Thank you for reviewing our manuscript. The responses to the comments are inserted below in blue color.

Overall, I think the idea has merit and could be a useful tool when a more complex computational model is not appropriate. However, I think that the manuscript in it's current form lacks enough validation or error analysis for the presentation of a new method. The comparison of the method to a single station for a single year is not enough; I would really like to see multiple locations with varying conditions and snow years to be convinced. Furthermore, I think that the comparisons to other models is lacking. While I am happy to see the comparisons to Jonas et al., 2009 and Sturm et al., 2010, much has been done in the past 8-9 years. Perhaps a comparison to a more complex model like SnowPack in addition to what is already shown. That could provide evidence that if all you need are bulk properties that this new approach could be just as good and computationally easier.

More complex snow model requires energy flux estimations, which typically functions of air temperature, humidity, radiation, wind speed, precipitation, soil temperature, etc., while this technique (SWEE algorithm) just estimates the SWE from the snow depth and temperature data. They are not comparable in our opinion. In fact, snow depth is one of the output variables of the complete snow model such as SnowPack model, which should be used when high-quality atmospheric forcing data are available. However, this simple technique is effective when the atmospheric data is insufficiently available in the historical sites.

We do not think that additional application is required for this **technical note** article. However, we applied it to four selected SNOTEL sites for 2016, 2017, and 2018 water years (total 12 years). The sites were arbitrarily chosen from the US SNOTEL with snow pillow in four regions (Pacific Northwest, Central Sierra Nevada, Northeast, and Alaska). The results are shown in the end of this reply document. Note that that all parameters except new snow density were kept the same for these computations. The results indicate that the SWEE algorithm can sometimes get better than the other data-driven approaches depending on the data quality.

I appreciate the listing of 7 possible reasons for the errors, but these should really be better quantified in magnitude of error and some can actually be directly addressed with the available data.

For example: 1. snow density of newly fallen snow: The authors show the sensitivity of the equation to this parameter, but that doesn't mean this parameter is the reason for the error. Furthermore, enough information is available to compare what the SWEE estimation is to the Snotel new snow density (depth change during storm and SWE increase can be used to determine new snow density).

We intend to show that the new snow density was very sensitive to the SWE estimation. Please note that the change of snow depth is the main part of the SWEE algorithm.

2. snow erosion and abrasion affect snow depth: By how much? what is the impact on the estimation (quantify)

This is an open question. Combining this methodology and some accurate snowmelt estimation may provide an opportunity to separate erosion and melt.

3. Snow pillow measurement error - again, how much? There is literature on this, it will depend on the time of the season, etc. but how will this impact your comparison? To this end, more snow pit observations would go quite far in this study.

This is beyond the scope of this Technical Note article, which should be concise.

4. air temperature substitution - how much does this impact your results?

Unfortunately, we do not have air temperature and snow surface temperature, concurrently. So, we could not quantify it.

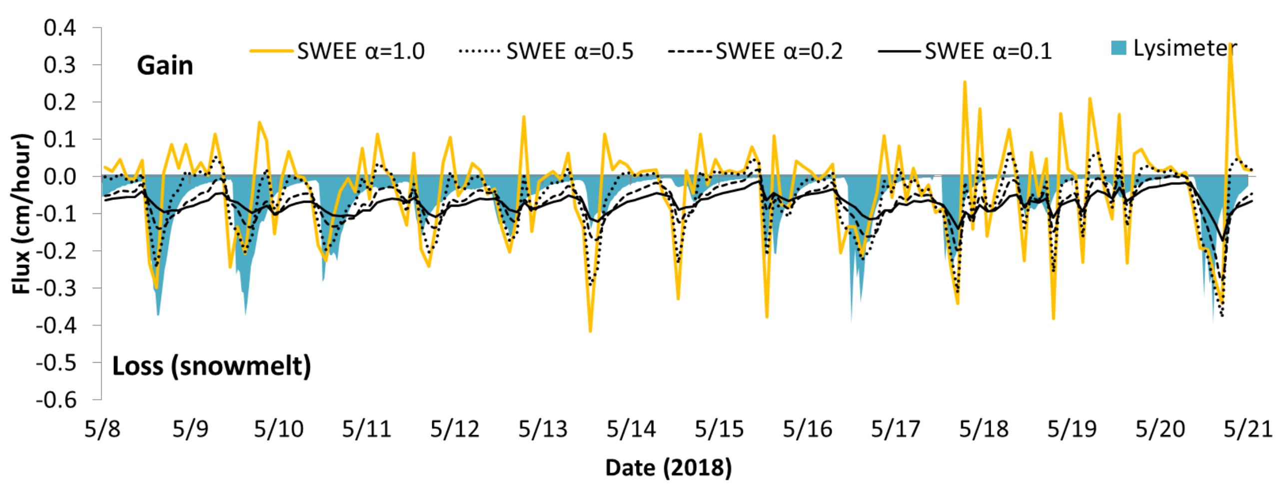
6. Accuracy of snow depth - this can be addressed a couple of ways. First there is literature on this and/or manufacturer defined accuracies that should be taken into account. Second, quantification of the theoretical error from this could easily be done. If the depth is off by 2 cm, how much does that change the SWEE result? Is this different for shallow or deep snowpacks?

The SWEE algorithm relies on the snow depth difference from the one time step prior. So, the fluctuation in the snow depth data would affect the SWEE estimation.

Assuming snow density is 0.30 g/cm^3, 2 cm error in snow depth should result in 0.6 cm error in SWE.

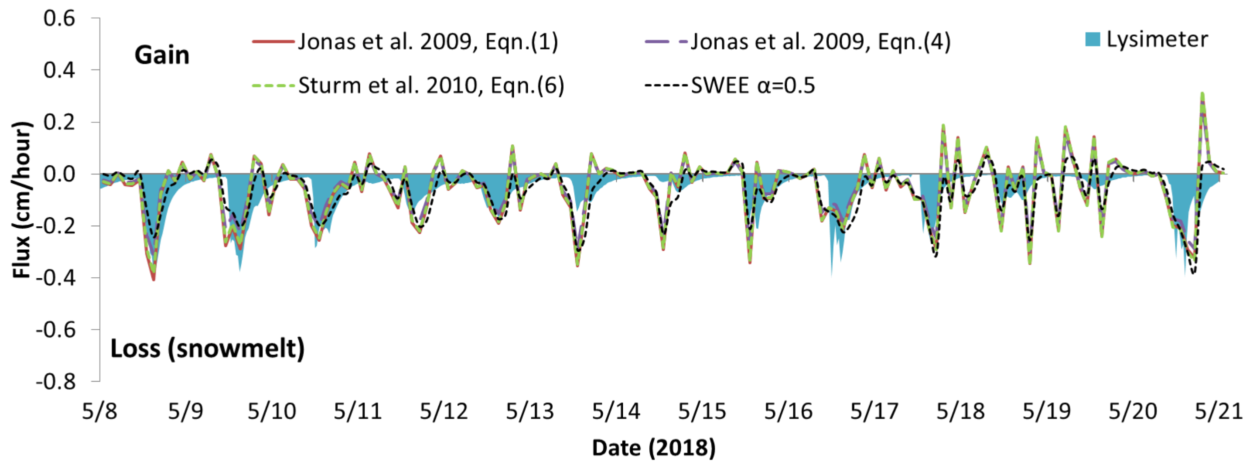
7. Treatment for snow depth is inappropriate - If this is the case, first quantify the effects, then second why not change the treatment? When applying a new method like this I think the data pre-processing can be huge. If your input is bad then your output will be bad. So why do you think the treatment may be inappropriate and how can you change it? Then do this to prove the presented method.

No matter what methodology you choose, the data cleaning/preprocessing is necessary. Otherwise, we end up with the "garbage in, garbage out" situation. To illustrate the case without exponential smoothing filter (α = 1.0), we adjusted the Figure 3 (see below). We think that the treatment for snow depth using the filter is appropriate and effective.

