Pragmatically ambitious multiscale global temperature reconstruction

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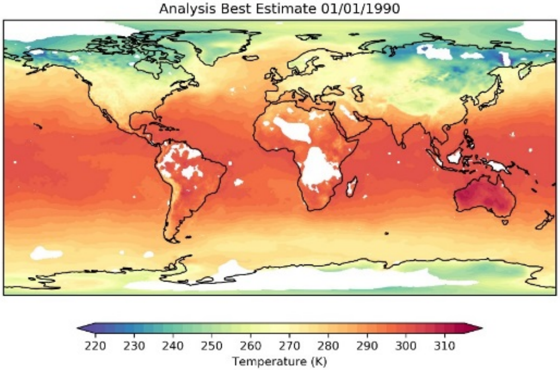
EUSTACE ANALYSIS

Combines in-situ and satellite data sources to derive daily air temperatures across the globe with quantified uncertainties.

- Daily mean air temperature (2 m) estimates from the mid-late 19th century at ¼ degree resolution.
- Observational dataset for use in climate monitoring, services and research.
  - Quantify bias and uncertainty arising from observational sampling (in space and time);
  - Quantify uncertainty from instrumental effects/network changes.
- Higher resolution daily gridded analyses for regional climate
  - Combine in situ and remote sensing data to support high resolution analysis.
  - Absolute temperature rather than anomaly product.



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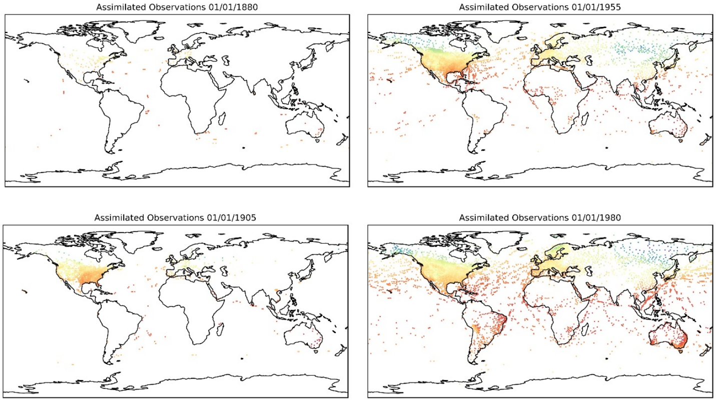
OBSERVATIONS

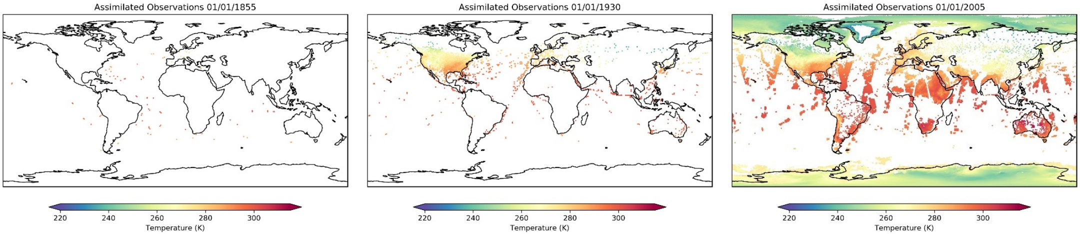
In situ air temperature:

- EUSTACE station dataset (UBERN) (GHCN-D, ECA&D, ISTI, DECADE, ERA-CLIM)
- HadNMAT-2 ship air temperatures (NOCS/Met Office)

Satellite skin temperature derived air temperature:

- Marine: ATSR (ESA CCI SST)
- Land: MODIS (USGS/NASA via ESA GlobTemperature)
- Ice: AVHRR (NOAA/FP7 NACLIM)





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Statistical model and method building blocks

Basic system components

- Temperature *processes on different spatial and temporal scales*
  - Seasonal
  - Slow climate processes
  - Medium-scale variability
  - Daily
- *Vast model size* ($\sim 10^{11}$ unknowns); need computationally efficient tools
- Hierarchical statistical model structure based on Gaussian processes
  - Stochastic PDEs translates to sparse precisions in *Gaussian Markov random fields*
- *Propagated uncertainty* via a Bayesian approach
  - Dependence structure parameters
  - Spatio-temporal process priors
  - Observation models; Multiple *observation sources*, with complex error *uncertainty structure*
- Goals:
  - a *best estimate*,
  - a *collection of samples*, and
  - more precise (and accurate) *uncertainty estimates*.

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Matérn driven heat equation on the sphere

The iterated heat equation is a simple non-separable space-time SPDE family:

$$(\kappa^2 - \Delta)^{\gamma/2} \left[\phi \frac{\partial}{\partial t} + (\kappa^2 - \Delta)^{\alpha/2} \right]^{\beta} x(\mathbf{s}, t) = \mathcal{W}(\mathbf{s}, t)/\tau$$

For constant parameters, $x(\mathbf{s}, t)$ has spatial Matérn covariance (for each t).

Discrete domain Gaussian Markov random fields (GMRFs)

$\boldsymbol{x} = (x_1, \ldots, x_n) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{Q}^{-1})$ is Markov with respect to a neighbourhood structure $\{\mathcal{N}_i, i = 1, \ldots, n\}$ if $Q_{ij} = 0$ whenever $j \neq \mathcal{N}_i \cup i$.

