Comments to the Author:

Dear Dr Beck,

Your manuscript “Evaluation of 18 satellite- and model-based soil moisture products using in situ measurements from 826 sensors” has been subjected now to re-review by two of the original reviewers. One reviewer recommends acceptance of the manuscript and another reviewer major revision. Please handle carefully the remaining comments. In particular, it will be important to highlight the details of the downscaling approach to get 3-hourly products. The authors should also motivate better other decisions in their work, which could have favored model-based approaches. These limitations should at least be discussed in more detail. I suggest moderate revision.

In your answer to the main points and also the many detailed comments, please indicate how comments have been handled exactly, indicating also whether text has been deleted and what the position of newly included text blocks is. Preferably, cite the newly added text in the manuscript. I am looking forward to the new version of the paper.

Best regards,

Harrie-Jan Hendricks Franssen – editor

We would like to thank you for handling the manuscript and the two reviewers for their assessments. Below we provide responses to Dr. Massari’s comments in green font, to explain how we believe our evaluation is fair and that we are not favoring model-based approaches. The following main changes have been made:

1. added a clarification regarding the downscaling of VIC-PGF and GLEAM from 3-hourly to daily;
2. added a figure illustrating the downscaling approach (the SWI filter) used to get the 3-hourly satellite products; and
3. improved the discussion of MeMo versus ESA-CCI performance.

Review #2 rebuttal

This is my second review of the manuscript “Evaluation of 18 satellite- and model-based soil moisture products using in situ measurements from 826 sensors”. Some of the issues that made the manuscript not really clear at the beginning have been clarified and

the manuscript has been improved in this respect, however, there are still some MAJOR and MODERATE pending issues the authors should address.

In the following:

a) **my new comments and replies to authors are written in bold red**

b) **authors replies to previous comments are in** *black italic*

c) **Old comments given by myself are inbold black**

My comments are listed below:

1) **MAJOR**

This comment is related to the clarification about the 3-hourly Pearson correlation coefficient.

I am a bit surprised the authors decide to use 3-hourly sampling to compute temporal correlation given that 13 out of the 18 products have temporal resolution >= 1 day (the majority of the models have native resolution equal to 3 hours given that they are forced by 3-hours rainfall, however, all satellite derived products plus one model forced by GPCP and GLEAM have resolution larger or equal than one day. The problem is that this forces the authors to downscale the majority of the products to something that is far from their original resolution. Of course a 3-hourly product has its strength but this can be still highlighted in the manuscript.

The satellite products do not have a daily (or coarser) temporal resolution in the conventional sense, since they represent instantaneous observations rather than integrated averages. If we would perform the evaluation at a daily time scale, we would be comparing daily *in situ* averages to instantaneous observations, which would be suboptimal. Instead, we are comparing 3-hourly averages to instantaneous observations, which should be more appropriate.

The fact that we downscaled two of the products (VIC-PGF and GLEAM) from daily to 3-hourly for the evaluation did not affect the robustness of the results. This is because, unlike precipitation time series, soil moisture time series tend to exhibit strong autocorrelation, resulting in relatively small differences between 3-hourly and daily time series. Note that the authors of these two products are included as co-authors in the present study.

That said, we agree with the reviewer that if a product has a daily (or coarser) resolution that this is a weakness that should be reflected in the evaluation results, as is currently the case.

Anyway, I am still fine with this approach but I have some doubts on how the downscaling has been carried out given that no details are found in the paper. For example I report below a couple of questions:

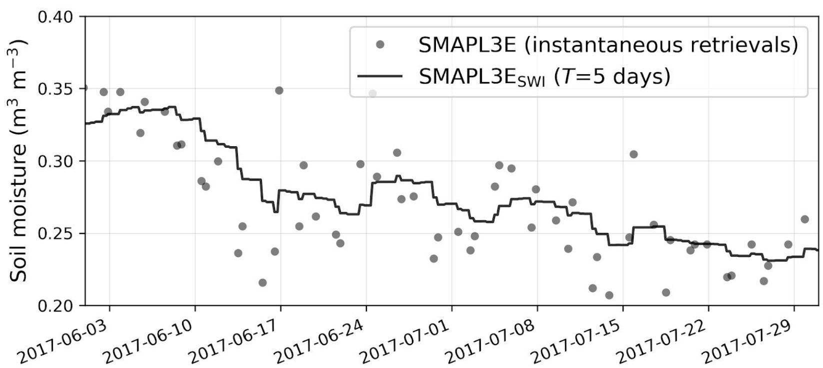
Thanks for your comment.