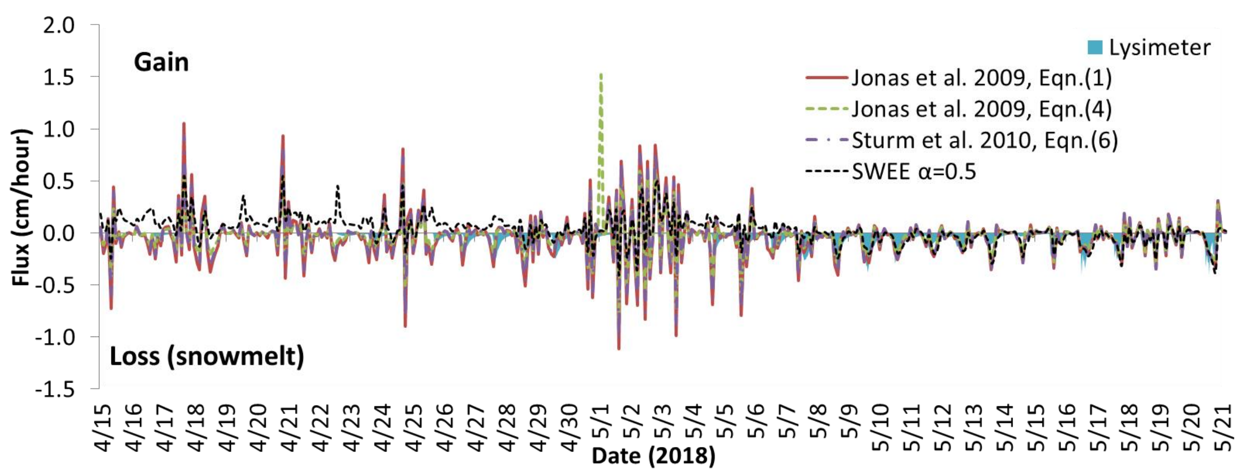


line 153: the authors state that "However, this could lead to better SWE change estimation" talking about the thought that SWEE may be better than the other regression models to estimate melt, then the manuscript compares the new method to lysimeter data, but not the other models. With a claim that the new method may be better, it should really be shown because you have the data to test this statement.

We computed the other methods in the NN. The results are shown below. We accordingly revised the text since the other models are as good as the SWEE algorithm.



The same graph with longer period is shown below. Due to the very large unrealistic variations in the snow depth measurement during the snow accumulation period, none of the models can accurately estimate the SWE change from this dataset except the snowmelt period.



According to table 1, there are two other methods that work better and are simpler to apply, please argue convincingly as to what the best method is and why (with data).

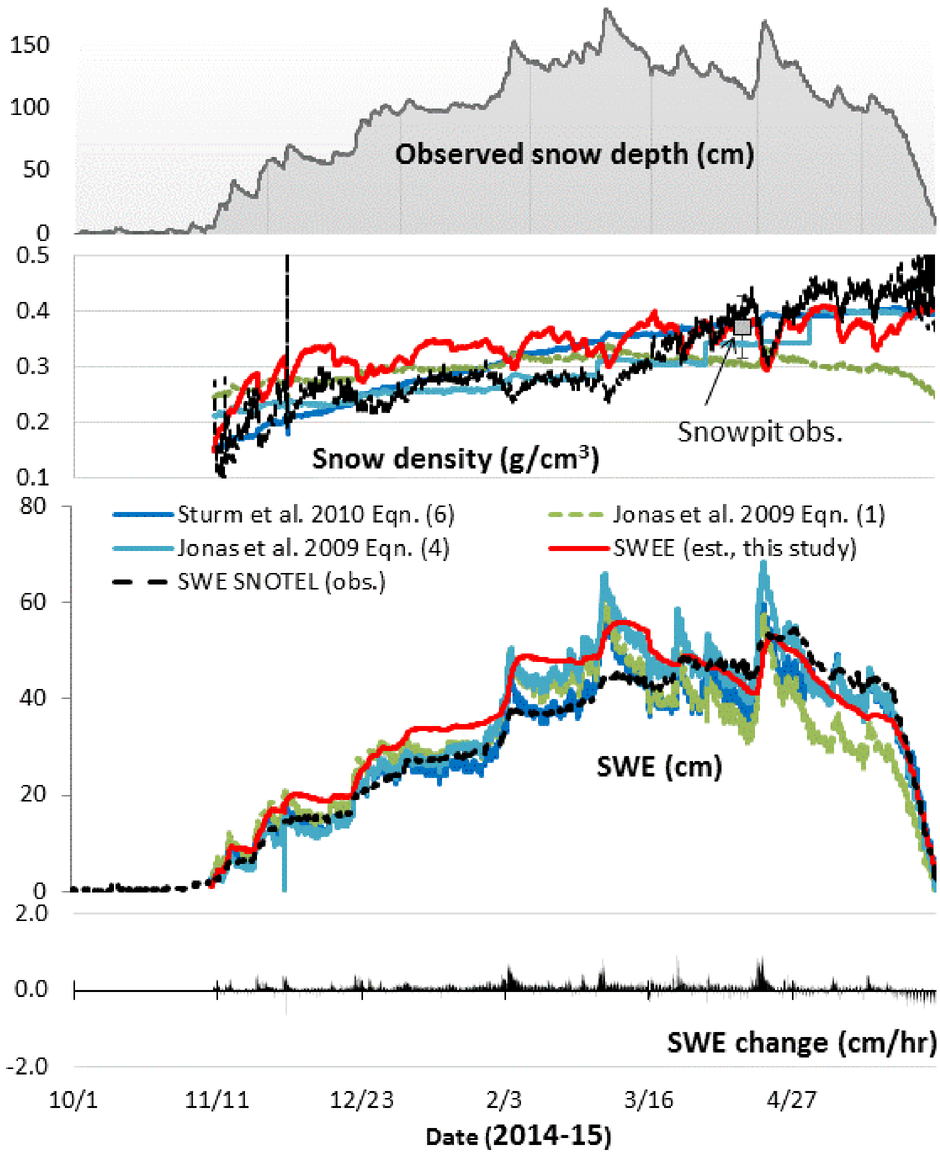
It is not surprising that the data driven approach (fitted regression model) shows better performance than a process-based model. We believe that process-based models be effective in the cases when historical data are not available or these observed data contains too much noise.

We updated the statistics as we found a minor error (the exponential smoothing filter was applied to the regression models by mistake). The conclusions were unchanged from this update.

Snow density model	R^2	NSME	Note
SWEE (this study)	0.864	0.816	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.716	0.707	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.931	0.926	Regression with a linear function with monthly parameters
Sturm et al. 2010, Eqn.(6)	0.906	0.852	Regression with an exponential with day-of-year

Fig. 1 - labeling each panel would help a lot. Why is the SNOTEL density not included in the density panel? This could help show how much better/worse each method is for estimating density.

This is a great suggestion. Thank you. We added the SNOTEL density in Fig 1. This addition line illustrates the advantage and disadvantage of the models. This graph implies that the snow density model can describes the snow dynamics fairly well while new snow density in the spring seemed to be underestimated.



Throughout the paper the authors use "change [delta]SWE", but the [delta] symbol is generally used to denote "change in". Is it supposed to be something different here, please double check.

As you described, ΔSWE denotes the change in SWE with respect to time. We double checked them throughout.

please correct "Strum et al." in figure 1 to "Sturm et al."