- Project the SPDE solution space onto local basis functions: random Markov dependent basis weights (Lindgren et al, 2011).

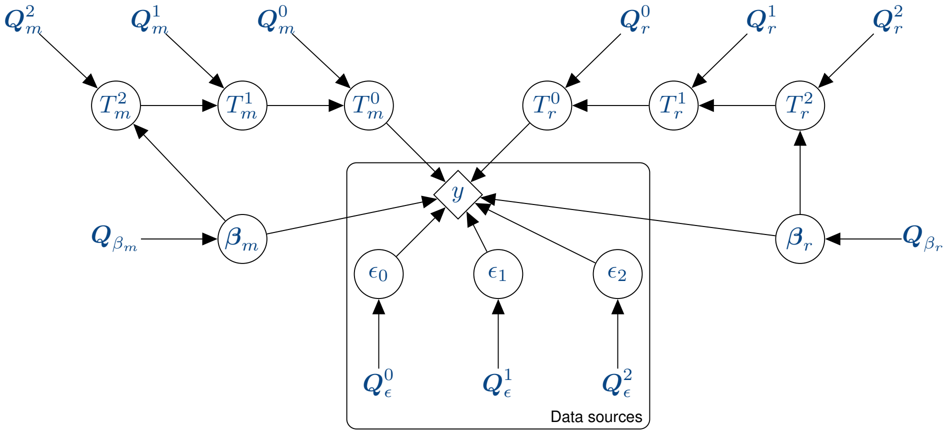
A finite element approximation has structure

$$x(\boldsymbol{s}, t) = \sum_{i,j} \psi_i^{[s]}(\boldsymbol{s}) \psi_j^{[t]}(t) x_{ij}, \quad \boldsymbol{x} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{Q}^{-1}), \quad \boldsymbol{Q} = \sum_{k=0}^{\alpha+\beta+\gamma} \boldsymbol{M}_k^{[t]} \otimes \boldsymbol{M}_k^{[\mathbf{s}]}$$

even, e.g., if the spatial scale parameter κ is spatially varying.

Partial hierarchical representation

Observations of *mean*, *max*, *min*. Model *mean* and *range*.



Conditional specifications, e.g.

$$(T_m^0 | T_m^1, \boldsymbol{Q}_m^0) \sim \mathcal{N}\left(T_m^1,\, {\boldsymbol{Q}_m^0}^{-1}\right)$$

$$T_r^0 = \exp(T_r^1)\; G^{-1}\left[U_r^0(\mathbf{s}, t)\right], \quad U_r^0 \sim \mathcal{N}\left(\mathbf{0}, {\boldsymbol{Q}_r^0}^{-1}\right)$$

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Standardised observation uncertainty models

- Each data source may have complicated dependence structure
- To facilitate information blending, use a common error term structure

Common satellite derived data error model framework

The observational&calibration errors are modelled as three error components:

- independent (ϵ_0),
- spatially and/or temporally correlated (ϵ_1), and
- systematic (ϵ_2),

with distributions determined by the uncertainty information from satellite calibration models.
E.g., $y_i = T_m(\mathbf{s}_i, t_i) + \epsilon_0(\mathbf{s}_i, t_i) + \epsilon_1(\mathbf{s}_i, t_i) + \epsilon_2(\mathbf{s}_i, t_i)$

In practice, each data source might have several different components of each type; independent components can be merged, but not necessarily correlated or systematic components.

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Station observation&homogenisation model

Daily means

For station k at day t_i,

$$y_m^{k,i} = T_m(\mathbf{s}_k, t_i) + \sum_{j=1}^{J_k} H_j^k(t_i) e_m^{k,j} + \epsilon_m^{k,i},$$

where $H_j^k(t)$ are temporal step functions, $e_m^{k,j}$ are latent bias variables, and $\epsilon_m^{k,i}$ are independent measurement and discretisation errors.

Daily mean/max/min

For station k at day t_i,

$$y_m^{k,i} = T_m(\mathbf{s}_k, t_i) + \widetilde{H}_m^k(t_i) + \epsilon_m^{k,i},$$

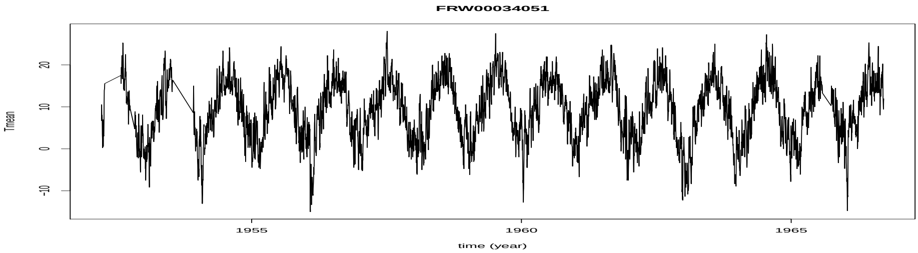
$$y_x^{k,i} = T_m(\mathbf{s}_k, t_i) + \frac{\exp[\widetilde{H}_r^k(t_i)]}{2} T_r(\mathbf{s}_k, t_i) + \epsilon_x^{k,i},$$