- **assuming one product has observations every day like GLEAM, the three hourly product results from the downscaling is a product having the same daily value for all the eight 3-hourly intervals? Is this obtained product compared with the 3-hourly in situ observations then?**

Indeed; this is explained in Section 2.1: *"Since the evaluation was performed at a 3-hourly resolution, we downscaled the two products with a daily temporal resolution (VIC-PGF and GLEAM) to a 3-hourly resolution using nearest neighbor resampling."* To avoid confusion, we have added the following text: *"(resulting in replication of the daily value for all 3-hourly periods on each day)".*

- **for satellite observations the exponential filter seems to be used as an interpolator to bring the information of satellite passes (even every three days for products like SMOS) to 3-hourly sampling. The obtained 3-hourly products are compared with 3-hourly in situ observations?**

Indeed; this is explained in Section 2.1: *"To deepen the vertical support of the superficial satellite observations and suppress noise, we also evaluated 3-hourly versions of the satellite products processed using the SWI exponential smoothing filter."* Note that we have added the following figure (Fig. 1 of the revised manuscript) to illustrate the SWI filter:



If so, it is likely that this creates an unfair evaluation between products with temporal sampling equal to 3 hours and those having native resolution larger or equal than one day. Indeed, the interpolation (downscaling) within such long temporal windows can yield significant interpolation errors. Please provide some more information on how the

downscaling has been carried out and on the impact of interpolation errors on the correlation.

The reviewer suggests that we are giving the model products an *"unfair advantage"* compared to the satellite products because the interpolation (i.e., the SWI exponential filter) introduces errors. We respectfully disagree: the satellite products perform much better with SWI filter than without — the filter thus reduces the errors (see Figs. 3 and 4 of the revised manuscript). We devoted a subsection to discussion of the impact of the filter (see Section 3.2).

2) MODERATE

I am still not convinced about the title. Just mentioning the number of sensors does not reflect where the validation has been carried out. However, this is my personal opinion and I leave the authors and the editor the last decision on that.

We appreciate the comment. We have once again considered changing the title but we feel this title best describes the content and novelty of the study.

3) MODERATE

I give my reply to the authors below.

Old comment 2:

Following point 1 the results can be a bit biased towards models (also considering the type of evaluation the authors chose, see my comment 3e) and product that require use calibration (e.g., HBV runs). The product evaluation is in practice carried out exactly where in situ observations are more dense and where are more dense more calibration stations are present. This is partly highlighted by the authors but only at the end of the document while I would add more discussion about this issue.

Reply by the authors:

We do not fully agree with the generalization that models perform better over data-rich regions, as this depends on the precipitation forcing used to drive the models. Our evaluation includes six models with non-gauge-based precipitation forcings (ERA5, ERA5-Land, HBV-ERA5 with and without data assimilation, and HBV-IMERG with and without data assimilation), and the performance of these models is largely representative of data-poor regions.

Thanks for the comment. We have changed several existing sentences and added the following sentence to Section 3.9: *"The calibrated models (HBV and the Catchment model underlying SMAPL4) may, however, perform slightly worse in regions with climatic and physiographic* *conditions dissimilar to the in situ sensors used for calibration (but probably still better than the uncalibrated models).*"

My reply:

- **I understand your point, however, model precipitation (ERA5 for instance) assimilates a large number of ground observations like 2-m temperature and humidity and, in US -- where most of the stations of the study are located -- also the NCEP Stage IV analysis rainfall which combines rain gauges and radars estimates (Lopez et al. 2011). Therefore, models forced by ERA5 have to be considered something not far from gauge-corrected products at least in the US and will likely to perform better with respect to what they can do within data scarce regions.**

We respectfully disagree that *"ERA5 [should be considered] something not far from gauge-corrected products [...] in the US"* for the following reasons:

1. the impact of the precipitation data assimilation is limited overall due to the large amount of other (ground and satellite) observations already assimilated (Lopez, 2013);
2. radar data were not used west of 105°W for quality reasons (Lopez, 2011);
3. very good performance in terms of precipitation was also found in regions without assimilated gauge observations (e.g., Nevada; Beck et al., 2019a, their Fig. 4b; Lopez, 2013, their Fig. 3); and
4. the values of actual gauge-corrected precipitation products, such as MSWEP and CHIRPS, are in complete agreement with gauges (in regions with a high gauge density), which is not the case for ERA5 due to physical constraints in terms of energy and water availability.