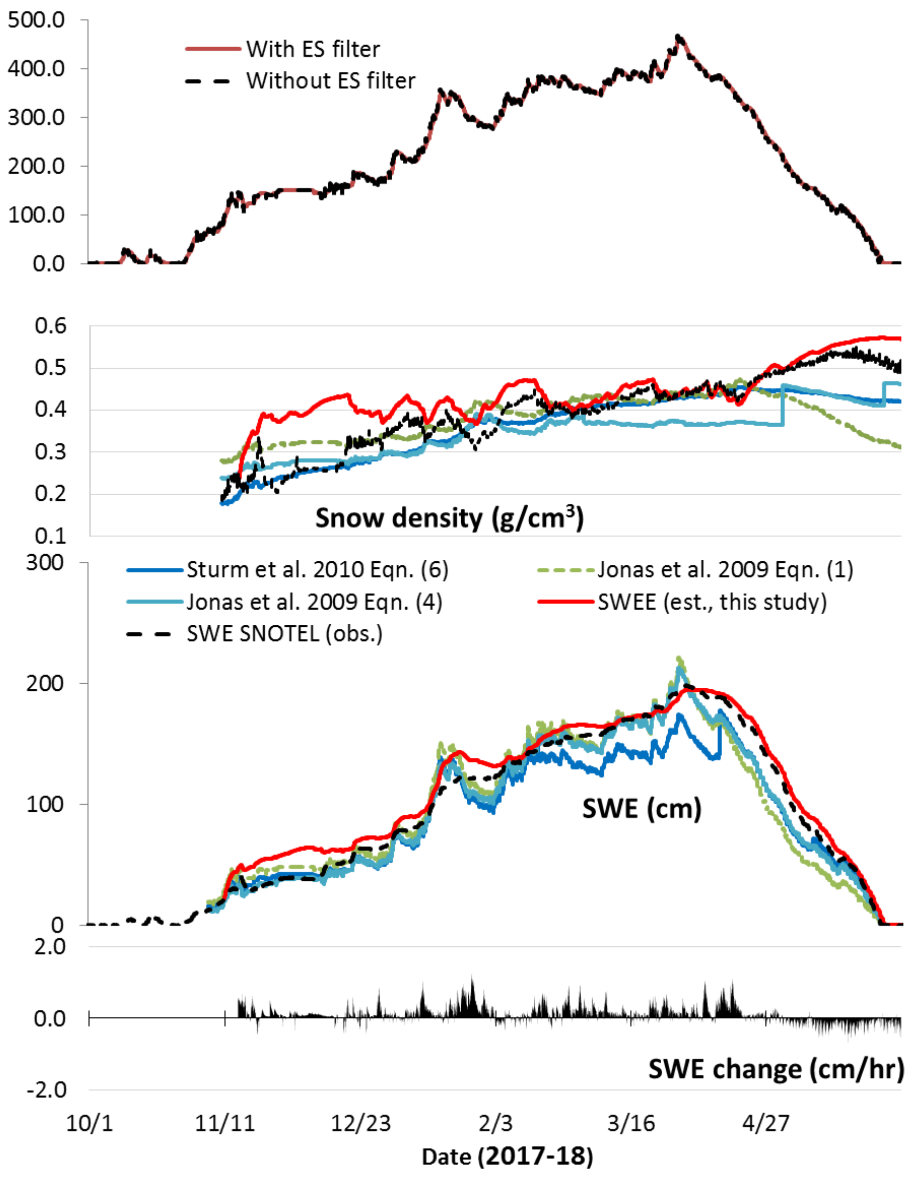
It has been corrected. Thank you.

the term "SWEE" is confusing to me, especially when the wording went back and forth with SWE observations comparing to SWEE. Perhaps changing it to "estimation of SWE (eSWE) to help the reader.

We just name it SWEE for convenience. We do not think that the name needs to be changed.

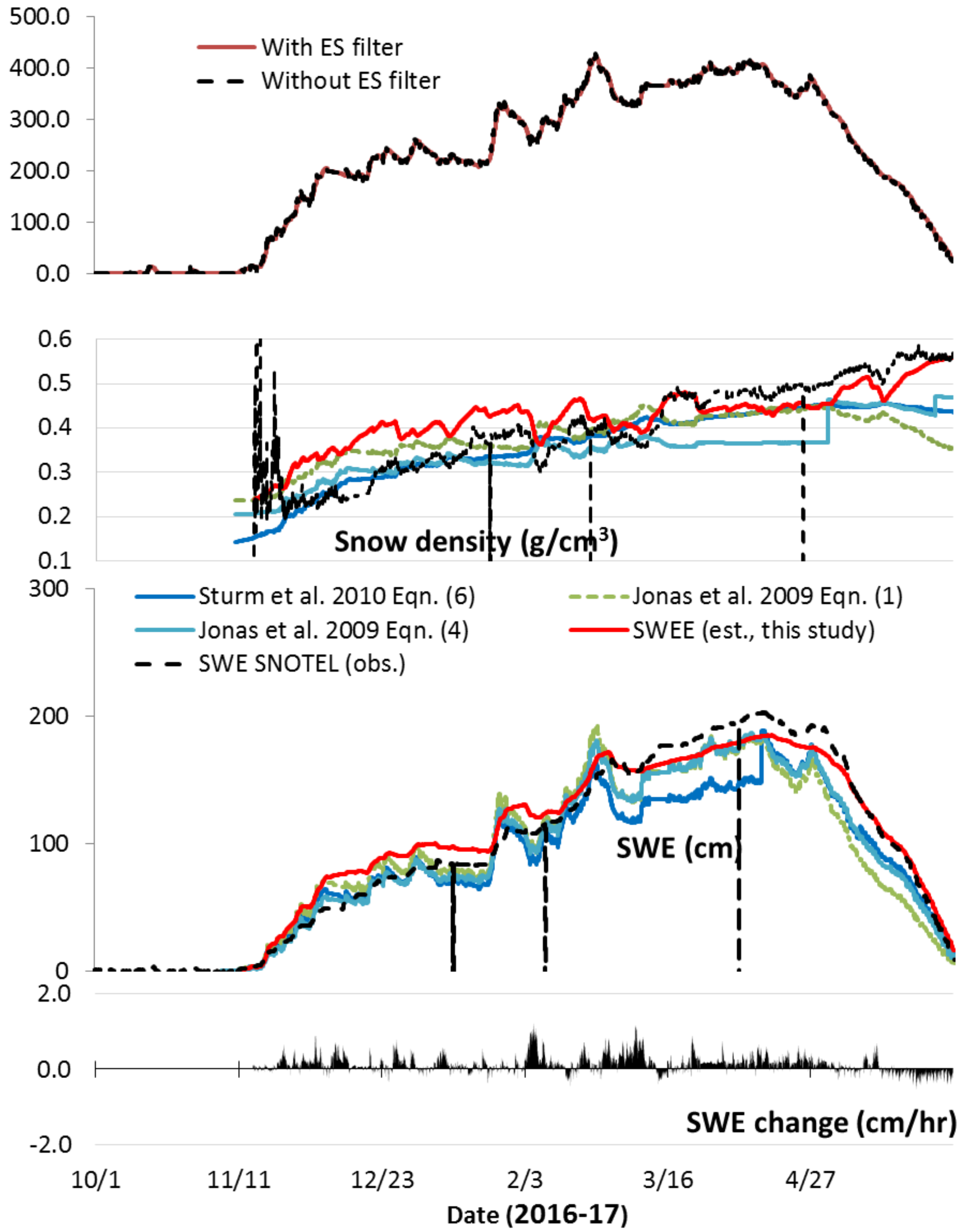
Following pages show the additional computations for four other SNOTEL sites.

Washington (PST) SNOTEL Site Cayuse Pass. (WY2018, ro_ns = 0.24 g/cm^3)