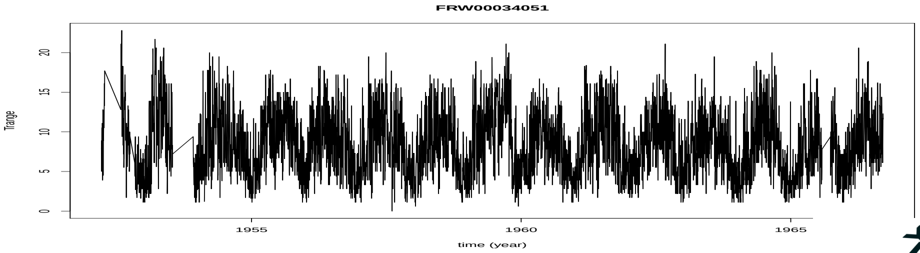
$$y_n^{k,i} = T_m(\mathbf{s}_k, t_i) - \frac{\exp[\widetilde{H}_r^k(t_i)]}{2} T_r(\mathbf{s}_k, t_i) + \epsilon_n^{k,i},$$

where $\widetilde{H}_\cdot^\cdot$ are the total bias correction variables for each observation.

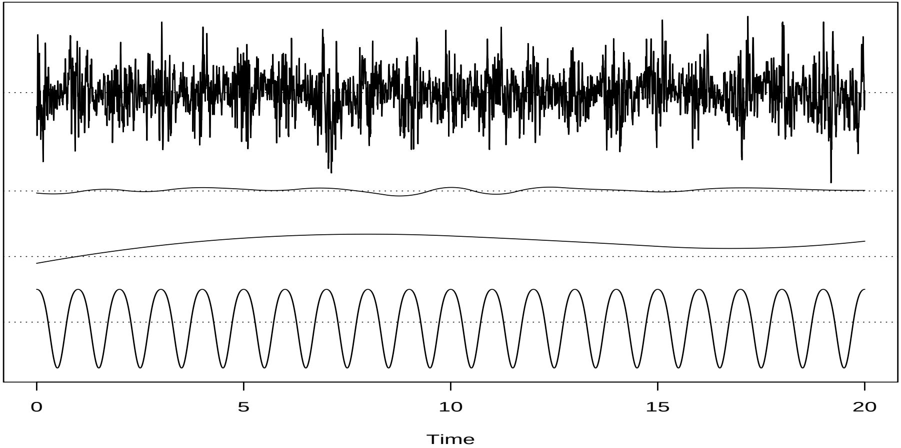
Observed data

Observed daily T_{mean} and T_{range} for station FRW00034051



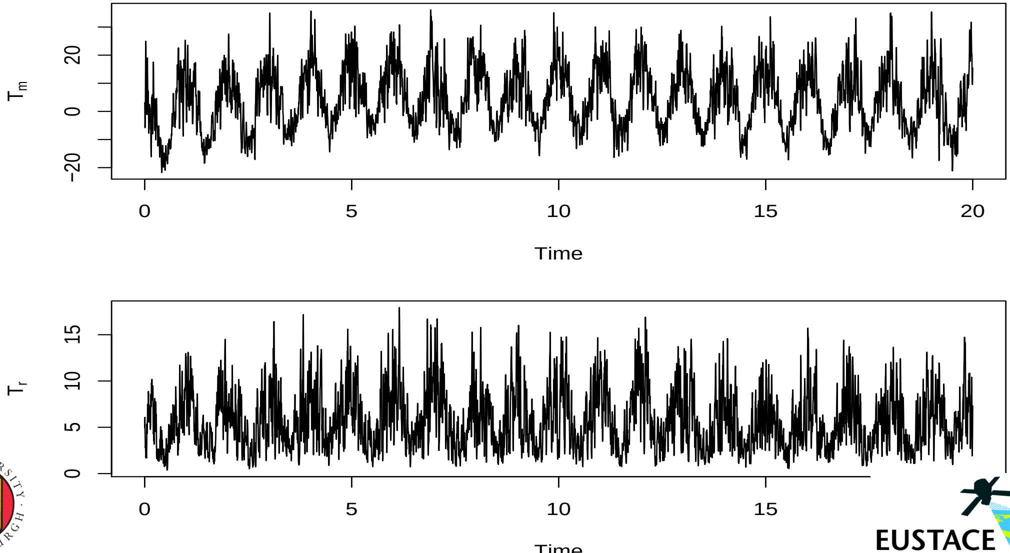


Multiscale model component samples



Combined model samples for T_m and T_r

(Proof of concept; no actual data was involved in this figure)



Modelling non-Gaussian quantities

Power tail quantile (POQ) model

The quantile function $F_{\boldsymbol{\theta}}^{-1}(p)$, $p \in [0, 1]$, is defined through a quantile blend of left- and right-tailed generalised Pareto distributions:

$$f_\theta^-(p) = \begin{cases} \frac{1-(2p)^{-\theta}}{2\theta}, & \theta \neq 0, \\ \frac{1}{2}\log(2p), & \theta = 0, \end{cases}$$

$$f_\theta^+(p) = -f_\theta^-(1-p) = \begin{cases} \frac{(2(1-p))^{-\theta}-1}{2\theta}, & \theta \neq 0, \\ -\frac{1}{2}\log(2(1-p)), & \theta = 0. \end{cases}$$