We note that one of the co-authors of the present study co-developed ERA5.

Lopez, P.: Direct 4D-Var Assimilation of NCEP Stage IV Radar and Gauge Precipitation Data at ECMWF, Mon. Weather Rev., 139,2098–2116, 2011.

Lopez, P.: Experimental 4D-Var Assimilation of SYNOP Rain Gauge Data at ECMWF, Mon. Weather Rev., 141, 1527–1544,2013.

Moreover, the calibration can significantly help to improve the performance of conceptual models like HBV where the soil moisture station density is high.

- *"but probably still better than the uncalibrated models"*. **Please either demonstrate this statement or provide a reference, otherwise remove.**

We prefer not to remove this statement. We have performed an independent evaluation of the calibrated model (see Sections 2.3 and 3.7) demonstrating that the performance also translates to completely independent soil moisture probes, which already have different climatic and physiographic conditions. We consider it highly unlikely that the benefit of the calibration suddenly disappears at other (slightly more different) locations. The statement is thus, in our opinion, accurate.

The reviewer's statement that *"the calibration can significantly help to improve the performance of conceptual models like HBV"* is problematic as it implies that calibration is an optional step for conceptual models. It is not as these models tend to have parameters without clear physical interpretation.

4) MODERATE. I still doubt about the validation exercise. I can finally accept this approach, but I provided below some of the reasons behind my doubts.

Old comment 3.e

This is an important aspect: "We did not average sites with multiple sensors to avoid potentially introducing discontinuities in the time series." Line 31 pag. 6. This means that if the satellite footprint of a specific product includes multiple in situ stations multiple correlations values are considered? If so, this makes the process of evaluation very random and not really under control as different products are characterized by a different spatial sampling and might include a different number of stations. Moreover, this exacerbates the problem of biased results towards model or products working well over US as many correlation values would originates from stations located in United States with an additional penalization of other locations which have already less stations. For a fair evaluation each pixel must count one correlation value. In this respect the product collocation is a crucial aspect that has not properly discussed and described in the manuscript. For example in Su et al. (2015) and Massari et al. (2017) the co-location

of the satellite data and model data was determined by nearest-neighbour association and a screening step for removing ground sensors non-representative at the coarse scale was implemented. In their study, if multiple valid stations co-located in a satellite pixel were present, the station with the highest mean correlation was retained (see section 2.6 of Su et al. 2015 for further details).

Reply of the reviewers:

We thank the reviewer for this thoughtful comment. This issue is commonly referred to as the collocation issue (Gruber et al., 2020) and unfortunately there are no satisfactory solutions, *particularly when the products have such a wide range of grid-cell and footprint sizes. After much deliberation we decided not to change the current approach for the following reasons:*

1. *A coarser spatial sampling should, in our opinion, be penalized (as is currently the case), since it reflects a technical limitation in the ability of the product to represent heterogeneous areas.*

My reply:

I partially agree as due to temporal stability issues (Vachaud, 1984) it is likely the temporal dynamic of the stations is similar (so the results in terms of correlation are potentially less affected than any other metric like bias and error).

Thank you for the comment.

We believe that grid-cells or footprints with multiple *in situ* sensors should be assigned more weight (as is currently the case), because the presence of multiple sensors reduces the sampling uncertainty and thus leads to a more reliable performance estimate.

My reply:

True but again this will favor calibrated runs.

We appreciate the comment but we do not fully agree that this will favor the products based on calibrated models. The calibration freedom for HBV is so low (just 7 parameters were calibrated) that it does not matter much (if at all) which *in situ* sensors we used. Furthermore, many *in situ* sensors used for calibration were not regions with dense monitoring networks (see the supplementary information).

2. The removal of *in situ*sensors that are not representative of the coarse scale is not straightforward in our evaluation due to the substantial variety in model grid-cell and satellite footprint sizes. We are not in favor of resampling all products to a common grid as this would penalize products with a higher spatial resolution.

My reply:

I agree with this.

We are happy to hear this.