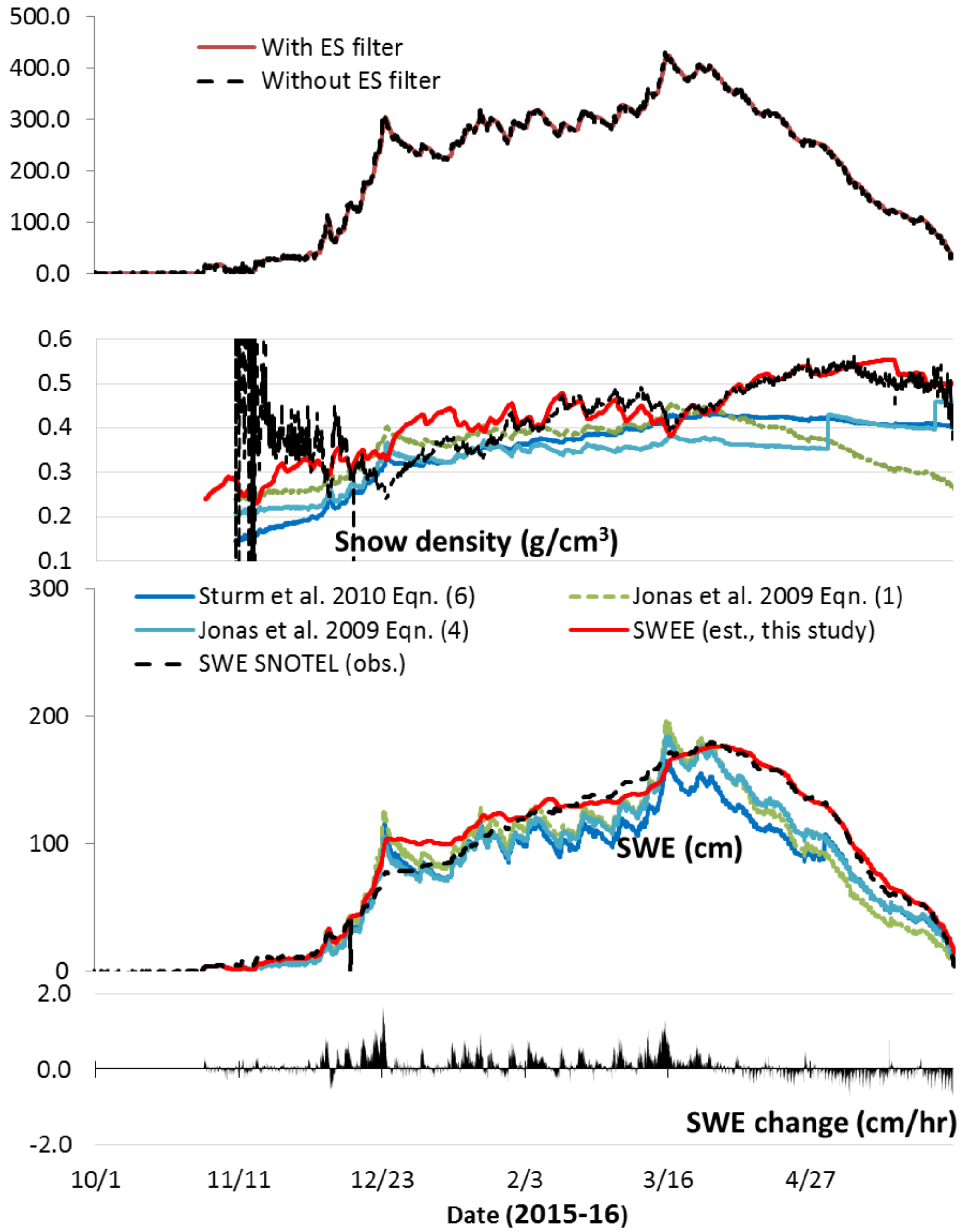
Snow density model	R^2	NSME	Note
SWEE (this study)	0.989	0.957	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.909	0.905	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.956	0.870	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.973	0.959	Regression with an exponential with day-of-year

Washington (PST) SNOTEL Site Cayuse Pass. (WY2017, ro_ns = 0.24 g/cm^3)



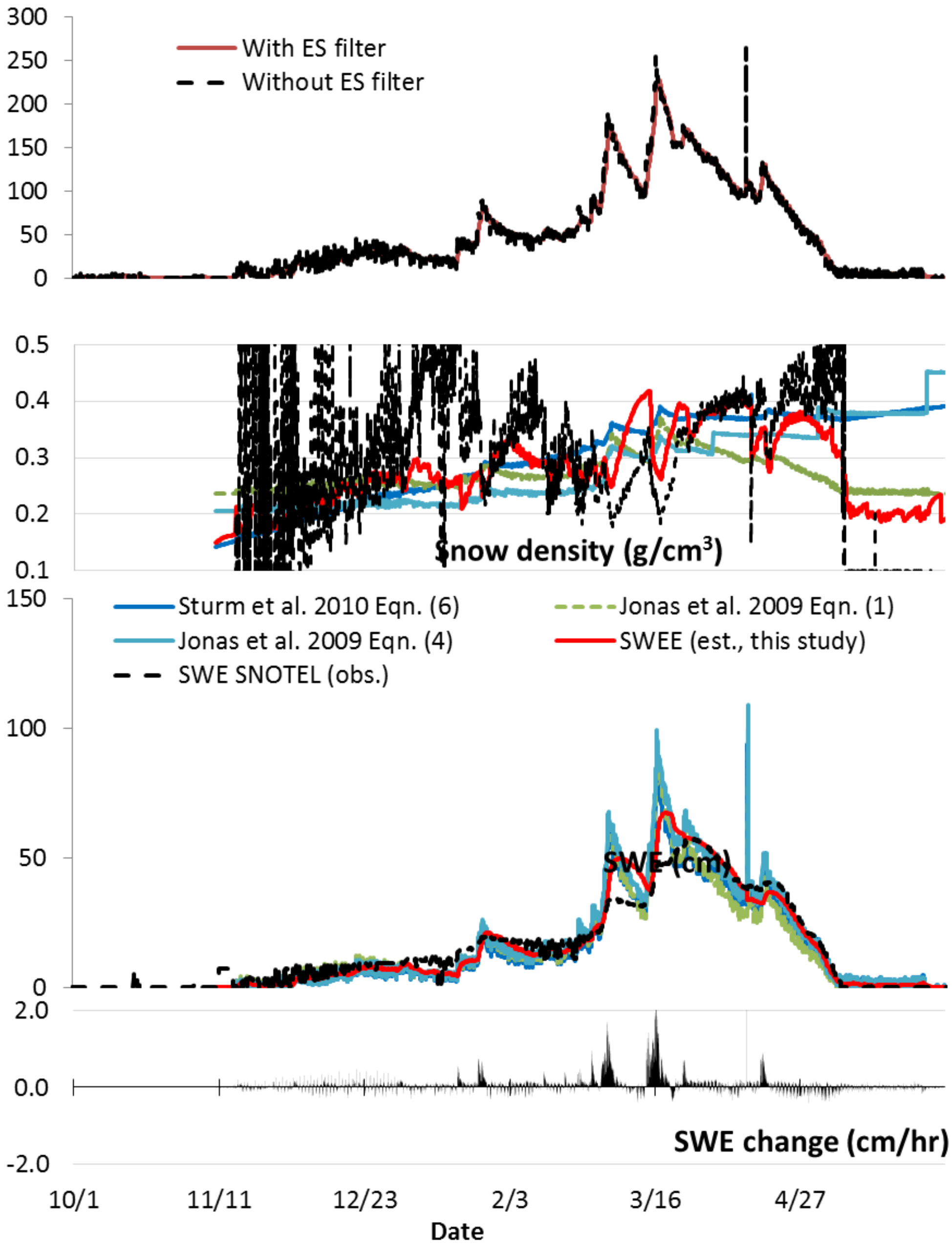
Snow density model	R^2	NSME	Note
SWEE (this study)	0.970	0.953	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.864	0.841	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.913	0.811	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.927	0.898	Regression with an exponential with day-of-year

Washington (PST) SNOTEL Site Cayuse Pass. (WY2016, ro_ns = 0.24 g/cm^3)