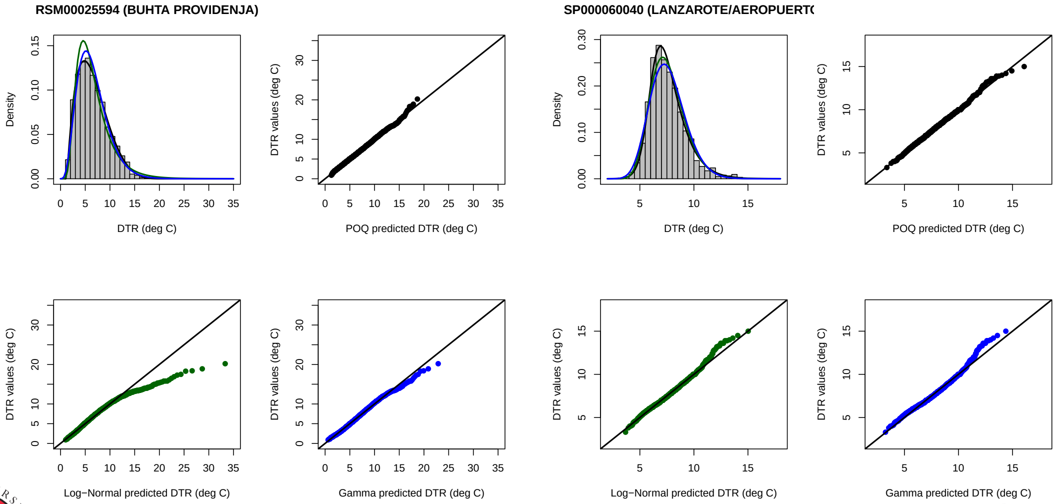
$$F_{\boldsymbol{\theta}}^{-1}(p) = \theta_0 + \frac{\tau}{2}\left[(1-\gamma)f_{\theta_3}^-(p) + (1+\gamma)f_{\theta_4}^+(p)\right].$$

The parameters $\boldsymbol{\theta} = (\theta_0, \theta_1 = \log\tau, \theta_2 = \operatorname{logit}[(\gamma+1)/2], \theta_3, \theta_4)$ control the median, spread/scale, skewness, and the left and right tail shape.

This model is also known as the *five parameter lambda model* (Gilchrist, 2000).

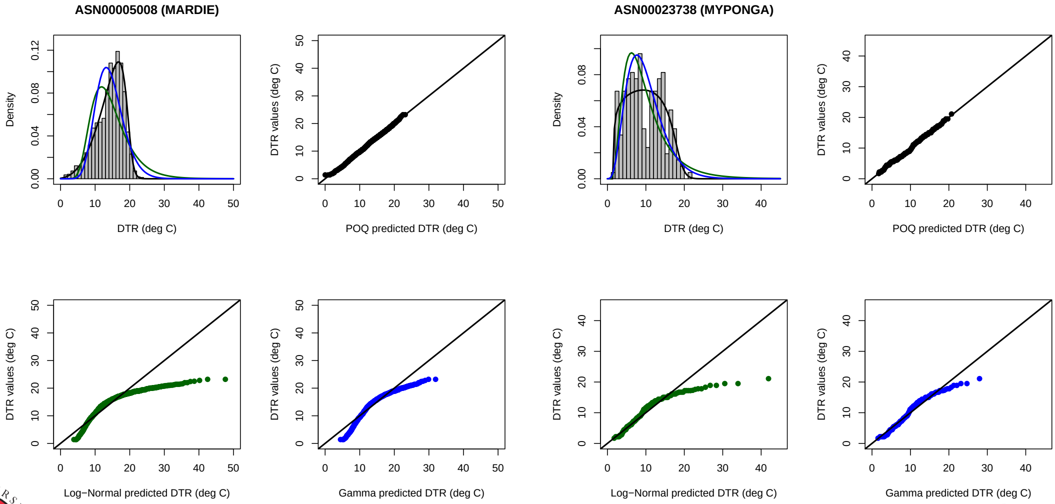
Copula transformation: $G^{-1}[u(\mathbf{s},t)] = F_{\boldsymbol{\theta}(\mathbf{s},t)}^{-1}\{\Phi[u(\mathbf{s},t)]\}$

Diurnal range distributions



For these stations, POQ does a slightly better job than a Gamma distribution.

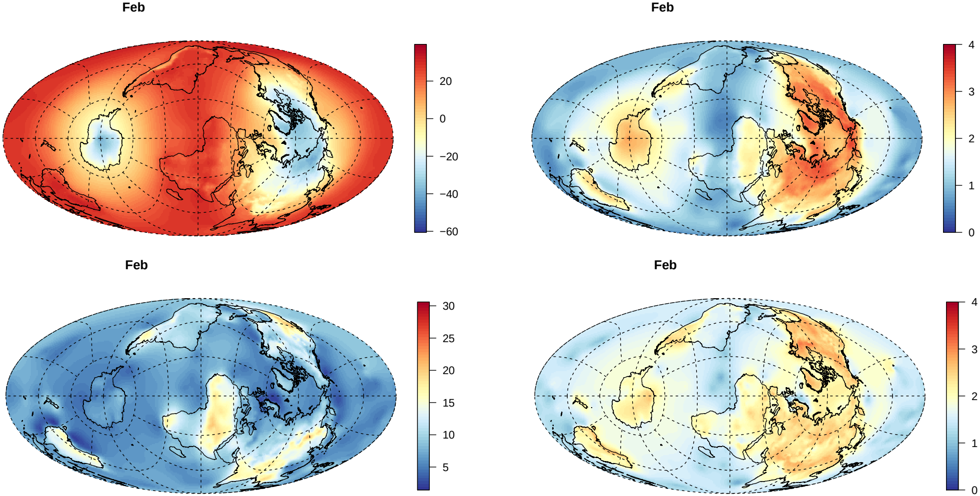
Diurnal range distributions



For these stations only POQ comes close to representing the distributions.

