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# Transdimensional Inverse Thermal History Modelling for Quantitative Thermochronology

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Since the seminal publication of Dodson (1973) quantifying the relationship between geochronogical ages and closure temperatures, an ongoing concern in thermochronology is reconstruction of thermal histories in various contexts, including tectonics, landscape evolution and resource exploration. Extracting thermal history information is best treated as an inverse problem, given the complex relationship between the observations and the thermal history. When solving the inverse problem (i.e. finding thermal acceptable thermal histories), stochastic sampling methods have often been used, as these are relatively global when searching the model space. However, the issue remains how best to estimate those parts of the thermal history unconstrained by independent information, i.e. what is required to fit the data ? To solve this general problem, we use a Bayesian transdimensional Markov Chain Monte Carlo method. This allows us to consider a wide range of possible thermal history as general prior information on time, temperature (and temperature offset for multiple samples in a vertical profile). We can also incorporate more focussed geological constraints in terms of more specific priors. Another useful feature of this method is that was can easily deal with imprecise parameter values (e.g. kinetics, data errors), by drawing samples from a user specified probability distribution, rather than using a single value. Finally, the method can be applied to either single samples, or multiple samples (from a borehole or vertical profile), the latter case allowing us to also estimate the palaeogeothermal gradient.
The Bayesian approach naturally prefers simpler thermal history models (which provide an adequate fit to the observations), and so reduces the problems associated with over interpretation of inferred thermal histories. The output of the method is a collection or ensemble of thermal histories, which quantifies the range of accepted models in terms of a (posterior) probability distribution. Individual models, such as the best data fitting (maximum likelihood) model or the expected model (effectively the weighted mean from the posterior distribution) can be examined. Different data types (e.g. fission track, U-Th/He, 4He/3He, vitrinite reflectance and in future 40Ar/39Ar) can be combined, requiring just a data-specific predictive forward model and data fit (likelihood) function for each data type. To demonstrate the main features and implementation of the approach, examples are presented using both synthetic and real data.