Spatio-temporal modeling 2

Large spatio-temporal problems often appear in contexts where the observation structure is complex at the same time as the latent or true spatio-temporal structures are non-trivial. This leads to numerous modelling and computational challenges. Some general issues are listed below.

1. Emergent behaviour; modelling phenomena, not descriptive statistics, moving beyond computational recipes (e.g., the kriging equations) and into analysis of general concepts (e.g., posterior means, variances, and quantiles in posterior distributions in generative models, using whatever computational method can provide them):
   - Generative models
   - Hierarchical multiscale models
   - Local differential operator specifications for SPDEs
2. Equivalent representations of Gaussian random fields; model vs method. Although the line is sometimes blurry, some distinctions can be useful:
   - Models: Covariance kernels, precision operators, power spectra, Markov properties
   - Methods: Tapering, basis expansions (finite elements, low-dimensional approximations, and combinations), sparse Cholesky decomposition, iterative solvers, fast Fourier transformation, Laplace approximation, MCMC
3. Computational challenges:
   - Iterative, matrix-free methods for large models; 10^6 is a relatively *modest* space-time dimension; what about 10^9 and beyond? Irregular data locations lead to non-standard numerical issues.
   - Using modern computational methods for uncertainties, not just point estimates. Approximations for intractable likelihood.
   - Turning approximate methods into preconditioners; allows the same freedom as designing MCMC proposals. E.g., Gauss-Seidel iterations converges slowly for the same reason as Gibbs sampling mixes slowly, but can be useful as a multigrid preconditioner.

See overleaf for reading suggestions, and contact Finn Lindgren (finn.lindgren@ed.ac.uk) or Wendy Meiring (meiring@pstat.ucsb.edu) for further suggestions and interests.

Reading material and references

- *Connection between covariances, spectra, Markov random fields and stochastic PDEs*
  Finn Lindgren, Håvard Rue, Johan Lindström (2011), *An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach, with discussion*, JRSS-B, Volume 73, Issue 4, Pages 423498,
  `http://onlinelibrary.wiley.com/doi/10.1111/j.1467-9868.2011.00777.x/abstract`

- *Low-dimensional expansions*
  Andrew Zammit-Mangion, Noel Cressie (2017), *FRK: An R Package for Spatial and Spatio-Temporal Prediction with Large Datasets*,
  `https://arxiv.org/abs/1705.08105`

- *Physics inspired model structure*
  Peter Guttorp and Alexandra M. Schmidt (2013), *Covariance structure of spatial and spatio-temporal processes*, WIREs Computational Statistics, vol 5, pp 279-287,
  `http://onlinelibrary.wiley.com/doi/10.1002/wics.1259/abstract`

- *Physics inspired model structure*
  Geir-Arne Fuglstad, Finn Lindgren, Daniel Simpson and Håvard Rue (2015), *Exploring a New Class of Non-stationary Spatial Gaussian Random Fields with Varying Local Anisotropy*, Statistica Sinica, Vol. 25, No. 1, pp. 115-133
  `https://www.jstor.org/stable/24311007`

- *An subset of some mostly non-Markovian models and methods*
  Alan E. Gelfand and Sudipto Banerjee (2017), *Bayesian Modeling and Analysis of Geostatistical Data*, Annual Review of Statistics and Its Application, Vol. 4, pp. 245266,
  `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2937751`

- *A recent update on the INLA software for fast MCMC-free Bayesian inference*
  Håvard Rue, Andrea Riebler, Sigrunn H. Sørbye, Janine B. Illian, Daniel P. Simpson, and Finn Lindgren (2017), *Bayesian Computing with INLA: A Review* Annual Review of Statistics and Its Application, Vol. 4, pp. 395421,
  `http://www.annualreviews.org/doi/abs/10.1146/annurev-statistics-060116-054045`

- *Computation for small and medium sized GMRFs*
  Finn Lindgren (2015), *Computation fundamentals of discrete GMRF representations of continuous domain spatial models*, draft chapter for a planned book on *Markovian Geostatistics*,
  `http://www.maths.ed.ac.uk/~flindgre/tmp/gmrf.pdf`

- *Hierarchical approximation for kriging and likelihood evaluation*
  Sivaram Ambikasaran, Daniel Foreman-Mackey, Leslie Greengard, David W. Hogg, Michael O'Neil (2015), *Fast Direct Methods for Gaussian Processes*,
  `https://arxiv.org/abs/1403.6015`
  Victor Minden, Anil Damle, Kenneth L. Ho, Lexing Ying (2017), *Fast spatial Gaussian process maximum likelihood estimation via skeletonization factorizations*,
  `https://arxiv.org/abs/1603.08057`