Note: Some shapes may be due to unmodeled station inhomogeneities.

Estimates of median & scale for T_m and T_r



February climatology

(Preliminary estimates, using only in-situ land station data)

Linearised inference

All Spatio-temporal latent random processes combined into $\boldsymbol{x} = (\boldsymbol{u}, \boldsymbol{\beta}, \boldsymbol{b})$, with joint expectation $\boldsymbol{\mu}_x$ and precision $\boldsymbol{Q}_x$:

$$(\boldsymbol{x} \mid \boldsymbol{\theta}) \sim \mathcal{N}(\boldsymbol{\mu}_x, \boldsymbol{Q}_x^{-1}) \qquad \text{(Prior)}$$

$$(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{\theta}) \sim \mathcal{N}(h(\boldsymbol{A}\boldsymbol{x}), \boldsymbol{Q}_{y|x}^{-1}) \qquad \text{(Observations)}$$

$$p(\boldsymbol{x} \mid \boldsymbol{y}, \boldsymbol{\theta}) \propto p(\boldsymbol{x} \mid \boldsymbol{\theta})\, p(\boldsymbol{y} \mid \boldsymbol{x}, \boldsymbol{\theta}) \qquad \text{(Conditional posterior)}$$

Non-linear and/or non-Gaussian observations

For a non-linear $h(\boldsymbol{A}\boldsymbol{x})$ with Jacobian $\boldsymbol{J}$ at $\boldsymbol{x} = \widetilde{\boldsymbol{\mu}}$, iterate:

$$(\boldsymbol{x} \mid \boldsymbol{y}, \boldsymbol{\theta}) \overset{\text{approx}}{\sim} \mathcal{N}(\widetilde{\boldsymbol{\mu}}, \widetilde{\boldsymbol{Q}}^{-1}) \qquad \text{(Approximate conditional posterior)}$$

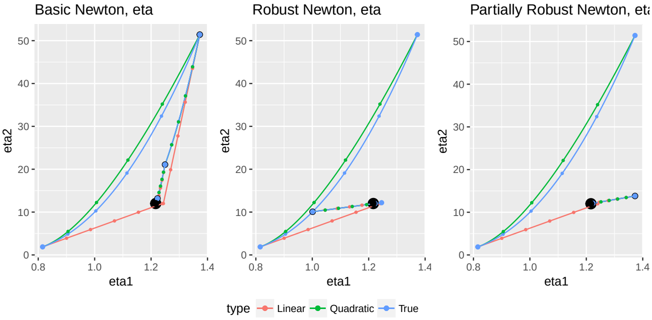
$$\widetilde{\boldsymbol{Q}} = \boldsymbol{Q}_x + \boldsymbol{J}^\top \boldsymbol{Q}_{y|x} \boldsymbol{J}$$

$$\widetilde{\boldsymbol{\mu}}' = \widetilde{\boldsymbol{\mu}} + a\widetilde{\boldsymbol{Q}}^{-1} \left\{ \boldsymbol{J}^\top \boldsymbol{Q}_{y|x} [\boldsymbol{y} - h(\boldsymbol{A}\widetilde{\boldsymbol{\mu}})] - \boldsymbol{Q}_x(\widetilde{\boldsymbol{\mu}} - \boldsymbol{\mu}_x) \right\}$$

for some $a > 0$ chosen by line-search.

Iterative solutions for $\sim 10^{11}$ latent variables

- Nonlinear Newton iteration with robust line-search



- Preconditioned conjugate gradient (PCG) iteration for
  $\boldsymbol{Q}(\boldsymbol{\mu} - \widehat{\boldsymbol{\mu}}) = \boldsymbol{r} = \boldsymbol{b} - \boldsymbol{Q}\widehat{\boldsymbol{\mu}}$
- Local and multiscale approximations for preconditioning: $\boldsymbol{M}^{-1}\boldsymbol{Q} \approx \boldsymbol{I}$
- Sampling with PCG: $\boldsymbol{Q}(\boldsymbol{x} - \widehat{\boldsymbol{\mu}}) = \boldsymbol{L}\boldsymbol{w}$
  Requires only a rectangular pseudo-Cholesky factorisation $\boldsymbol{L}\boldsymbol{L}^\top = \boldsymbol{Q}$.
  Possible due to the kronecker product sum precision structure.

