

The Cryosphere Discuss., referee comment RC2
<https://doi.org/10.5194/tc-2022-103-RC2>, 2022
© Author(s) 2022. This work is distributed under
the Creative Commons Attribution 4.0 License.

Comment on tc-2022-103

Anonymous Referee #2

Referee comment on "Compensating errors in inversions for subglacial bed roughness: same steady state, different dynamic response" by Constantijn J. Berends et al., The Cryosphere Discuss., <https://doi.org/10.5194/tc-2022-103-RC2>, 2022

In this manuscript the authors explore the sensitivity of the inverted bed roughness to errors in the model and in the data.

While the topic is important and deserves attention, I have significant concerns with the manuscript:

- The literature review is not adequate and at times not accurate. In the introduction (lines 46-57) the authors mention several papers as examples of bed roughness inversion, where in fact most of those papers target the inversion of the basal drag (or basal friction), not the bed roughness. While these quantities can be related, they are certainly not interchangeable. Also I think there are some relevant papers that should be cited. Babaniyi et al, TC 2021, present a rigorous approach on how to account for model errors (in particular in the rheology) when inverting the basal friction. Other studies that look at the impact of rheology on inverted quantities are Seroussi et al., Journal of Glaciology 2013 and Ranganathan, Journal of Glaciology, 2020. A preliminary study of how errors in SMB could affect inverted basal parameters were featured in perego et al, JGR, 2014.
- The authors present a clever but involved and ad-hoc way to invert for the bed roughness. I find this anachronistic. Nowadays, the large majority of work performing inversion of ice sheet quantities uses PDE-constrained optimization approaches, which are very well understood and naturally linked to Bayesian inference problems. Key parts of the PDE-constrained optimization problem are the regularization terms, that avoid overfitting, and the ability to weigh observations according to their trustworthiness (i.e. root mean square errors in observations). The proposed method has a regularization step in the form of a Gaussian filtering, but it's not clear to me how to link that to the typical regularization term in the formal optimization approach. In my understanding, their method does not account for root means square errors in the velocity or thickness data, which is a significant limitation. I think the author should discuss these limitations and also investigate how different choices of the radius of the Gaussian filters affect their results. I suspect that there is too much overfitting in their inversion.

Minor comments:

- eq. (1): In general, τ_b and u_b are vectors. Please write the equation in vector form (using the vector u_b and its magnitude $|u_b|$).
- eq. (1): How do you compute N ?
- line 172: how do you choose the radii of the Gaussian filters?
- section 4.2. Typically we distinguish errors in the data (e.g. in velocity/thickness observation and, possibly, SMB), from model errors (specific laws and model parameters like A , ρ , etc). The latter are harder to account for. I think it would be better to do this distinction in your perturbed experiments.
- Figs 4 and 4: The range of the colorbar for the bed roughness is too wide. I would limit it to the interval $[0.5,2]$ or so, rather than $[0.1,10]$. More ticks on the colorbar might help as well.