_\epsilon \boldsymbol{A} & -\boldsymbol{B} \otimes \boldsymbol{Q}_a \\ -\boldsymbol{B}^\top \otimes \boldsymbol{Q}_a & \boldsymbol{Q}_z + \boldsymbol{B}^\top \boldsymbol{B} \otimes \boldsymbol{Q}_a \end{bmatrix}$$

can be pseudo-Cholesky-factorised:

$$\boldsymbol{Q}_{x|y} = \widetilde{\boldsymbol{L}}_{x|y} \widetilde{\boldsymbol{L}}_{x|y}^\top, \qquad \widetilde{\boldsymbol{L}}_{x|y} = \begin{bmatrix} \boldsymbol{I} \otimes \boldsymbol{L}_a & \boldsymbol{0} & \boldsymbol{A}^\top \boldsymbol{L}_\epsilon \\ -\boldsymbol{B} \otimes \boldsymbol{L}_a & \widetilde{\boldsymbol{L}}_z & \boldsymbol{0} \end{bmatrix}$$

Posterior expectation, samples, and marginal variances:

$$\boldsymbol{Q}_{x|y}(\boldsymbol{\mu}_{x|y} - \boldsymbol{\mu}_x) = \boldsymbol{A}^\top \boldsymbol{Q}_\epsilon (\boldsymbol{y} - \boldsymbol{\mu}_x),$$

$$\boldsymbol{Q}_{x|y}(\boldsymbol{x} - \boldsymbol{\mu}_{x|y}) = \widetilde{\boldsymbol{L}}_{x|y} \boldsymbol{w}, \quad \boldsymbol{w} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}), \quad \text{or}$$

$$\boldsymbol{Q}_{x|y}(\boldsymbol{x} - \boldsymbol{\mu}_x) = \boldsymbol{A}^\top \boldsymbol{Q}_\epsilon (\boldsymbol{y} - \boldsymbol{\mu}_x) + \widetilde{\boldsymbol{L}}_{x|y} \boldsymbol{w}, \quad \boldsymbol{w} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}),$$

$$\mathsf{Var}(x_i | \boldsymbol{y}) = \texttt{diag(inla.qinv(}\boldsymbol{Q}_{x|y}\texttt{))} \quad \text{(requires Cholesky)}$$

Preconditioning for e.g. conjugate gradient solutions

Solving $\boldsymbol{Q}\boldsymbol{x} = \boldsymbol{b}$ is equivalent to solving $\boldsymbol{M}^{-1}\boldsymbol{Q}\boldsymbol{x} = \boldsymbol{M}^{-1}\boldsymbol{b}$. Choosing $\boldsymbol{M}^{-1}$ as an approximate inverse to $\boldsymbol{Q}$ gives a less ill-conditioned system. Only the *action* of $\boldsymbol{M}^{-1}$ is needed, e.g. one or more fixed point iterations:

Block Jacobi and Gauss-Seidel preconditioning

Matrix split: $\boldsymbol{Q}_{x|y} = \boldsymbol{L} + \boldsymbol{D} + \boldsymbol{L}^\top$

Jacobi: $\boldsymbol{x}^{(k+1)} = \boldsymbol{D}^{-1}\left(-(\boldsymbol{L} + \boldsymbol{L}^\top)\boldsymbol{x}^{(k)} + \boldsymbol{b}\right)$

Gauss-Seidel: $\boldsymbol{x}^{(k+1)} = (\boldsymbol{L} + \boldsymbol{D})^{-1}\left(-\boldsymbol{L}^\top\boldsymbol{x}^{(k)} + \boldsymbol{b}\right)$

Remark: Block Gibbs sampling for a GMRF posterior

With $\boldsymbol{Q} = \boldsymbol{Q}_{x|y}$, $\boldsymbol{b} = \boldsymbol{A}^\top\boldsymbol{Q}_\epsilon(\boldsymbol{y} - \boldsymbol{\mu}_x)$ and $\widetilde{\boldsymbol{x}} = \boldsymbol{x} - \boldsymbol{\mu}_x$,

$$\widetilde{\boldsymbol{x}}^{(k+1)} = (\boldsymbol{L} + \boldsymbol{D})^{-1}\left(-\boldsymbol{L}^\top\widetilde{\boldsymbol{x}}^{(k)} + \boldsymbol{b} + \widetilde{\boldsymbol{L}}_D\boldsymbol{w}\right), \quad \boldsymbol{w} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$$

