EGUsphere, author comment AC2
https://doi.org/10.5194/egusphere-2022-470-AC2, 2022

Reply on RC2

Xiaoyu Ma et al.

Author comment on "Estimating spatiotemporally continuous snow water equivalent from intermittent satellite observations: an evaluation using synthetic data" by Xiaoyu Ma et al., EGUsphere, https://doi.org/10.5194/egusphere-2022-470-AC2, 2022

Response to Reviewers

Re: HESS Manuscript egusphere-2022-470: "Estimating spatiotemporally continuous snow water equivalent from intermittent satellite track observations using machine learning methods" by Ma et al.

The comments from the editor and the reviewers are reproduced below in italics bold and our corresponding responses are in normal type.

Thanks for the great points and comments made by Reviewer #2, which are entirely constructive and will, we believe improve the manuscript. We provide a point-by-point response below.

Reviewer #2 (Formal Review for Authors (shown to authors)):

The manuscript 'Estimating spatiotemporally continuous snow water equivalent from intermittent satellite track observations using machine learning methods' by Ma et al. provides an interesting synthetic study regarding SWE observations from potential satellite tracks for track-to-area transformations. In general, I think such studies are important to be prepared for novel satellite missions and their 'real world' applications. The study is carried out in the Upper Toulomne River Basin in California in the Western United States. The authors apply statistic and machine learning techniques to answer the following four research questions:

- ***How does the spatially distributed April 1st SWE inferred from TTA compare with the synthetic truth, and how do their differences vary in dry, normal, and wet years?***
- ***What are the dominant variables for the April 1st SWE estimation in statistical and machine learning TTA methods, and which method has the highest accuracy?***
- ***How does the accuracy of the domain-wide SWE estimates from TTA approaches evolve within a season at different temporal observation resolution?***

- ***How does the performance of TTA change as a function of the spatial sampling density (number of hypothetical ground tracks), and what is the preferred number of tracks?***

The manuscript is well written and organized. I agree with all points raised by reviewer 1. In addition, I have some further points, which need clarification and/or additional information before publication.

Please change the unit of SWE in mm (instead of m or cm) throughout the paper (text, figures, tables), as mm is the unit for SWE.

We will change the unit of SWE from m to mm throughout the paper as suggested, including text, figures, and tables.

In general, please discuss if the pixel size and satellite track width of approx. 1 km is suitable to accurately describe the quantity of snow and SWE accumulation and ablation within the catchment (and, also for which applications is this resolution sufficient?). Could there be any limitations and need for higher spatial resolutions?

Thank you for the suggestions. The pixel size is 480m and the track width is about 1 km. We did not design the parameters, but just used the best available data. The synthetic tracks are consistent with a notional design for a P-band signal of opportunity proposed mission (by NASA’s Jet Propulsion Laboratory; see Yueh et al., 2021 for more information). The “truth” for the analysis of SWE estimates is the snow reanalysis data (F2022), which is at a 480 m spatial resolution. Designing a satellite with finer spatial resolution is expected to increase the training size of ML-based TTA SWE transformation, which may lead to better performance of continuous SWE estimation, but about 1-km seems to be what is now technically feasible. Due to space limitations, we only explored one SWE spatial resolution, and we prefer to defer analysis of the sensitivity of ML performance to observation resolution to future studies. We will add some discussion to this effect in the conclusions section.

Title: The title is a bit misleading. The study is fully synthetic, but the title ‘promises’ somehow ‘real’ satellite track observations. I would recommend to at least include the word ‘synthetic’ (or ‘hypothetic’) in the title. Moreover, as you use statistic and machine learning methods it would make sense to add also statistic in the title. Suggestion:

‘Estimating spatiotemporally continuous snow water equivalent from intermittent synthetic satellite track observations using statistic and machine learning methods’.

Thank you for your suggestion. We propose to add “potential” to the title to avoid implying that the observations are real. We found that the other qualifiers make the title too cumbersome, and instead we suggest “The potential for estimating spatiotemporally continuous snow water equivalent from intermittent satellite track observations”.

Abstract: The abstract should be revised: Please add information on the potential future satellite mission (P-SoOP), on which you relate your work on TTA, and give information on the spatial resolution of your synthetic satellite tracks.

Thank you for your suggestions. What is a bit tricky is that some of the technical background is in a NASA proposal under consideration, and we're limited in what we can say, On the other hand, the Yueh et al. (2021) paper, which we cite, can be leveraged for more information, including some on P-SoOP, which we will mention briefly in the abstract as the starting point for our synthetic SWE observations. We also will state in the abstract that that the spatial resolution of the synthetic satellite observations is 480 m.

38+: I am missing a solid literature review

a) on satellite based SWE and snow height derivation. This should at least include the following references:

Lievens, H., Brangers, I., Marshall, H.P., Jonas, T., Olefs, M. and De Lannoy, G., 2022. Sentinel-1 snow depth retrieval at sub-kilometer resolution over the European Alps. The Cryosphere, 16(1), pp.159-177.