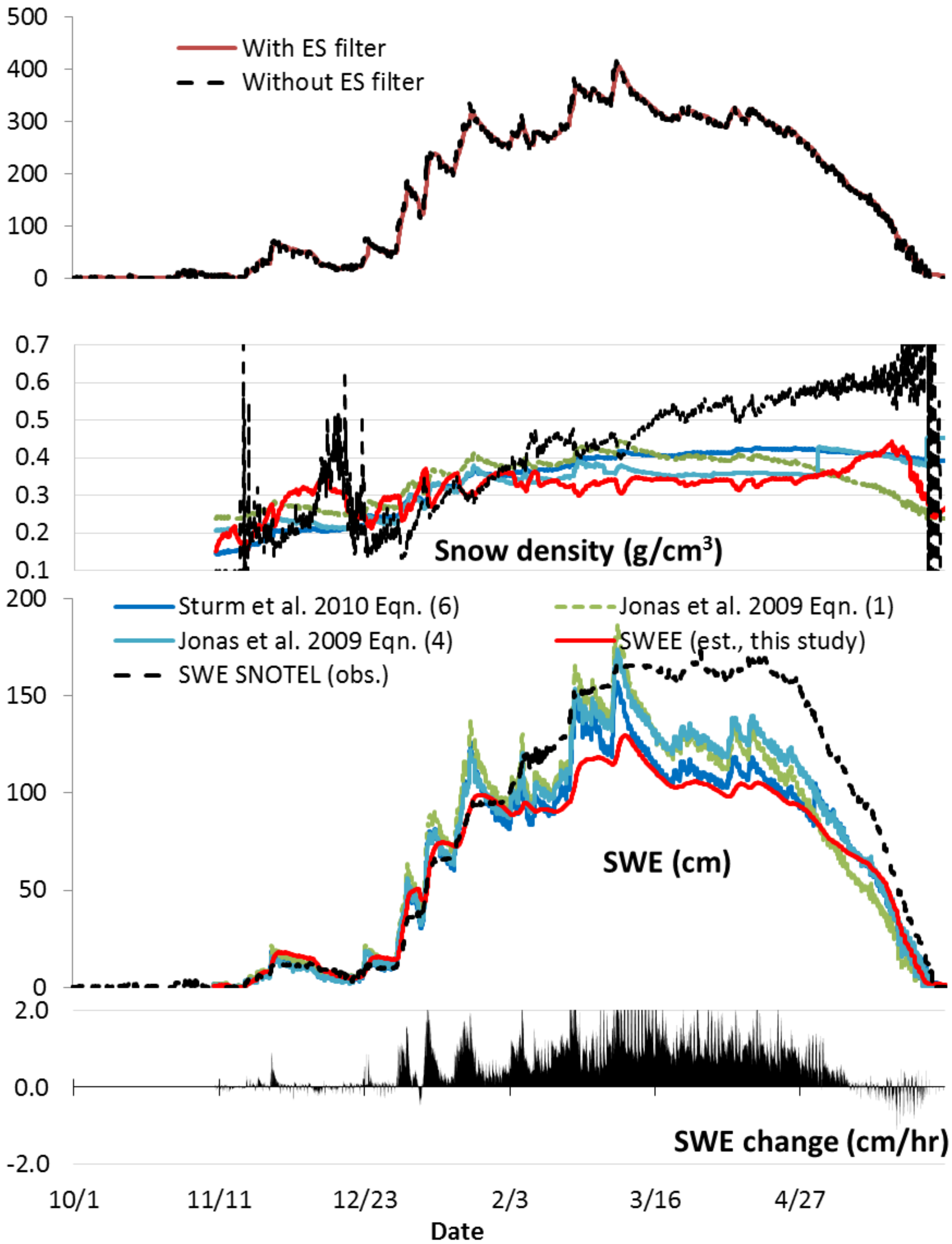
Snow density model	R^2	NSME	Note
SWEE (this study)	0.976	0.973	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.893	0.855	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.923	0.791	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.961	0.910	Regression with an exponential with day-of-year

California (PST) SNOTEL Site Ward Creek #3 (WY2018, ro_ns = 0.167 g/cm^3)



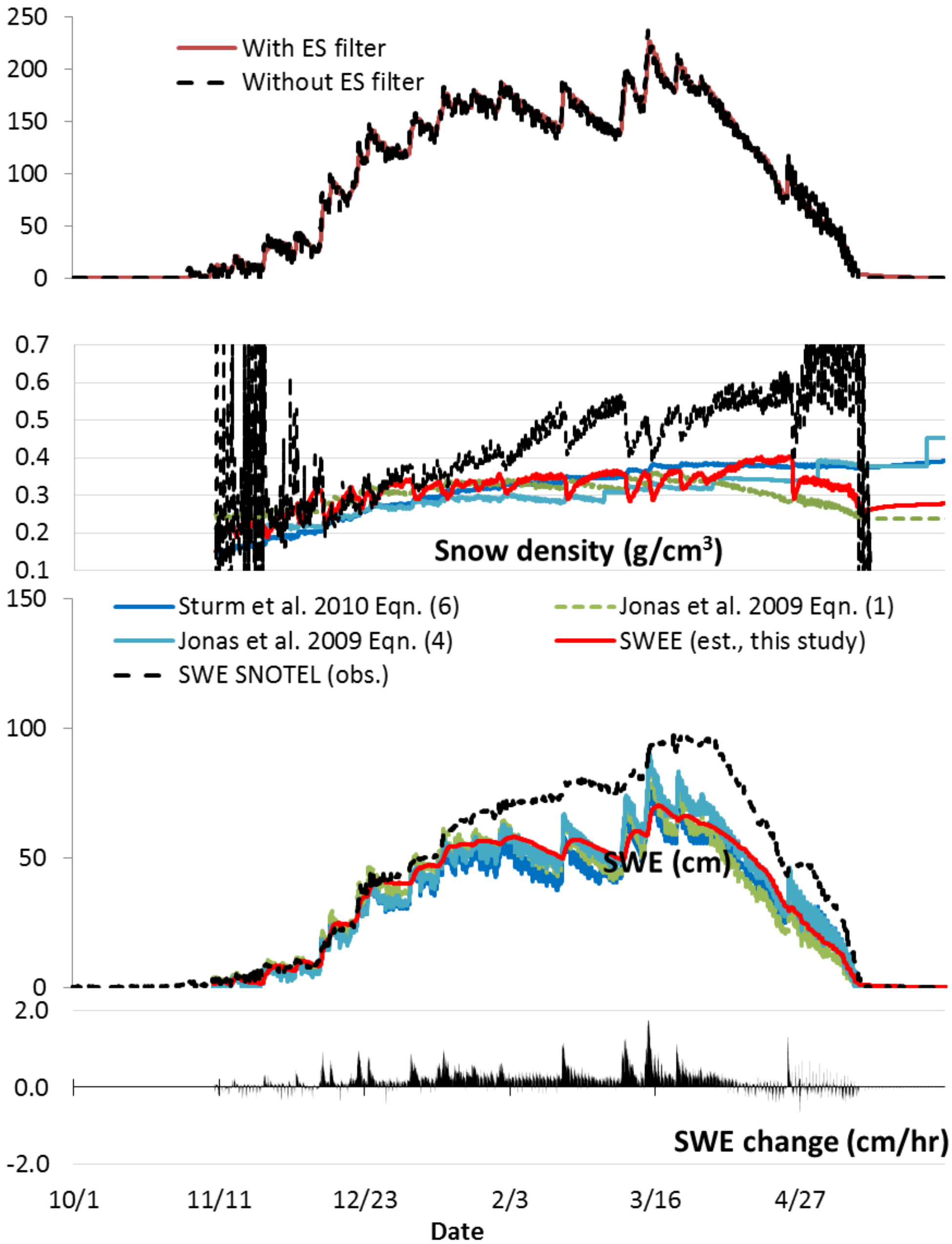
Snow density model	R^2	NSME	Note
SWEE (this study)	0.937	0.909	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.835	0.802	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.884	0.862	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.882	0.791	Regression with an exponential with day-of-year

California (PST) SNOTEL Site Ward Creek #3 (WY2017, ro_ns = 0.167 g/cm^3)