Multiscale Schur complement approximation

Solving $Q_{x|y}x = b$ can be formulated using two solves with the upper block $I \otimes Q_a + A^\top Q_\epsilon A$, and one solve with the *Schur complement*

$$Q_z + B^\top B \otimes Q_a - B^\top \otimes Q_a \left(I \otimes Q_a + A^\top Q_\epsilon A\right)^{-1} B \otimes Q_a$$

By mapping the fine scale anomaly model onto the coarse basis used for the climate model, we get an *approximate* (and sparse) Schur solve via

$$\begin{bmatrix} \widetilde{Q}_B + \widetilde{B}^\top A^\top Q_\epsilon A \widetilde{B} & -\widetilde{Q}_B \\ -\widetilde{Q}_B & Q_z + \widetilde{Q}_B \end{bmatrix} \begin{bmatrix} \text{ignored} \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ \widetilde{b} \end{bmatrix}$$

where $\widetilde{B} = B \otimes I$, $\widetilde{Q}_B = B^\top B \otimes Q_a$, and the block matrix can be interpreted as the precision of a bivariate field on a common, coarse spatio-temporal scale.

Multigrid

Construct a sequence of increasingly detailed models, $\left(\boldsymbol{Q}^{(0)}, \boldsymbol{Q}^{(1)}, \ldots, \boldsymbol{Q}^{(L)}\right)$.

Basic idea:

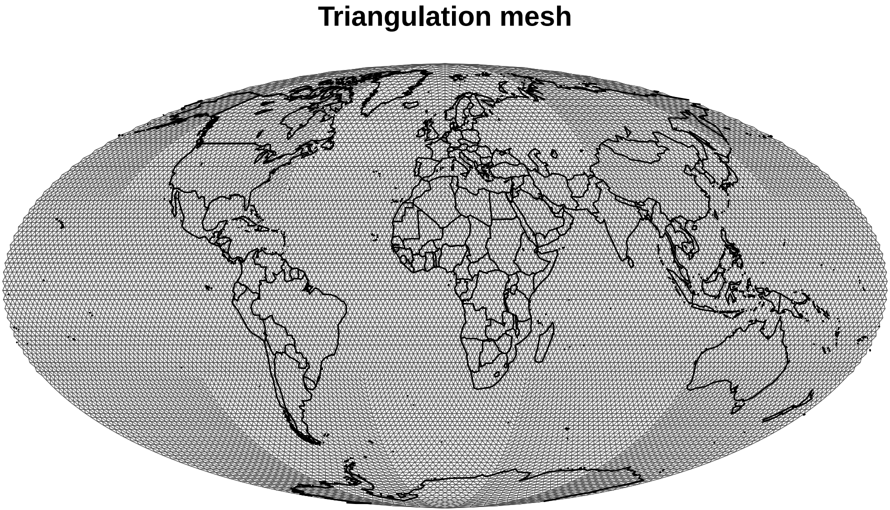
- On each level, a simple local fixed point iteration can eliminate small scale residual errors efficiently, but not large scale errors.
- Project the residual onto the next coarse level, where the large scale is now small, and then interpolate the result back onto the finer level.
- On the coarsest level, solve the exact problem.

Simple multigrid model traversal: $L = 4, 3, 2, 1, 0, 1, 2, 3, 4 = L$
Full multigrid: $L = 4, 3, 2, 1, 0, 1, 0, 1, 2, 1, 0, 1, 2, 3, 2, 1, 0, 1, 2, 3, 4 = L$

