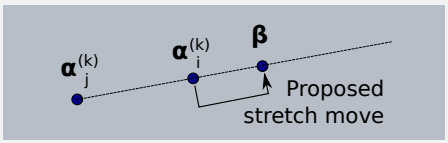
1 EMCEE Sampler

Sample 2n parameter sets $\{\boldsymbol{\alpha}_i\}$ from the prior distribution $\Pi(\mathbf{x})$ and split them evenly into 2 sets, S_1 and S_2:

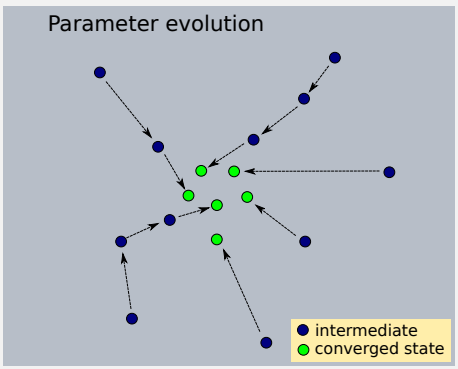
$S_1 = \{\boldsymbol{\alpha}_1^{(0)}, \ldots, \boldsymbol{\alpha}_n^{(0)}\}$ $S_2 = \{\boldsymbol{\alpha}_{n+1}^{(0)}, \ldots, \boldsymbol{\alpha}_{2n}^{(0)}\}$

For each parameter in both sets, estimate its marginal likelihood.

We now evolve the parameters in S_1. For each $\boldsymbol{\alpha}_i^{(k)} \in S_1$, we propose an update $\boldsymbol{\beta} = \boldsymbol{\alpha}_i^{(k)} + Z[\boldsymbol{\alpha}_i^{(k)} - \boldsymbol{\alpha}_j^{(k)}]$,where $\boldsymbol{\alpha}_j^{(k)}$ is a random element from S_2.

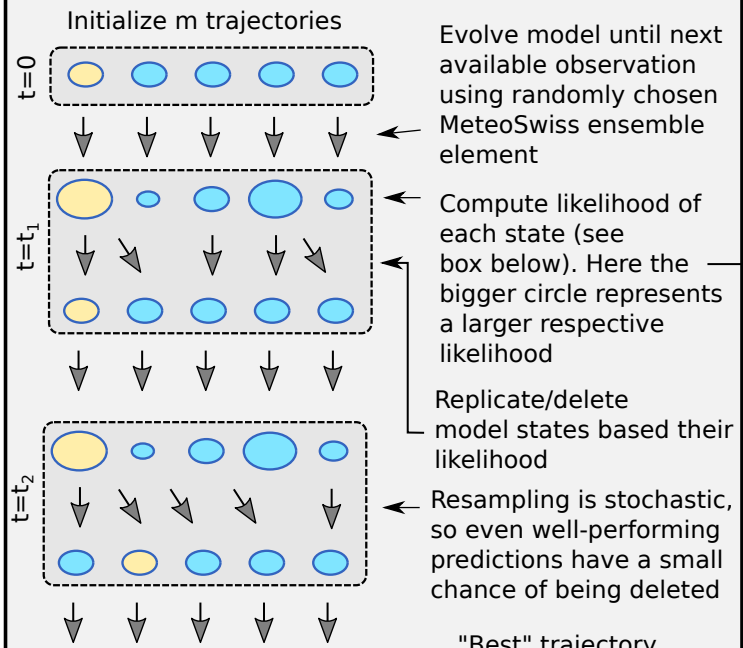


If $\boldsymbol{\beta}$ is accepted (probability depends on the performance of its computed marginal likelihood), then we set $\boldsymbol{\alpha}_i^{(k+1)} = \boldsymbol{\beta}$. Next, we update S_2 using the same procedure and the updated elements from S_1. This makes one full EMCEE iteration.



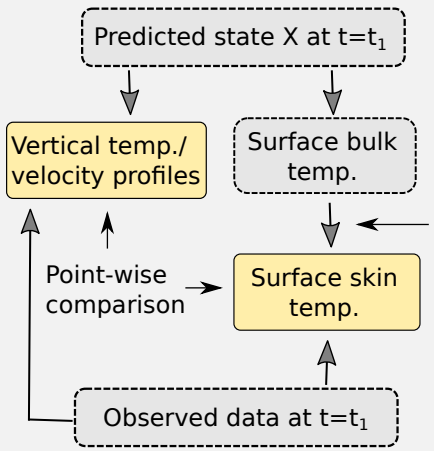
After a number of iterations, we obtain a set of parameters together with their respective likelihoods, which are used to obtain the posteriors. Note that intermediate parameters are also used for posterior computations.

2 Particle Filter



The overall marginal likelihood is simply the product of the individual snapshot likelihoods.

3 State Likelihood Estimate



From the model prediction, extract subsets to compare to observational data

BiLSTM conversion, which provides skin temp. estimate and uncertainty from bulk temp. and other values

The marginal likelihood is the product of the individual point prediction likelihoods

4

The PF returns the marginal likelihood of the model parameters