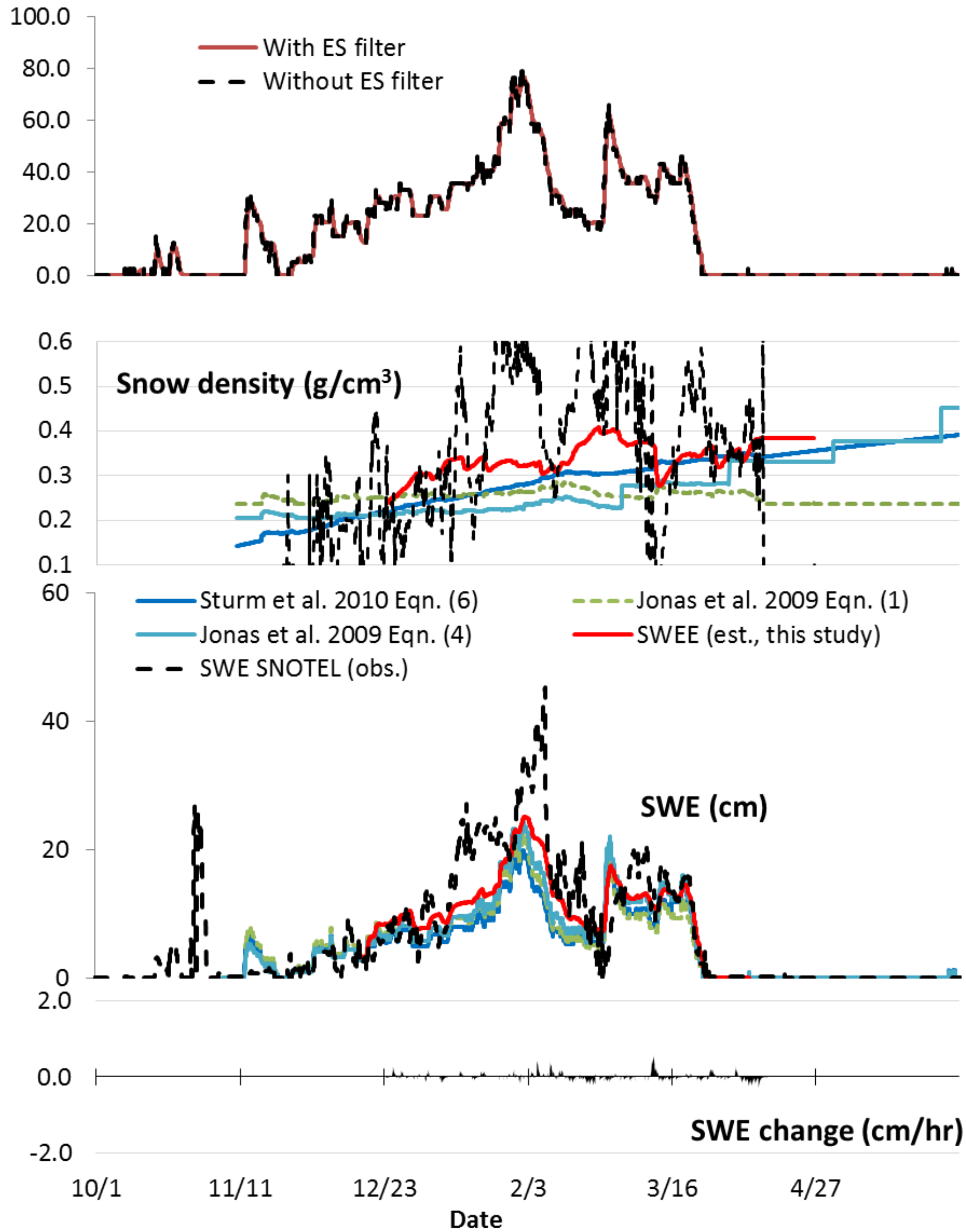
Snow density model	R^2	NSME	Note
SWEE (this study)	0.924	0.699	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.876	0.817	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.912	0.766	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.947	0.878	Regression with an exponential with day-of-year

California (PST) SNOTEL Site Ward Creek #3 (WY2016, ro_ns = 0.167 g/cm^3)



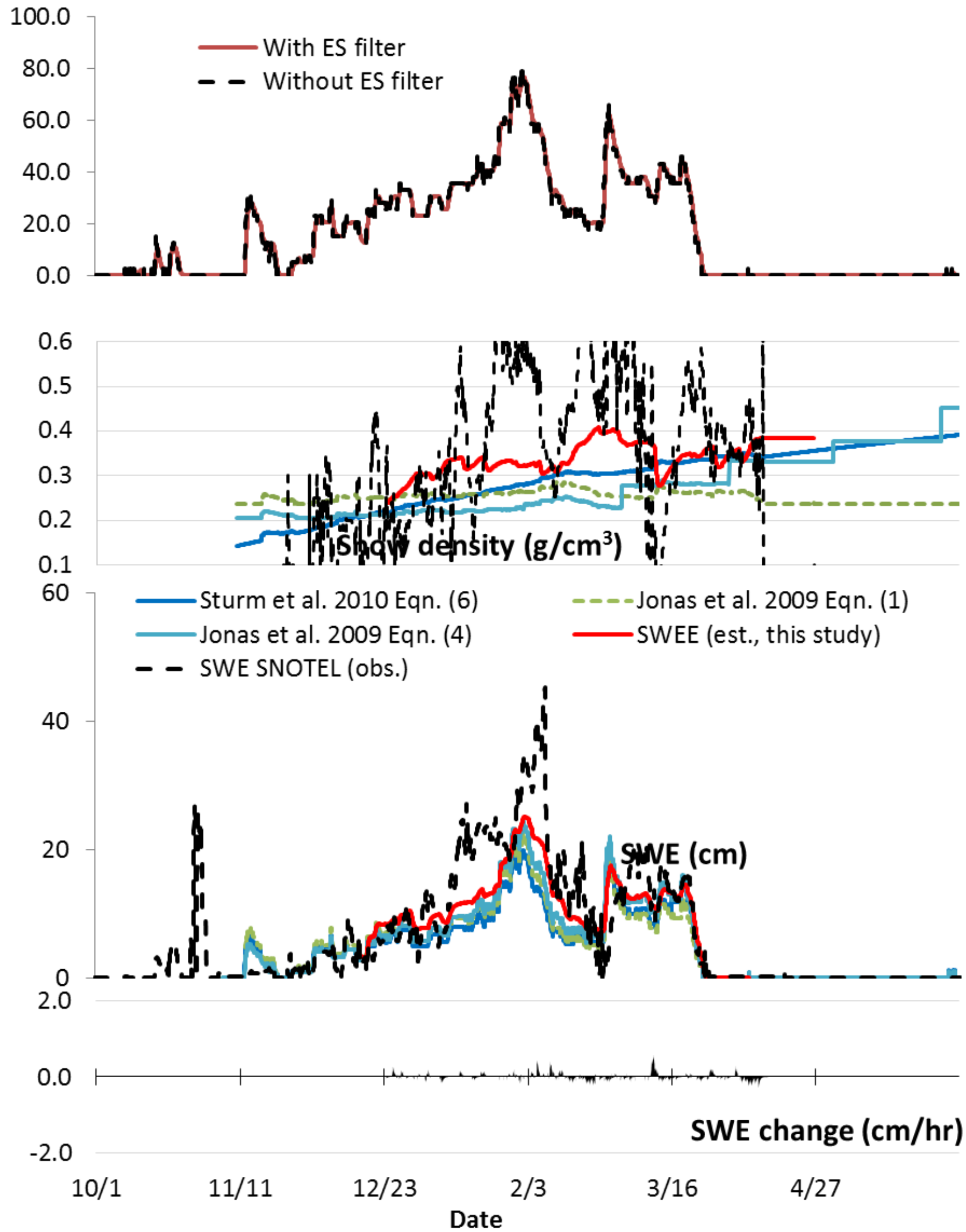
Snow density model	R^2	NSME	Note
SWEE (this study)	0.949	0.756	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.886	0.680	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.942	0.635	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.960	0.786	Regression with an exponential with day-of-year

Vermont (AST) SCAN Site Lye Brook (WY2018, ro_ns = 0.24 g/cm^3)



