- Supplementary 1: Sequential Monte Carlo
- methods for data assimilation problems
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- 1 Metropolis Hastings Acceptance ratio (MHAR)
- for proposed model
- $_{12}$  1.1 MHAR for particle MCMC defined by Andrieu *et al.* (2010)
- Particle Markov chain Monte Carlo (pMCMC hereafter) (Andrieu et al. 2010)
- proposes a value for the top-level parameter  $(\theta^*)$  from a proposal distribution
- $(\pi(\theta^{\star}|\theta))$ . A sequential monte carlo (SMC) method is fitted with the proposed
- value  $\theta^*$  and this proposed value is accepted or rejected based on a Metropolis
- Hasting acceptance ratio (MHAR) defined by Andrieu et al. (2010):

$$MHAR = \frac{p_{\theta}(y_{1:t})p(\theta^{\star})\pi(\theta|\theta^{\star})}{p_{\theta^{\star}}(y_{1:t})p(\theta)\pi(\theta^{\star}|\theta)};$$
(1)

- where  $p_{\theta}(y_{1:t})$  is the marginal distribution of the observed data given the pa-
- rameter  $\theta$ ,  $p(\theta^*)$  and  $p(\theta)$  is the prior distribution of  $\theta^*$  and  $\theta$  respectively and
- $\pi(.|.)$  is the proposal distribution for the parameters  $\theta$ .
- We use the same definitions and descriptions of state space models (SSMs)
- described in the main paper (equation 1 and Table 1).

## $_{\mbox{\tiny 24}}$ 1.1.1 Importance weights for proposed model $w^i_{t|\theta}$

- 25 As we defined in equation (3) of the main paper (which is repeated here for
- <sub>26</sub> emphasis in the formulation of the MHAR), the importance weights for the
- 27 proposed model was defined as:

$$\left\{ \begin{array}{ll} w_{t|\theta}^{(i)} = 1 & \text{for } 1 \leq t \leq t_r \\ w_{t|\theta} \text{ defined by equations (2) - (4) in main paper} & \text{for } t_{r+1} \leq t \leq T \end{array} \right.$$
 (2)

where  $t_r$  is the last time step we have fitted the reduced SSM.

## <sup>29</sup> 1.1.2 Marginal likelihood $p_{ heta}(y_{1:T})$

- so Sequential Monte Carlo approaches provide estimates of the marginal likelihood
- of the observed data. From equation (9) in Andrieu et al. (2010), the estimate
- of the marginal likelihood  $p_{\theta}(y_{1:T})$  is given by:

$$\begin{split} \hat{p}_{\theta}(y_{1:t}) &= \hat{p}_{\theta}(y_{1}) \prod_{t=2}^{T} \hat{p}_{\theta}(y_{t}|y_{t-1}) \\ &= \hat{p}_{\theta}(y_{1}) \prod_{t=2}^{T} \frac{1}{M} \sum_{i=1}^{M} w_{t|\theta}^{i}; \end{split} \tag{3}$$
 with 
$$\hat{p}_{\theta}(y_{t}|y_{t-1}) = \frac{1}{M} \sum_{i=1}^{M} w_{t|\theta}^{i}$$

- $w^i_{t|\theta}$  is the  $i^{th}$  importance weight at time t given the value of  $\theta$ .
- For our proposed model, the estimated marginal likelihood in equation (3)
- is modified with our proposed model importance weights in equation (2) and
- obtain the an updated marginal likelihood  $\tilde{p}_{\theta}(y_{1:t})$  as:

$$\begin{split} \tilde{p}_{\theta}(y_{1:t}) &= \tilde{p}_{\theta}(y_{1}) \frac{1}{M} \bigg[ \prod_{t=2}^{t_{r}} \sum_{i=1}^{M} w_{t|\theta}^{i} \prod_{t=t_{r}+1}^{T} \sum_{i=1}^{M} w_{t|\theta}^{i} \bigg]; \\ &= \tilde{p}_{\theta}(y_{1}) \frac{1}{M} \bigg[ M(t_{r}-1) \prod_{t=t_{r}+1}^{T} \sum_{i=1}^{M} w_{t|\theta}^{i} \bigg]; \quad \text{since } w_{t|\theta}^{i} = 1 \quad \forall t \leq t_{r} \quad (4) \\ &= (t_{r}-1) \tilde{p}_{\theta}(y_{1}) \prod_{t=t_{r}+1}^{T} \sum_{i=1}^{M} w_{t|\theta}^{i} \end{split}$$

## 37 1.2 Updated MHAR for our proposed framework

- Substituting equation (4) instead of (3) into the MHAR proposed by Andrieu et
- as al. (2010) defined by equation (1), we obtain the updated MHAR ( $MHAR_{upd}$ ):

$$\begin{split} MHAR_{upd} &= \frac{(t_r - 1)\tilde{p}_{\theta}(y_1) \prod_{t=t_r+1}^T \sum_{i=1}^M w_{t|\theta}^i p(\theta^\star) \pi(\theta|\theta^\star)}{(t_r - 1)\tilde{p}_{\theta}(y_1) \prod_{t=t_r+1}^T \sum_{i=1}^M w_{t|\theta^\star}^i p(\theta) \pi(\theta^\star|\theta)} \\ &= \frac{\prod_{t=t_r+1}^T \sum_{i=1}^M w_{t|\theta}^i p(\theta^\star) \pi(\theta|\theta^\star)}{\prod_{t=t_r+1}^T \sum_{i=1}^M w_{t|\theta^\star}^i p(\theta) \pi(\theta^\star|\theta)}; \end{split} \tag{5}$$

- where  $w^i_{t|\theta}$  is the  $i^{th}$  importance weight at time t given the value of  $\theta$ ,  $p(\theta^*)$  and
- $p(\theta)$  is the prior distribution of  $\theta^{\star}$  and  $\theta$  respectively and  $\pi(.|.)$  is the proposal
- distribution for the parameters  $\theta$ .

## <sup>43</sup> 2 References

- Andrieu, C., Doucet, A. & Holenstein, R. (2010). Particle markov chain monte
- carlo methods. Journal of the Royal Statistical Society: Series B (Statistical
- 46 Methodology), **72**, 269–342.