3. The removal of ‘unrepresentative’ *in situ* sensors is further confounded by the fact that the location of satellite footprints varies over time (i.e., the footprint of today’s satellite overpass is not exactly the same as the footprint of the next overpass). Su et al. (2015) and Massari et al. (2017) did not have this issue as their products were all gridded.

My reply:

Fine, but this means that the stations considered at different time steps will vary in your evaluation from time to time? Can you provide more details on this? If so this must be specified.

Thanks for the comment. The stations used do differ depending on the time step and product, which we explicitly mention in the paper (Section 2.6): *"The final number of R, R_{hi}, and R_{lo} values thus varied depending on the product."* This is, however, unavoidable, as the different products have different spatio-temporal coverages. Note that we also explicitly list the number of observations for each product in Figures 2 and 3. The satellite products without SWI filter, in particular, will use different sets of observations because of the different satellite overpass times. This is probably the case for every satellite soil moisture product evaluation to date and does not affect the robustness of the results.

4. Retaining only the *in situ* sensors with the best performance may paint an overly rosy picture of the products.

My reply:

I do not fully agree with this. For the same temporal stability issue described above, the stations with the best performance are potentially the ones more representative of the spatial mean related to the domain of the satellite footprint. So it is not unfair to consider them but, to my opinion, it would be the best thing to do.

We do not think it is always the case that the stations with the best performance are *"the ones more representative of the spatial mean related to the domain of the satellite footprint."* Regardless, it is not possible to implement this change; we have many different products with different footprint and grid-cells size, so which one should we choose? Should we choose a different measurement for each satellite product and time step and grid-cell? We believe this would make the evaluation extremely complicated, confusing, and irreproducible.

Vachaud, G., Passerat de Silans, A., Balabanis, P., & Vauclin, M. (1985). Temporal stability of spatially measured soil water probability density function. *Soil Science Society of America Journal*, *49*(4), 822-828.

5) MAJOR

Old comment 3.

The overall methodology needs to be strongly improved and detailed as many aspects are not clear and/or not well discussed and justified:

a. **The evaluation is carried by considering the temporal dynamic which is fine for the considerations done in the paper and from previous literature (see Koster et al. 2009), however, it is not clear how the evaluation at 3 hour resolution is done for satellite data with a revisit time larger than 1 day (e.g. SMAP, SMOS) and for model forced with rainfall with daily resolution. This must be clarified.**

Reply by the authors:

We agree and have added the following text to explain this more clearly in the revised manuscript: "For the satellite products without SWI filter, we matched the instantaneous soil moisture retrievals with coincident 3-hourly in situ measurements to compute the R values."

My reply:

Thanks, this is clearer now for products where the Exponential filter was not applied. However, where the Exponential filter has been applied please refer to my comment 1 above.

We are glad things are clearer now. Please see our earlier response regarding the exponential filter.

6) MODERATE/MAJOR

Old Comment:

"T was set to 5 days for all products, as the performance did not change markedly using different values, as also reported in previous studies". The application of the exponential filter with a constant parameter T=5 days might be not appropriate for all the satellite products as the different products have a different vertical support. Since the calibration was carried out for the model why T was not calibrated also for the satellite products?

We strongly considered optimizing the time lag constant Tfor each product in the revised manuscript but in the end decided against this for two main reasons. First, we did not want to deviate too much from the original data because we want to make statements about the accuracy of the original data, not a post-processed product. Secondly, we did not want to give the satellite products an unfair advantage compared to the uncalibrated models, which would likely also benefit from the application of the SWI filter (though likely not as much).

My replies:

"First, we did not want to deviate too much from the original data because we want to make statements about the accuracy of the original data, not a post-processed product."

I think that downscaling satellite time series at 3-hourly resolution (from original revisit time of more than one day) by the application of the exponential filter (it does not matter whether T is 5, 7 or 3 days) already provides a strongly post-processed product.

We appreciate the comment but respectfully disagree. Unlike the model products, the satellite products inevitably have gaps in their time series due to the limited number of satellite overpasses. In general, users of satellite soil moisture products will choose the observation nearest to the time of interest and thus implicitly apply a nearest neighbor filter. Since the exponential filter is very similar to the nearest neighbor filter, we do not agree that the products with exponential filter represent *"strongly post-processed products"*.