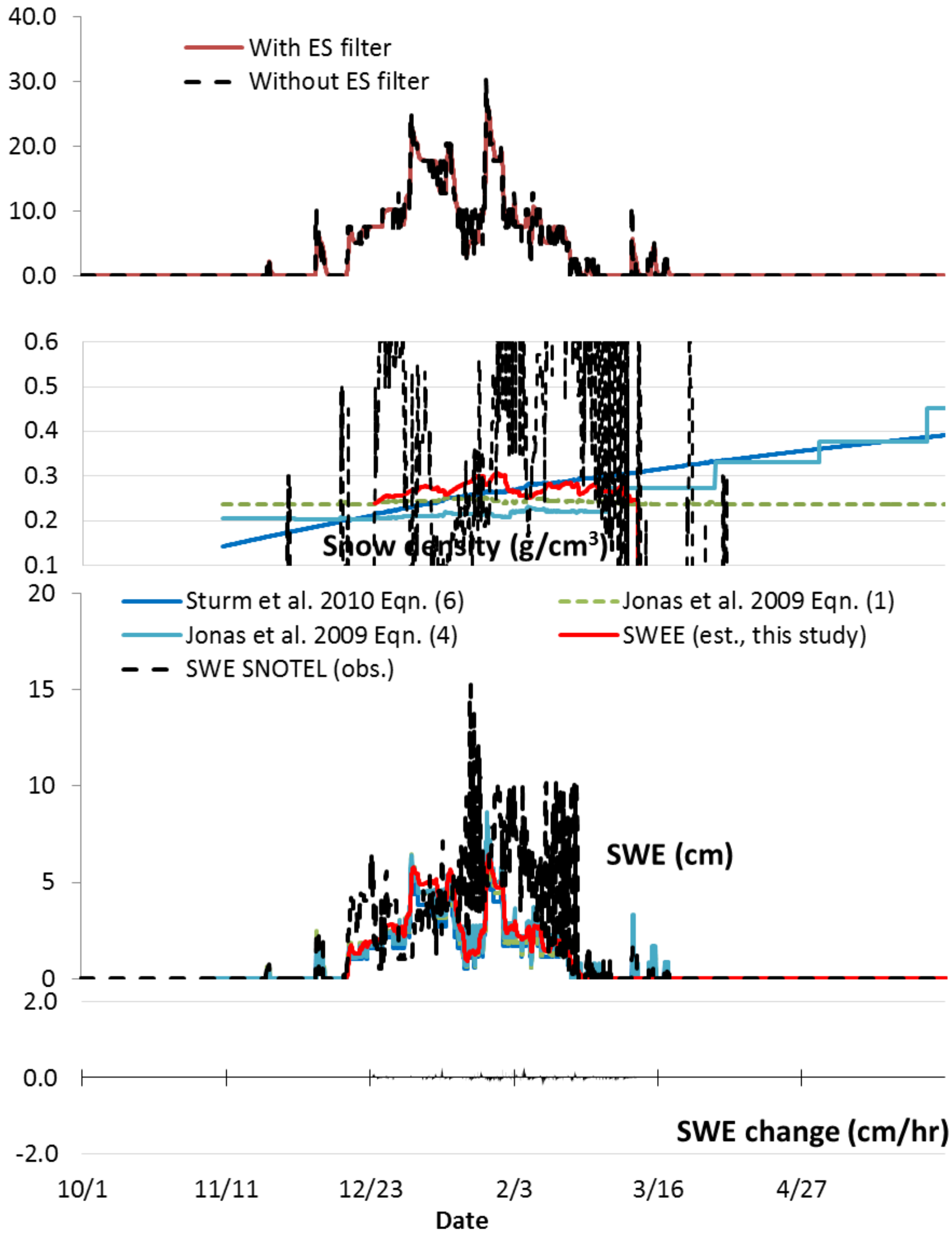
Snow density model	R^2	NSME	Note
SWEE (this study)	0.734	0.784	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.732	0.582	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.700	0.529	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.753	0.664	Regression with an exponential with day-of-year

Vermont (AST) SCAN Site Lye Brook (WY2017, ro_ns = 0.24 g/cm^3)



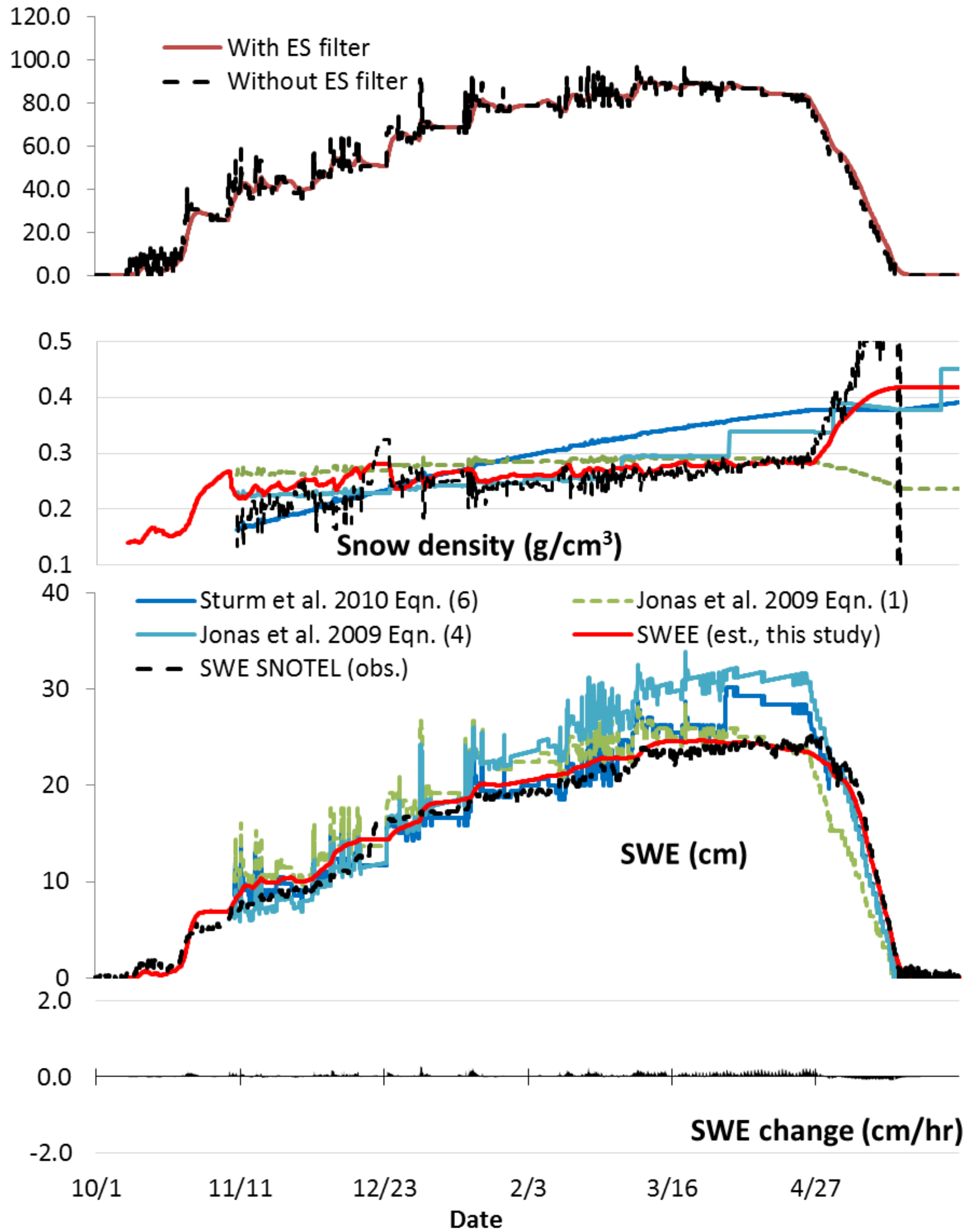
Snow density model	R^2	NSME	Note
SWEE (this study)	0.734	0.784	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.732	0.582	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.700	0.529	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.753	0.664	Regression with an exponential with day-of-year

Vermont (AST) SCAN Site Lye Brook (WY2016, ro_ns = 0.24 g/cm³)