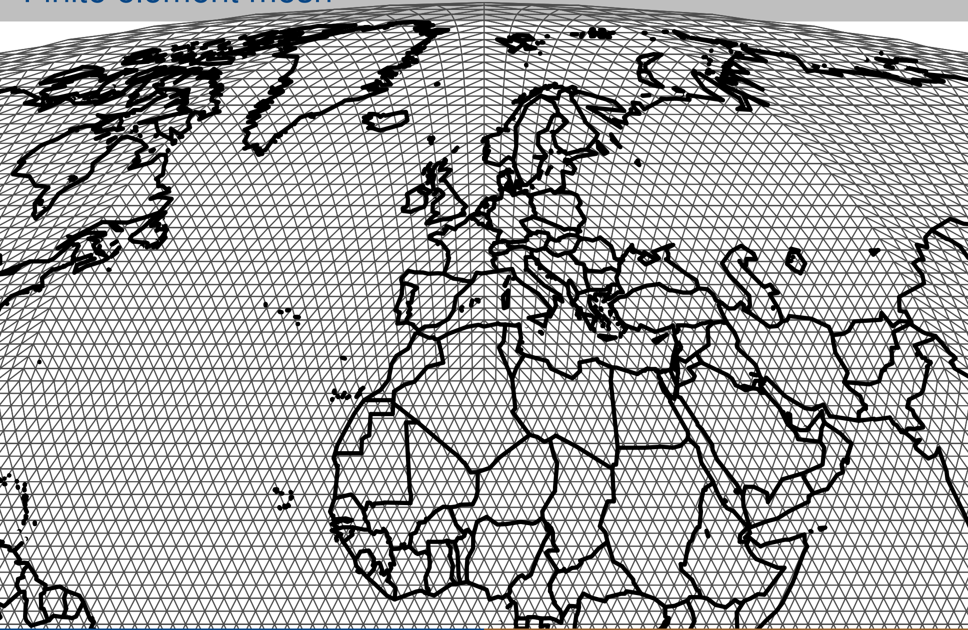
In theory, full multigrid can be $\mathcal{O}(n)$!

Can be used as complete solver with small tolerance, or as preconditioner with large tolerance.

Finite element mesh



Finite element mesh



Domain decomposition

- Divide the domain into a collection of overlapping subdomain blocks
- Solve a local problem, e.g. the conditional solution, maintaining coherence by enforcing constraints on overlapping nodes.

Monte Carlo variance reduction for posterior variances

$$\mathsf{E}(\boldsymbol{x}_i \mid \boldsymbol{y}) = \mathsf{E}\left(\mathsf{E}(\boldsymbol{x}_i \mid \boldsymbol{y}, \boldsymbol{x}_{\notin\text{subblock}})\right)$$

$$\mathsf{Var}(\boldsymbol{x}_i \mid \boldsymbol{y}) = \mathsf{Var}\left(\boldsymbol{x}_i \mid \boldsymbol{y}, \boldsymbol{x}_{\notin\text{subblock}}\right) + \mathsf{Var}\left(\mathsf{E}(\boldsymbol{x}_i \mid \boldsymbol{y}, \boldsymbol{x}_{\notin\text{subblock}})\right)$$

Also works for linear combinations, with some complications

Subdomain boundary adjustment (new idea)

- Apply stochastic boundary correction for each subdomain
- Solve the full local problem, reusing the appropriate randomness for overlapping subdomains
- Blend the results for overlapping domains.
- Apply this as a preconditioner in an iterative solver

Laplace approximations for non-Gaussian observations

Quadratic posterior log-likelihood approximation

$$p(\boldsymbol{u} \mid \boldsymbol{\theta}) \sim \mathcal{N}(\boldsymbol{\mu}_u, \boldsymbol{Q}_u^{-1}), \quad \boldsymbol{y} \mid \boldsymbol{u}, \boldsymbol{\theta} \sim p(\boldsymbol{y} \mid \boldsymbol{u})$$

$$p_G(\boldsymbol{u} \mid \boldsymbol{y}, \boldsymbol{\theta}) \sim \mathcal{N}(\widetilde{\boldsymbol{\mu}}, \widetilde{\boldsymbol{Q}}^{-1})$$

$$\mathbf{0} = \nabla_{\boldsymbol{u}} \left\{ \ln p(\boldsymbol{u} \mid \boldsymbol{\theta}) + \ln p(\boldsymbol{y} \mid \boldsymbol{u}) \right\} \big|_{\boldsymbol{u}=\widetilde{\boldsymbol{\mu}}}$$

$$\widetilde{\boldsymbol{Q}} = \boldsymbol{Q}_u - \nabla_{\boldsymbol{u}}^2 \ln p(\boldsymbol{y} \mid \boldsymbol{u}) \big|_{\boldsymbol{u}=\widetilde{\boldsymbol{\mu}}}$$

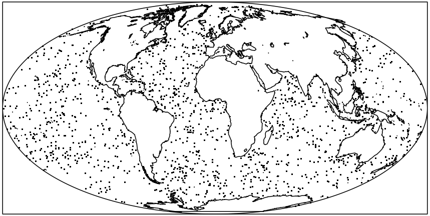
Direct Bayesian inference with INLA (`r-inla.org`)

