EGUsphere, author comment AC1
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Reply on RC1

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-AC1, 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 #1, which are entirely constructive and will, we believe improve the manuscript. We provide a point-by-point response below.

Reviewer #1 (Formal Review for Authors (shown to authors)):

Ma et al. investigate the use of machine learning for track-to-area transformation of satellite observations of SWE in swathes that cover a small fraction of a watershed (it is worth noting that point-to-area transformation with horizontal and vertical distance weighting has long been used for assimilation of in situ snow observations in numerical weather prediction). This study is entirely synthetic, but interesting in anticipation of real remote sensing opportunities. Some clarifications and numerous minor corrections are required. Explainability of the ML results is promised, but there is very little physical explanation in the discussion of the input feature sensitivity tests.

Thanks for the general comments on this manuscript. We will add more physical explanation and related references relative to the input feature sensitivity test as follows:

- Missing feature analysis:

Winter precipitation in general is more influential than other meteorological forcings in SWE estimation (see e.g. Raleigh and Lundquist, 2012, Luce et al., 2014).

- Feature sensitivity analysis:

Positive biases of net longwave radiation and biases in precipitation cause large SWE estimation errors in the normal and wet years (Sicart et al., 2006). This is because decreasing longwave radiation cannot increase 1 April SWE above the accumulated snowfall but increasing longwave radiation can decrease SWE all the way to zero (in theory), so increased net longwave radiation influences the SWE estimates more than decreases.

71

LiDAR can produce continuous SWE maps; the Airborne Snow Observatory does for this very basin.

We suggest deleting "LiDAR" here. More generally, our intent was to demonstrate that the "track-to-area" method is useful for obtaining spatially continuous SWE where SWE observations are only available along ground tracks. In fact, we selected this basin because LiDAR data are available, but the idea is to demonstrate the track to area method in anticipation of a future satellite mission that provides data only along tracks, rather than images as ASO does.

76

"TTA transformation could be achieved by leveraging snow pattern repeatability", but that is not what is done here.

Here we aimed to introduce the application of other TTA or point-based SWE transformation methods. In addition to the method using snow pattern repeatability (Pflug and Lundquist, 2020), we intend, in the revised MS, to add and discuss briefly the following references:

(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.

253

Is a 50% perturbation in temperature applied to the Kelvin temperature (which would be enormous) or Celsius temperature (which would be meaningless)? A 50% error in air pressure is also unphysical. To be clear, is the perturbation a fixed bias (as described) and not a random error? If so, why does the DNN not just learn the bias?

The unit here should be Celsius. The 50% error doesn't mean we increase or decrease 50% of the original value. Instead, we added 50% of the difference of maximum and minimum temperature for a specific pixel during the study period to the original value. The perturbation is a fixed bias. The reason why we added biases rather than random errors to meteorological inputs is that in snow hydrology, systematic SWE estimation biases is the primary source of estimation error, and it mainly comes from the biases of input meteorological forcings in SWE modeling. We intend to clarify this in the revised MS.

323

What is intended by saying "a simple ANN … is capable of learning non-linear relationships… while DNN … can learn more complicated relationships"? More complicated than nonlinear?

Our intention here was to point out the superiority of Multilayer Perceptron (MLP) relative to a single-layer Perceptron. A single-layer Perceptron is a neural network with only one neuron and can only understand linear relationships between the input and output data, while with Multilayer Perceptron, horizons are expanded and the neural network can have multiple layers of neurons, which are better adapted to more complex patterns (Gardner and Dorling, 1998). We will add clarification to this effect.

330

Levenberg-Marquardt is not the cost function, it is the algorithm used to minimize the cost function.

Thanks for pointing out the error. We suggest changing "cost function" to the "algorithm used to minimize the cost function".

Time series of SWE observations would not be available for wet snow after peak SWE.

We leverage the SWE reanalysis dataset (F2022 introduced in Section 2.2) as the synthetic "truth" for evaluating our SWE estimates. It is available over a full water year, whether or not the snow is wet. We will clarify this.

There is no discussion of why removing a particular variable will sometimes increase and sometimes decrease MAE in Figure 8.

We will add some discussion as to why some variables are not important in SWE estimation, and, for others that are, we will discuss their different roles in SWE estimation in a dry, normal, and wet year.

The biases in Figure 9 are fractions, not %. Why are there non-zero changes of MAE for zero bias in WY 2015 and 2017?

Thanks for pointing this out; we will change the X-axis by a factor of 100. The non-zero changes of MAE for zero bias were an error in plotting Figure 9, which is corrected below.