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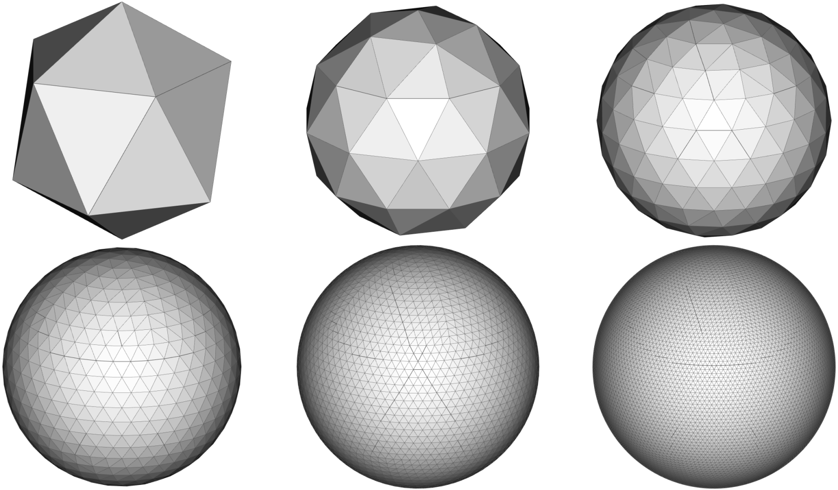
Triangulations for all corners of Earth



Variance calculations

Sparse partial inverse: Takahashi recursions postprocesses Cholesky

Takahashi recursions compute $\boldsymbol{S}$ such that $\boldsymbol{S}_{ij} = (\boldsymbol{Q}^{-1})_{ij}$ for all $Q_{ij} \neq 0$. Postprocessing of the (sparse) Cholesky factor.

Basic Rao-Blackwellisation of sample estimators

Let $\boldsymbol{x}^{(j)}$ be samples from a Gaussian posterior and let $\boldsymbol{a}^\top \boldsymbol{x}$ be a linear combination of interest. Then, for any subdomain $\Omega_k \subset \Omega$,

$$\mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x}) = \mathsf{E}\left[\mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*})\right] \approx \frac{1}{J}\sum_{j=1}^{J} \mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*}^{(j)})$$

$$\begin{aligned}\mathsf{Var}(\boldsymbol{a}^\top \boldsymbol{x}) &= \mathsf{E}\left[\mathsf{Var}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*})\right] + \mathsf{Var}\left[\mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*})\right] \\ &\approx \mathsf{Var}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*}^{j}) + \frac{1}{J}\sum_{j=1}^{J}\left[\mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x} \mid \boldsymbol{x}_{\Omega_k^*}^{(j)}) - \mathsf{E}(\boldsymbol{a}^\top \boldsymbol{x})\right]^2\end{aligned}$$

Efficient if $\boldsymbol{a}\boldsymbol{a}^\top$ sparsity matches $\boldsymbol{S}$ for each subdomain.

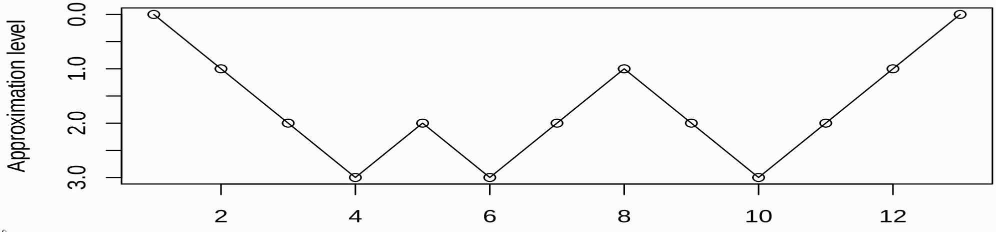
Overlapping blocks and multigrid

Overlapping block preconditioning

Let $\boldsymbol{D}_k^\top$ be a restriction matrix to subdomain Ω_k, and let $\boldsymbol{W}_k$ be a diagonal weight matrix. Then an additive Schwartz preconditioner is

$$\boldsymbol{M}^{-1}\boldsymbol{x} = \sum_{k=1}^{K} \boldsymbol{W}_k \boldsymbol{D}_k (\boldsymbol{D}_k^\top \boldsymbol{Q} \boldsymbol{D}_k)^{-1} \boldsymbol{D}_k^\top \boldsymbol{W}_k \boldsymbol{x}$$

Multigrid and/or approximate multiscale Schur complements



Data reading issue: Schur complements vs conditional block updating

MULTI-SCALE ANALYSIS MODEL

Statistical model for temperature variations and different scales (space and time):

- **Climatological variation**: local seasonal cycle with effects of latitude, altitude and coastal influence.
- **Large-scale variation**: Slowly varying climatological mean temperature field. Station homogenisation.
- **Daily Local**: daily variability associated with weather. Satellite retrieval biases.

Simultaneously estimates observational biases of known bias structures:

- e.g. satellite biases, station homogenisation.

Processed on STFC's LOTUS cluster www.jasmin.ac.uk:

- Largest solves processed on 20 core/256GB RAM node.
- Highly parallel observation pre-processing.

Element	Resolution	N Variables
Seasonal	Bimonthly x 1° SPDE	245,772
Slow-scale*	5 year x 5° SPDE	107,604
Latitude	0.5° latitude SPDE	721
Altitude	(0.25° grid)	1
Coastal	(0.25° grid)	1
Grand mean	Analysis mean	1

Element	Resolution	N Variables
Large-scale	3 monthly x 5° SPDE	1,752,408
Station bias	NA	82,072

Element	Resolution	N Variables per day
Daily local	~0.5 degree SPDE	162,842
Satellite bias (marine)	Global	1
Satellite bias (land)	Global + 2.5 degree SPDE	1 + 40,962
Satellite bias (ice)	Hemispheric + 2.5 degree SPDE*	2 + 40,962