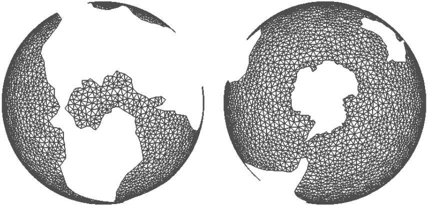
$$\widetilde{p}(\boldsymbol{\theta} \mid \boldsymbol{y}) \propto \left. \frac{p(\boldsymbol{\theta}) p(\boldsymbol{u} \mid \boldsymbol{\theta}) p(\boldsymbol{y} \mid \boldsymbol{u}, \boldsymbol{\theta})}{p_G(\boldsymbol{u} \mid \boldsymbol{y}, \boldsymbol{\theta})} \right|_{\boldsymbol{u}=\widetilde{\boldsymbol{\mu}}}$$

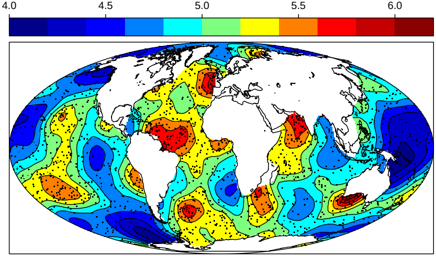
$$\widetilde{p}(\boldsymbol{u}_i \mid \boldsymbol{y}) \propto \int p_{GG}(\boldsymbol{u}_i \mid \boldsymbol{y}, \boldsymbol{\theta}) \widetilde{p}(\boldsymbol{\theta} \mid \boldsymbol{y}) \, d\boldsymbol{\theta}$$

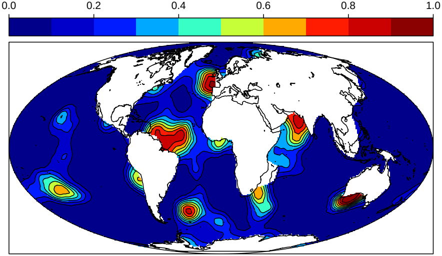
The latent Gaussian parts to some degree do scale to large non direct methods, but evaluating likelihoods becomes a very challenging problem.

SPDE based inference for point process data









Excursion sets for random fields

Excursion sets

Let $x(s)$, $s \in \Omega$ be a random process. The positive and negative level u excursion sets with probability $1-\alpha$ are

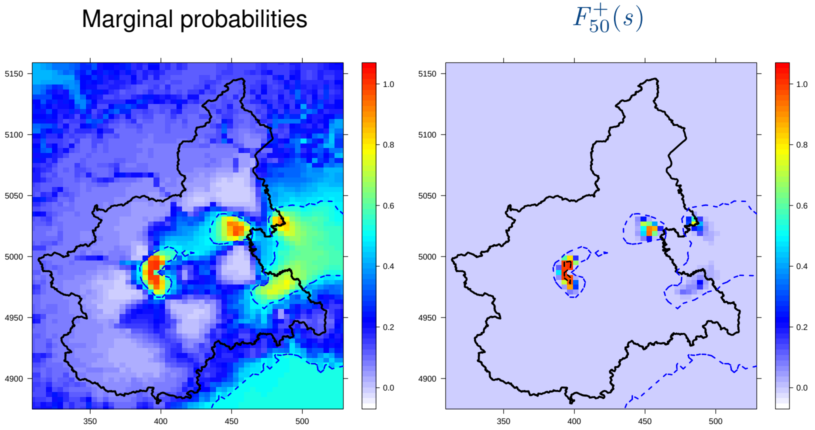
$$E^+_{u,\alpha}(x) = \operatorname*{argmax}_D \{|D| : \text{Pr}(D \subseteq A^+_u(x)) \geq 1-\alpha\}.$$
$$E^-_{u,\alpha}(x) = \operatorname*{argmax}_D \{|D| : \text{Pr}(D \subseteq A^-_u(x)) \geq 1-\alpha\}.$$

Excursion functions

The positive and negative u excursion functions are given by

$$F^+_u(s) = \sup\{1-\alpha; s \in E^+_{u,\alpha}\},$$
$$F^-_u(s) = \sup\{1-\alpha; s \in E^-_{u,\alpha}\}.$$

PM_{10} exceedances in Piemonte, January 30, 2006



Model estimated with INLA, result passed onward to `excursions()`, evaluating high dimensional GMRF probabilities and finding credible regions. latest version has user friendly options for continuous domain interpretations.

References

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  Development: `http://bitbucket.org/davidbolin/excursions`