Deschamps-Berger, C., Gascoin, S., Berthier, E., Deems, J., Gutmann, E., Dehecq, A., Shean, D. and Dumont, M., 2020. Snow depth mapping from stereo satellite imagery in mountainous terrain: evaluation using airborne laser-scanning data. The Cryosphere, 14(9), pp.2925-2940.

b) on other TTA or point-based methods.

a) Thank you for the suggestions, which we will add to the introduction.

b) In addition to the TTA and point-based method using snow pattern repeatability (Pflug and Lundquist, 2020), we will add the following references that discuss other TTA or point-based methods:

(Magnusson et al., 2014)

Magnusson, J., Gustafsson, D., Hüsler, F., and Jonas, T.: Assimilation of point SWE data into a distributed snow cover model comparing two contrasting methods, Water Resources Research, 50, 7816–7835, https://doi.org/10.1002/2014WR015302, 2014.

(Schneider and Molotch, 2016)

Schneider, D. and Molotch, N. P.: Real-time estimation of snow water equivalent in the Upper Colorado River Basin using MODIS-based SWE Reconstructions and SNO☐ data, Water Resources Research, 52, 7892–7910, https://doi.org/10.1002/2016WR019067, 2016.

57: Please add 'wet snow' as further limitation.

We will add a comment on this limitation of PM-based SWE remote sensing, with a reference to (Walker and Goodison, 1993).

82: Please give some more information on P-SoOP in the manuscript, including when it is planned to be launched and if the track width matches your synthetic assumption. What is the expected accuracy of P-band based SWE estimates?

We cited Yueh et al., 2021 to provide more information on P-SoOP, which is a proposed project that does not yet incorporate snow sensing into the schedule. However, our project was not limited to P-SoOP but is appliable to any intermittent satellite observations. We will make this clearer in the revised MS.

103: Why not also areas in high latitudes?

Good point. We will rewrite this statement to indicate that the method has potential for all snow-covered areas globally.

122: The F2022 snow reanalysis dataset should be described in more detail. What is the meteorological input to generate SWE? Are the applied meteorological variables for the F2022 snow reanalysis dataset the same than those you used for your machine learning approaches (is independency given)?

We will add a little more detail, but of course this is a published paper, so we only give a high-level summary and refer the reader to the archival paper for details.

195: Please define how you classified the years in dry, normal and extremely wet. What are the thresholds?

We will add more details in section 3.2.1 as to the classifications.

338 and Figure 3: As you clearly mention, DNN performs best. However, it is worth to mention that RF shows the lowest PEBAS values for the normal and wet years. Also, more clear statements why DNN performs best would help.

Thank you for the suggestion. We will mention that RF performed best in terms of PEBAS in wet and normal years. We will also provide more information and related references as to why DNN (MLP) performs best.

565: Please add some more discussion on the fact that topography plays an important role regarding the 'choice' of the satellite tracks. Does this play a role in Figure 11 as an increase in the number of ground tracks shows outliers in the course of MAE for WY2017 – 3 ground tracks and WY2008 – 5 ground tracks.

We will add more discussion regarding Figure 11 and Figure S9 in section 4.4 and note that topography plays an important role in the performance of TTA SWE transformation.

References

Magnusson, J., Gustafsson, D., Hüsler, F., and Jonas, T.: Assimilation of point SWE data into a distributed snow cover model comparing two contrasting methods, Water Resour. Res., 50, 7816–7835, https://doi.org/10.1002/2014WR015302, 2014.

Pflug, J. M. and Lundquist, J. D.: Inferring Distributed Snow Depth by Leveraging Snow Pattern Repeatability: Investigation Using 47 Lidar Observations in the Tuolumne Watershed, Sierra Nevada, California, Water Resour. Res., 56, https://doi.org/10.1029/2020WR027243, 2020.

Schneider, D. and Molotch, N. P.: Real-time estimation of snow water equivalent in the Upper Colorado River Basin using MODIS-based SWE Reconstructions and SNO☐ data, Water Resour. Res., 52, 7892–7910, https://doi.org/10.1002/2016WR019067, 2016.

Walker, A. E. and Goodison, B. E.: Discrimination of a wet snow cover using passive microwave satellite data, Ann. Glaciol., 17, 307–311, https://doi.org/10.3189/S026030550001301X, 1993.

Yueh, S. H., Shah, R., Xu, X., Stiles, B., and Bosch-Lluis, X.: A Satellite Synthetic Aperture Radar Concept Using P-Band Signals of Opportunity, IEEE J. Sel. Top. Appl., 14, 2796–2816, https://doi.org/10.1109/JSTARS.2021.3059242, 2021.

Please also note the supplement to this comment:
https://egusphere.copernicus.org/preprints/2022/egusphere-2022-470/egusphere-2022-470-AC2-supplement.pdf