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ITERATIVE SOLUTION

Condition on expected value of other components

(1) Climatology:
Global mean T
Seasonal cycle
Latitude
Altitude
Water fraction
$\boldsymbol{T}^{clim}(\boldsymbol{s},t)$

(2) Large-scale:
Multi-annual SPDE
Multi-month SPDE
Station biases
$\boldsymbol{T}^{large}(\boldsymbol{s},t)$

(3) Daily local:
Daily fields
Satellite land bias
Satellite marine bias
Satellite ice bias
$\boldsymbol{T}^{local}(\boldsymbol{s},t)$

Model Factorisation

The model is factorised into $m = 1, ..., 3$ components that are estimated interatively, substituting $\tilde{\boldsymbol{y}}_m$ for $\boldsymbol{y}$:

$$\tilde{\boldsymbol{y}}_m = \boldsymbol{y} - \sum_{n \neq m} \boldsymbol{J}_n \boldsymbol{\mu}_{\boldsymbol{x}_n|\tilde{\boldsymbol{y}}_n}$$

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Simultaneously estimates observational biases of known bias structures:

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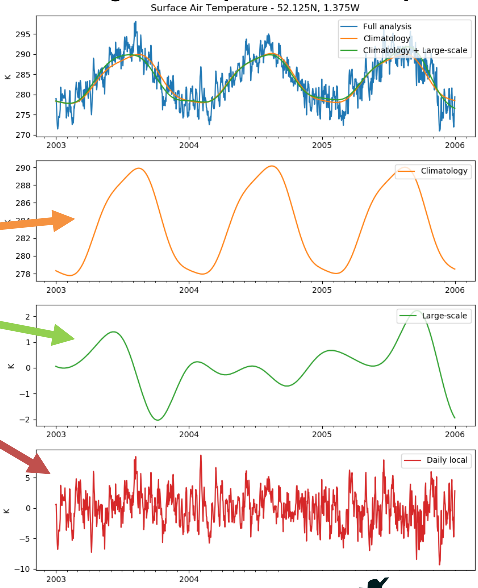
Central England Temperature Decomposition



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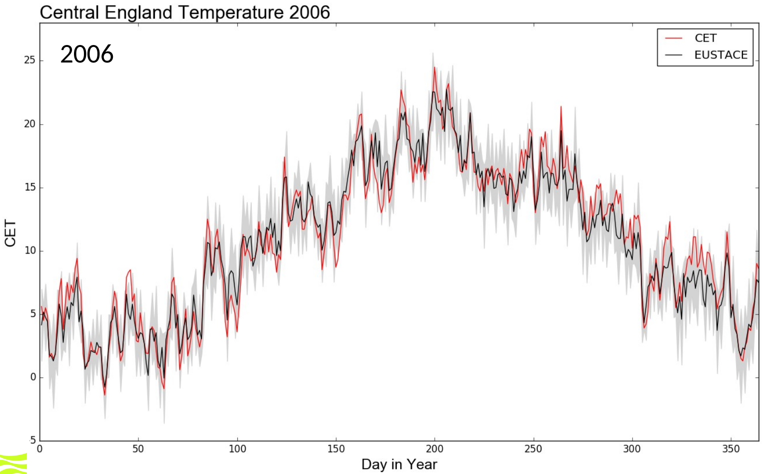
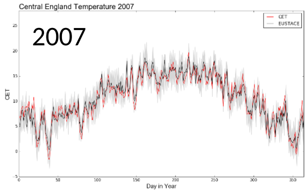
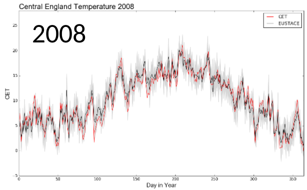
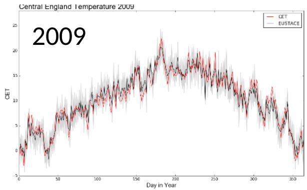
COMPARING EUSTACE WITH CENTRAL ENGLAND TEMPERATURE









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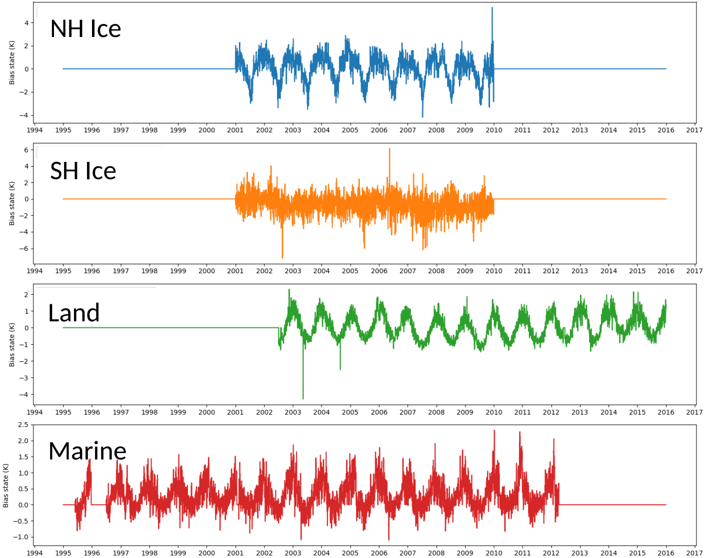
SATELLITE BIAS MODELS

- Simplified model of known error structures in satellite air temperature retrievals:
  - Global/hemispheric systematic bias covariates.
  - Daily estimates of spatially varying bias as a spatial random field.

