

Interactive comment on “Assimilating near real-time mass balance observations into a model ensemble using a particle filter” by Johannes M. Landmann et al.

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Summary

In ‘Assimilating near real-time mass balance observations into a model ensemble using a particle filter,’ Landmann and co-authors describe the installation of a set of cameras aimed at measuring point ablation rates at several locations in the Alps, and then assimilate those measurements into an ensemble of ablation models using a novel implementation of a particle filter. They compare their model results favorably with a much more laborious empirical mass balance measurement for each of their three glaciers.

C1

The key ideas of this paper are excellent and important. First, the use of telemetered cameras to provide continuous measurements of melt has the potential to substantially improve the temporal and spatial resolution of monitoring in regions where it is feasible. Second, the probabilistic assimilation of these observations into models is a clear advancement in the way that data is extrapolated into broader conclusions.

From a scientific perspective, I think that the paper is sound. There are statistical modelling choices that I disagree with and that I hope that the authors will address, but this can be done through added discussion in the text rather than any new analysis or methodology. From a stylistic perspective, I hope that the authors will carefully look through the paper and critically identify jargon and unclear descriptions; the paper would make a more enthusiastic reader if the language were simplified as much as possible. I have made specific comments in relation to both of these points below.

Comments

Title The observations are not of mass balance, but of surface elevation (specifically in the negative direction). I suggest changing the title to be more precise.

L10 The reader does not yet know what ‘model probability’ is in the abstract, nor is the abstract notion of ‘custom resampling’ useful here.

L39 Of the three points (first, second, third) made after this line, only one logically follows this statement.

L49 List of references should have an e.g. in front of it. There are many other examples of ensemble modelling for ice sheet projection.

L55 ‘discussed how’ → ‘not clear whether’(?)

C2

- L63** surface point mass balance \rightarrow surface point ablation. You don't measure mass balance, you measure volume change in one direction.
- L80** as above.
- L103** 'cumulative surface height change' is (mathematically) equivalent to 'surface height'. I suggest the latter for brevity.
- Eq. 1** This equation is only valid for bare ice. This is briefly touched on elsewhere, but should be reiterated here. In fact, it might be better to state that the operation operation relates $h(t, z)$ to a_{sfc} .
- L111** 'Short snow events ...'. We never see this notion of assigning a high uncertainty SWE estimate again. Is this actually done, and specifically how?
- L133** I'm confused by the lapse rate thing. Why don't you continue to be a Bayesian and just use the probability distribution over the lapse rate inferred from the data without injecting questionable notions of 'significance'? This could then be propagated into downstream analysis.
- L151** In what sense is an outline a surface? I don't understand this line.
- L158** 'Values of glacier-wide mass balance ...' I don't understand what 'partly harmonized' means in this context?
- Eq. 2** Perhaps it's standard notation, but having c_{prec} mean an entirely different thing (with different units) than c_{cfc} is really confusing.
- L214** It would be useful to make a note that G is a function of I .
- Eq. 8** Suggest using Δt rather than dt , as the latter is usually reserved for infinitesimals.

C3

- Eq. 10** The 'general framework' also has ϵ inside of $\mathcal{H}(x)$, although it doesn't appear that way in this work.
- Sec. 3.3** I find it confusing that the parameter update process appears at the end, even though Figure 6 indicates that it happens at the same time as the state prediction.
- L289** It might be clearer to state explicitly that a particle is always associated with only 1 model over its "lifetime".
- Eq. 16** I strongly disagree with the choice of setting $\beta_t = 0$. This is because this is tantamount to the assumption that the model predictions are perfect, which is certainly not the case. In reality, two models are only different in their reliability to the extent that their predictions differ by more than their internal uncertainty and one fits the data better than the other. Setting this model error to zero artificially accentuates the differences in the likelihoods computed for different model and encourages the mode collapse (what you call 'model dominance') exhibited in Figure 11.
- Table 2 Caption** By covariance, do you mean standard deviation?
- L320** the standard symbol for variance would be σ_ϵ^2 .
- Eq. 18** An implicit assumption made throughout is that a single model's probability is marginally uniform, or alternatively that $P(m_t) = \text{Dirichlet}(1)$, to wit that one model being dominant is just as probable as all four models contributing equally. This is a weird assumption for a time dependent problem, because it means that physical reality is subject to sudden switches between governing principles. Again, this leads to the mode collapse seen in Fig. 11. Predictions might be made substantially more robust by putting a prior on $P(m_t)$ such that the more probable case is an averaging of the four models, and deviation from that has to be the result of significant evidence.

C4

L338 It's not that there's no stochasticity, it's that m_t for a given particle doesn't evolve at all!

Sec. 3.4 This section is essentially incomprehensible, with the section on proper scoring reading like it was pasted from a statistical methods paper. This being the Cryosphere, it's important to try to help your reader with some intuition as to what the CRPS actually means, and why its potential impropriety matters. A figure describing the metric might be useful, or perhaps a simple example describing circumstances where the value is high or low. While the rest of the paper is still accessible not understanding CRPS, the analysis breaks down to 'big number bad, low number good,' which is unfortunate given that there is probably much more insight to be gained from the following sections.

Sec. 4.2.1 This section is quite unclear, specifically what the differences are that these include relative to the 'full' forecast.

L435 Perhaps I missed it, but I can't find anything describing what the number in brackets means.

Sec. 4.2.2 This section on cross-validation is very clear and good. Maybe it would be useful to comment on the temporal pattern evident in Figure 9, with CRPS increasing through time, but at different rates between different cross-validation folds.

L481 I don't understand where the '45 distinct model runs' come from. Also, what is a 'random coupling'?

L495–496 I don't understand this sentence, nor why conditioning initial conditions on observations leads to poorer results.

Figure 11 To emphasize earlier comments again, this pattern of mode collapse is strongly indicative of an over-confident likelihood operating in an M-open frame-

C5

work. It's well known that Bayesian inference only 'works' when the models are correctly specified. For Bayesian model averaging (which is what the particle filter is doing in a time dependent way), this still holds: because the true physics are not contained in the set of equations that the filter has available to pick from, yet this additional uncertainty is not explicitly specified, the filter hops between the model that fits the observations in the moment. While I don't expect any additional analysis, I think it would be appropriate to make this assumption explicit in the text, and to perhaps reference it when describing the fast switching between dominant models.

Figure ?? Two things that are missing from the paper are time series' of state and parameter distributions. It would be very interesting to see the evolution of uncertainty in the predictions away from observations, and also to see how quickly parameters change or revert to the mean.

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