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Modelling the Palaeoclimate

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The world's climate is entering into a period of change described by the IPCC (Nov, 2007) as potentially 'abrupt'. Yet we know pitifully little about such changes. The instrumental record on past climates is limited to about two centuries and shows no abrupt changes. The general circulation models (GCMs) used to explore future climates are essentially equilibrium models: given assumed 'forcing scenarios', we can learn something about future 'steady states' but very little about transitions. The palaeoclimate provides a complementary source of information. For example, in Jan 2007, Working Group 1 of the IPCC reported: 'During the last glacial period, abrupt regional warmings (probably up to 16^{o}C within decades over Greenland) occurred repeatedly over the North Atlantic region'. Yet inference on the palaeoclimate is indirect and uncertain. This paper discusses some of the successes of Bayesian space-time inference and several of the challenges; a first attempt was reported in Haslett et al (2006), Bayesian Palaeoclimate Reconstruction - with discussion, JRSS(A). Our focus here is on Europe for the period since the onset of rapid deglaciation towards the end of the last glacial stage, a little less than 15,000 calendar years ago. The presentation will convey the general scientific context and will concentrate on the methodological challenges for Bayesian space-time modelling.

What information we have is mostly available via biological and chemical proxies. Examples include: changes in pollen composition as found in sediments, for this reflects changes in vegetation and hence in climate; changes in the composition of oxygen isotopes in Greenland ice, for this reflects past evaporation. Here we focus on pollen, although in principle the methodology is capable of application to many compositional proxies. Such data derive from counts of pollen, from different types of plant, that have been preserved in sedimentary records, in lakes and in bogs. Inference relies on the 'modern analogue' hypothesis: the climate 8,000 years ago in, eg Glendalough in Ireland, is like the modern climate somewhere in the Northern Hemisphere. More abstractly, useful information is contained in models of the relationship between climate and pollen composition in the modern world.

Statistically, the simplest version of the problem may be stated as follows. For each of a number of samples (referred to as sites), n^m modern and n^f fossil, vectors of compositional data $p^m = \{p_j^m; j = 1, \ldots, n^m\}$ and $p^f = \{p_j^f; j = 1, \ldots, n^f\}$, are available for study; these are often referred to as 'pollen assemblages' or 'pollen spectra'. For the modern sample, vectors of climate data $c^m = \{c_j^m; j = 1, ..., n^m\}$ are also available as covariates; the climate values c^f for the fossil sites are missing. Ancient sites have spatial and depth (whence time) coordinates; modern sites have no time coordinates. Inference on depth age relationship is informed by radio-carbon dating. The objective is to estimate the missing values and thus to reconstruct the prehistoric climate. As the dimensionalities are high the challenge is very considerable.

The key advance is in *joint* analysis of the many sources of uncertainty. This permits: (a) borrowing strength across multiple sites, and indeed multiple proxies, by a reliance on a degree of spatio-temporal smoothness in climate change; (b) a modular approach, separately focussed on the climate responses of individual taxa and on radiocarbon dating uncertainties, coherently linked by Monte Carlo methods; and (c) the subsequent sampling of joint space-time climate histories. This latter is of great importance; it directly addresses the need for detailed information on space-time changes, and it does so in the context a careful analysis of the many uncertainties.

Specific technical issues include: (a) the circumventing of MCMC in several modules by exploiting the numerical integration within the GMRF approximations of Rue ; (b) the approximation of certain joint inferences by approximations based on marginal inference; (c) the use of a simple, monotone, continuous and piece-wise linear Markov process for making inferences about the calendar of samples; and (d) the modelling of prior 'temporal smoothness' by long tailed random walks based on Normal Inverse Gaussian increments.