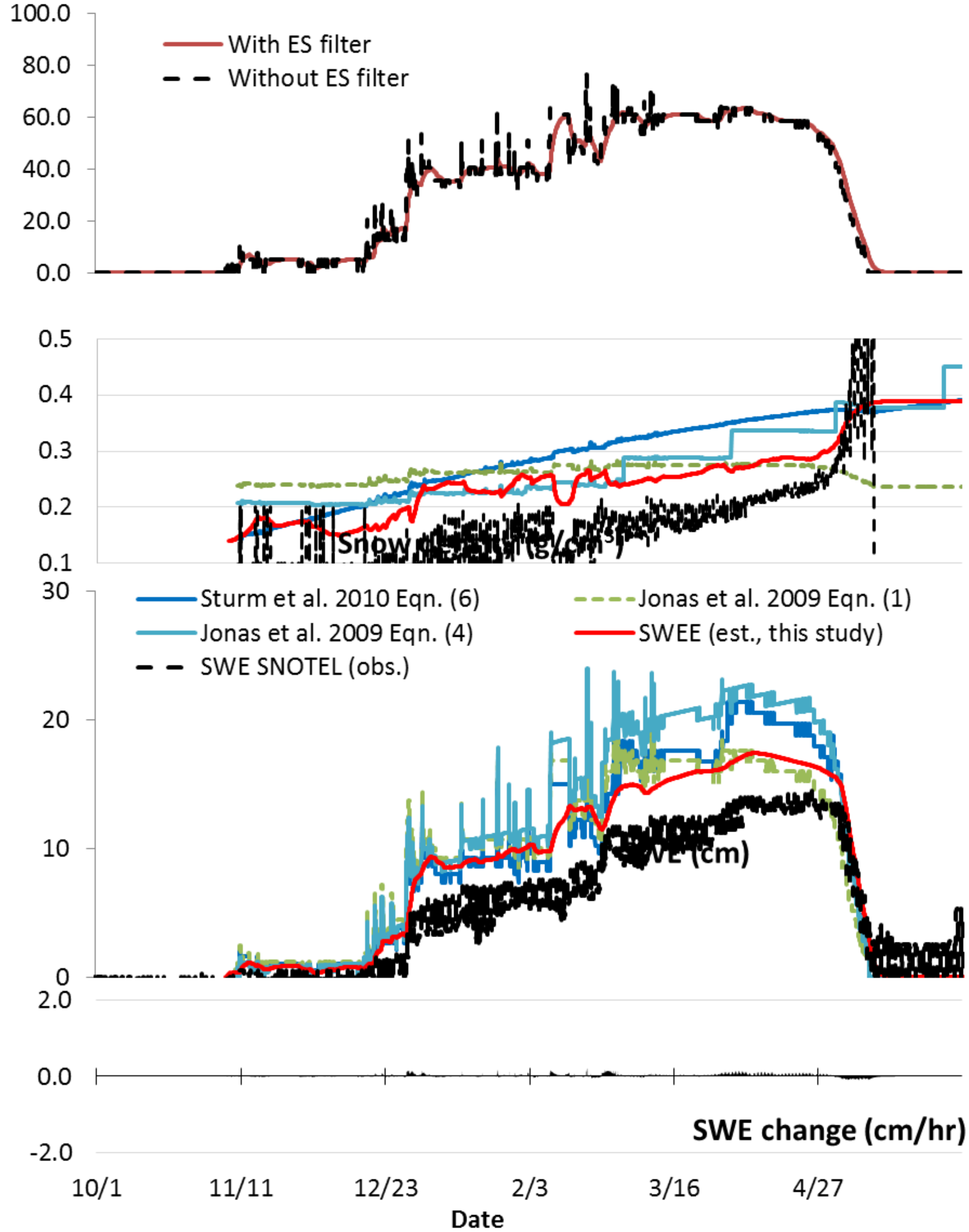
Snow density model	R^2	NSME	Note
SWEE (this study)	0.388	0.352	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.399	0.301	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.417	0.274	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.439	0.355	Regression with an exponential with day-of-year

Alaska (YST) SNOTEL Site Bettles Field (WY2018, ro_ns = 0.14 g/cm^3)



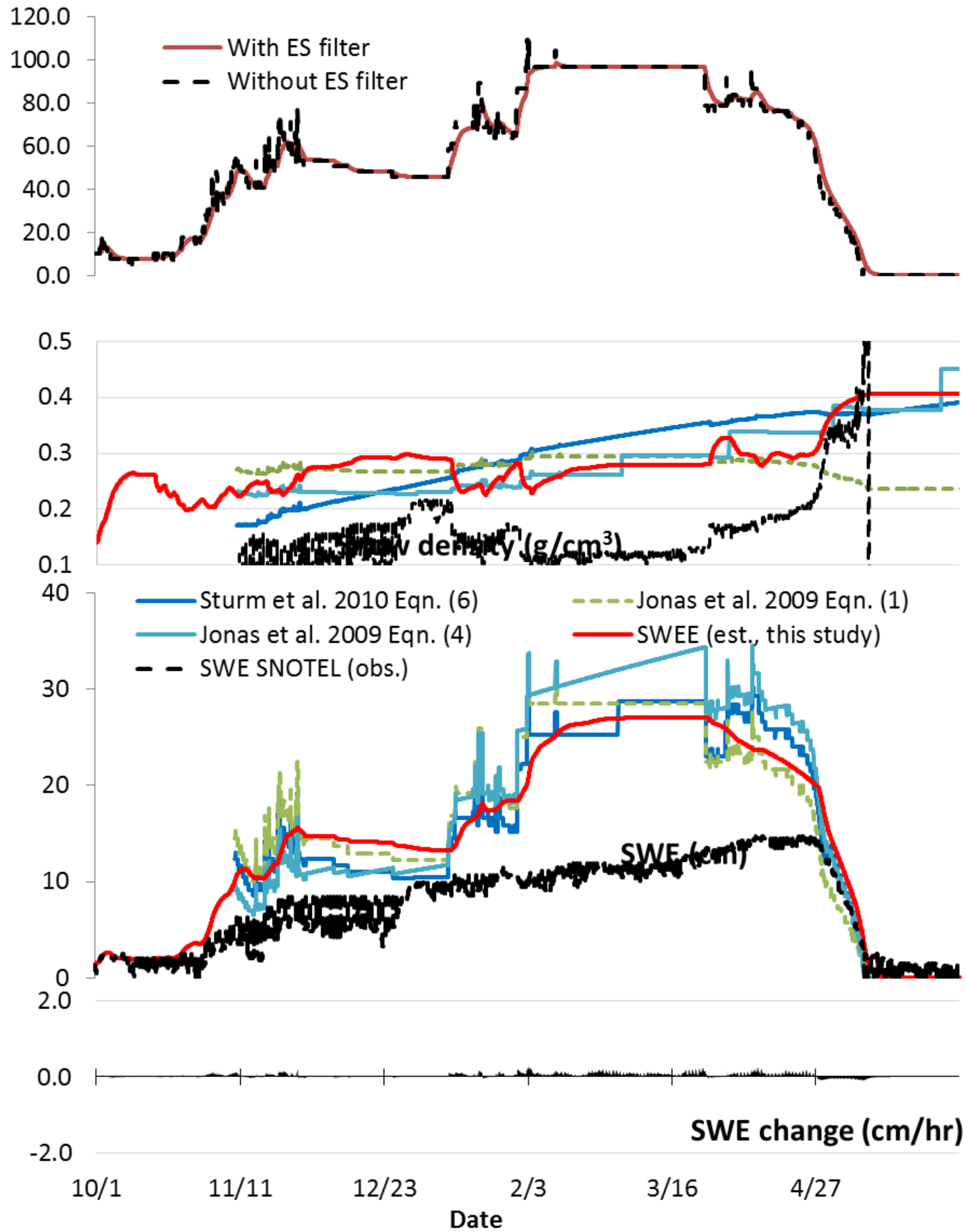
Snow density model	R^2	NSME	Note
SWEE (this study)	0.976	0.971	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.846	0.798	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.937	0.889	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.930	0.630	Regression with an exponential with day-of-year

Alaska (YST) SNOTEL Site Bettles Field (WY2017, ro_ns = 0.14 g/cm^3)



Snow density model	R^2	NSME	Note
SWEE (this study)	0.843	0.338	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.690	-0.032	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.823	-0.063	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.798	-0.825	Regression with an exponential with day-of-year

Alaska (YST) SNOTEL Site Bettles Field (WY2016, ro_ns = 0.14 g/cm^3)



Snow density model	R^2	NSME	Note
SWEE (this study)	0.747	-4.715	Dynamic snow density model
Jonas et al. 2009, Eqn.(1)	0.604	-5.885	Regression with a power function
Jonas et al. 2009, Eqn.(4)	0.753	-4.961	Regression with a linear function with monthly p
Sturm et al. 2010, Eqn.(6)	0.755	-8.290	Regression with an exponential with day-of-year