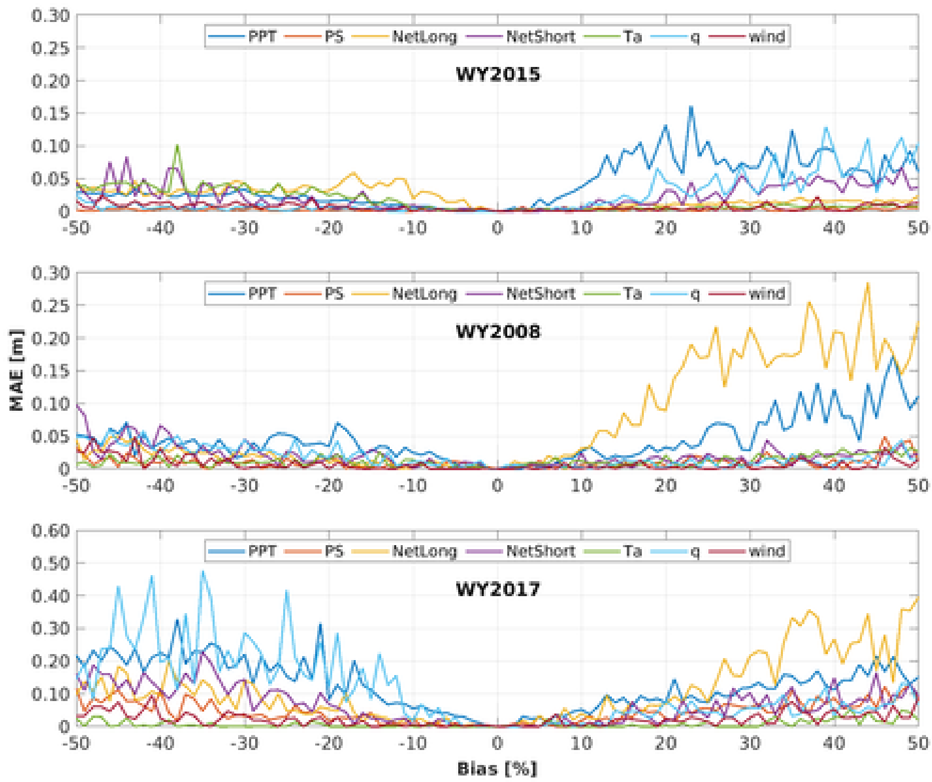

Figure 9.

535

I do not follow the argument for why positive longwave radiation errors cause larger errors. Is it that decreasing longwave radiation cannot increase 1 April SWE above the cumulated snowfall, but increasing longwave radiation can decrease SWE all the way to zero?

We will modify the explanation to make it more clear in the revised MS. Essentially decreasing longwave radiation cannot increase 1 April SWE above the accumulated snowfall but increasing longwave radiation can decrease SWE all the way to zero, so increased net longwave radiation influences the SWE estimates more than decreases.

The legend "Observation coverage" could be removed from Figure 10 so that it does not overlap the ground tracks (and four decimal places is excessive for the percentage).

Thanks for the suggestion, which we will follow. We will also move the information about observation coverage to the supplement (Table S1).

Minor Corrections

We've carefully proofread the MS and will make minor corrections throughout to eliminate the grammatical mistakes noted by the reviewer as indicated below.

32

"it therefore, mitigates" – delete comma

Revised.

"it therefore mitigates"

43

"whether large amounts of snow accumulate"

Revised.

"high-elevation mountains where large amounts of snow accumulates"

52

"spatial, rather than point observations" – delete comma

Revised.

"spatial rather than point observations"

56

"except during periods of precipitation"

Revised.

59

"topographically complex areas etc. (Le et al. 2017),"– delete etc. and comma

Revised.

"topographically complex areas (Le et al. 2017)"

113

"snow dominated"

Revised.

157

"Each of the experiments used one of four algorithms"

Revised.

221

"We investigated the performance of the SWE TTA estimation"

Revised.

231

"from the closest previous observation day"

Revised.

352

"for all four algorithms"

Revised.

358

"The reason for larger values"

Revised.

372

"for all three years"

Revised.

375

It would make more sense to say that April 1st SWE is highly correlated with cumulative winter precipitation.

Agreed. We will change this sentence to "April 1st SWE is highly correlated with cumulative winter precipitation."

379

"The error range is larger in WY2008 than in the dry year"

Revised.

391

"underestimation tends to occur"

Revised.

449

The information in this first sentence is repeated in the next sentence.

Revised. We will delete the redundant sentence.

451

"(dry, average and wet)"

Revised.

460

Delete "are more obvious"

Revised.

463

"are shown in Fig. 7"

Revised.

472

"becoming more apparent"

Revised.

505

"that provides the most useful information"

Revised.

507

"The dominance of precipitation is most significant"

Revised.

518

"larger biases have larger impacts"

Revised.

525

"so SWE estimates from the network are slightly different"

Revised.

534

"In addition, we propose"

Revised.

580

"is larger than two"

Revised.

581

"if more than two ground tracks pass"

Revised.

603

"more satellite overpasses do not improve the estimates much"

Revised.

621

"can be used"

Revised.

628

"and wet years"

Revised.

634

"The DNN method is the most accurate"

Revised.

635

"and reduction in the training data size"

Revised.

References

Luce, C. H., Lopez-Burgos, V., and Holden, Z.: Sensitivity of snowpack storage to precipitation and temperature using spatial and temporal analog models, Water Resour. Res., 50, 9447–9462, https://doi.org/10.1002/2013WR014844, 2014.

Raleigh, M. S. and Lundquist, J. D.: Comparing and combining SWE estimates from the SNOW-17 model using PRISM and SWE reconstruction, Water Resour. Res., 48, https://doi.org/10.1029/2011WR010542, 2012.

Please also note the supplement to this comment:
https://egusphere.copernicus.org/preprints/2022/egusphere-2022-470/egusphere-2022-470-AC1-supplement.pdf