- Estimated jointly with daily temperature variability.



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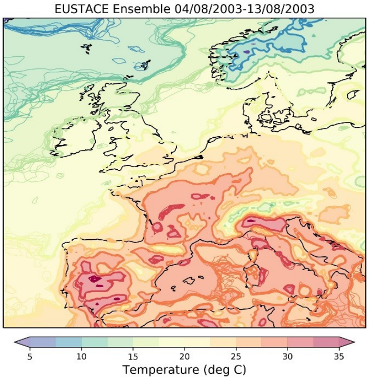
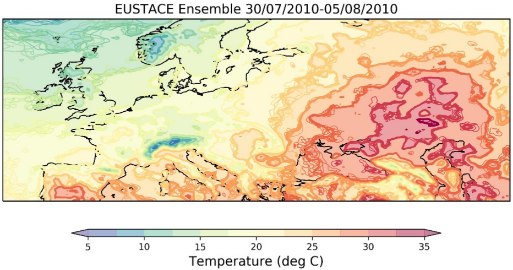
ENSEMBLE ANALYSIS

- Samples drawn from joint posterior distribution of temperature and bias variables.
- Temperature model samples projected onto analysis grid.
- Spatial/temporal correlation in analysis errors is encoded into the ensemble.
- Summary statistics can be derived from the ensemble. Expected value, total uncertainty and observation constraint information also available.





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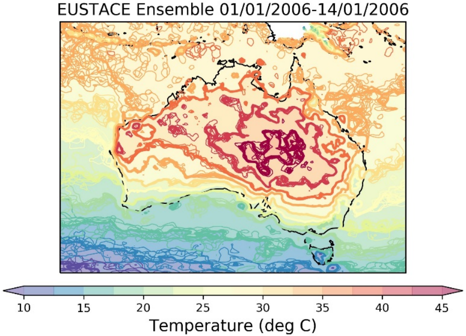

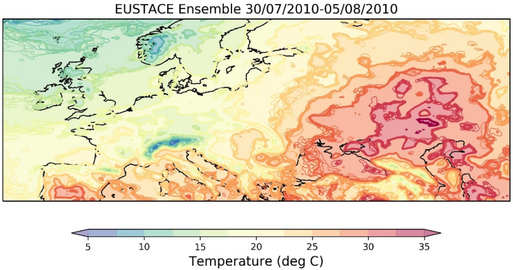

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Summary

Only partially covered in this talk:

- Pure conditional block updates risk getting stuck;
  need for convergence acceleration
- Overlapping space-time blocks for preconditioning
- Non-stationary random field parameter estimation
- Direct&iterative variance calculations to eliminate or reduce
  Monte Carlo error in the reconstruction uncertainties
- Fast approximate handling of correlated error components

Summary:

- Challenging statistical problem, in both size and complexity
- Approximate calculation techniques allows some of the complexity
  to be handled with reasonable computational resources
  - SPDEs and Gaussian Markov random fields
  - Fast local sparse solves
  - Global multiscale block iteration
- Close collaboration between climate scientistis, statisticians,
  and software engineers is essential

The hierarchy of scales and preconditioning ($\boldsymbol{x}_0 = \boldsymbol{B}\boldsymbol{x}_1 +$ fine scale variability):

Multiscale Schur complement approximation

Solving $\boldsymbol{Q}_{\boldsymbol{x}|\boldsymbol{y}}\boldsymbol{x} = \boldsymbol{b}$ can be formulated using two solves with the upper (fine) block $\boldsymbol{Q}_0 + \boldsymbol{A}^\top\boldsymbol{Q}_\epsilon\boldsymbol{A}$, and one solve with the *Schur complement*

$$\boldsymbol{Q}_1 + \boldsymbol{B}^\top\boldsymbol{Q}_0\boldsymbol{B} - \boldsymbol{B}^\top\boldsymbol{Q}_0\left(\boldsymbol{Q}_0 + \boldsymbol{A}^\top\boldsymbol{Q}_\epsilon\boldsymbol{A}\right)^{-1}\boldsymbol{Q}_0$$

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

$$\begin{bmatrix} \widetilde{\boldsymbol{Q}}_B + \boldsymbol{B}^\top\boldsymbol{A}^\top\boldsymbol{Q}_\epsilon\boldsymbol{A}\boldsymbol{B} & -\widetilde{\boldsymbol{Q}}_B \\ -\widetilde{\boldsymbol{Q}}_B & \boldsymbol{Q}_1 + \widetilde{\boldsymbol{Q}}_B \end{bmatrix} \begin{bmatrix} \text{ignored} \\ \boldsymbol{x}_1 \end{bmatrix} = \begin{bmatrix} \boldsymbol{0} \\ \widetilde{\boldsymbol{b}} \end{bmatrix}$$

where $\widetilde{\boldsymbol{Q}}_B = \boldsymbol{B}^\top\boldsymbol{Q}_0\boldsymbol{B}$.

The block matrix can be interpreted as the precision of a bivariate field on a common, coarse spatio-temporal scale, and the same technique applied to this system, with $\boldsymbol{x}_{1,1} = \boldsymbol{B}_{1|2}\boldsymbol{x}_{1,2} +$ finer scale variability.

Also applies to the station data bias homogenisation coefficients.