"Secondly, we did not want to give the satellite products an unfair advantage compared to the uncalibrated models, which would likely also benefit from the application of the SWI filter (though likely not as much)."

R: Well, HBV is calibrated with 7 parameters on the 177 stations so I do not see limitations on doing the same calibration of the exponential filter with one single parameter (which, in its original formulation, is itself a conceptual approach to obtain root zone soil moisture). That is, the 177 calibration stations could be used to calibrate the parameter *T* which best fits observations in terms of correlation.

Conceptual models like HBV do not have parameters with a clear physical meaning and therefore cannot be applied without some sort of calibration. This is not the case for the satellite products, which provide meaningful soil moisture values directly out of the box, without any optimization.

We could definitely have used an optimized *T* for each satellite product, but we decided to use a constant because, as stated in the manuscript, the results are fairly insensitive to the specific value of *T*, so an optimization would not have changed the results much (if at all).

The calibration of HBV was carried out because the model cannot be run without calibration, as it is a conceptual model with parameters that do not represent physical properties of the land surface. Note that we added the following regarding the generalization of the performance of the calibrated models to Section 3.9: *"The calibrated models (HBV and the Catchment model underlying SMAPL4) may, however, perform slightly worse in regions with climatic and physiographic conditions dissimilar to the in situ sensors used for calibration (but likely still better than the uncalibrated models)."*

R: remove the *"but likely still better than the uncalibrated models"* **as it is not demonstrated or provide a reference to validate this statement.**

We consider it highly unlikely that the clear benefit of the calibration, demonstrated in the present study using completely independent *in situ* sensors, will disappear for *in situ* sensors in other regions. We are therefore not in favor of removing this accurate and informative statement.

7) **MODERATE/MAJOR**

Old comment 6.

"The satellite products provided the least reliable soil moisture estimates and exhibited the largest regional performance differences on average, whereas the models with satellite data assimilation provided the most reliable soil moisture estimates and exhibited the smallest regional performance differences on average.". I think the authors should highlight again here that this result is expected given the high density gauge observations used in the study area. Highlighting this is very important as for instance ground validation conducted in data-rich areas does not adequately reflect the added values of satellite observations (Dong et al. 2019).

Reply by the authors:

Thanks for the comment. Even when excluding the three models with data assimilation using gauge-corrected precipitation forcings (GLEAM, SMAPL4, HBV-MSWEP+SMAPL3E), the remaining three models with data assimilation (ERA5, HBV-ERA5+SMAPL3E, and HBV-IMERG+SMAPL3E) still provide more reliable soil moisture estimates and smaller regional performance differences on average. This conclusion is thus not simply attributable to the inclusion of gauge observations in some of the precipitation forcings.

My Reply:

All ERA5 runs contain gauge precipitation in the US where most of the stations are located, so in practice, only HBV-IMERG+SMAPL3E (which is a calibrated product) has in theory no gauge information in it.

Thank you for the comment. As explained earlier in this response, ERA5 cannot be considered a gauge-corrected product in the conventional sense.

8) **MODERATE**

Old comment:

Line 24 pag. 12, "First, ESA-CCISWI incorporates ASCAT, which performed less well in the present evaluation, whereas". This cannot be a reason if the integration is "optimal" as the different parent products are weighed according to their relative performance. So the second one is more likely the reason. Please rephrase or justify with more solid arguments.

Reply of the authors:

The reviewer is right in theory; as discussed earlier in our response, given the difficulty of satisfying all triple collocation assumptions, our merging approach is unlikely to be fully "optimal," and we did not claim it was. For this reason, the inclusion of a product of lower quality results in a performance degradation. As mentioned before, we have added the following statement to the preceding paragraph to highlight this: "Triple collocation-based merging techniques rely on several assumptions (linearity, stationarity, error orthogonality, and zero cross-correlation; Gruber et al., 2016) which are generally difficult to fully satisfy in practice, affecting the optimality of the merging procedure."

My reply:

I think that ESA-CCI contains so many products and the merging procedure so complex that it is impossible to affirm that the guilty is one product rather than another one. ESA-CCI contains also SMOS which in Figure 2 is worse/equal to ASCAT but I do not feel to say the guilty is SMOS. Please revise this sentence or provide a more solid argument to state that.

We agree and have revised the discussion of MeMo versus ESA-CCI as suggested by the reviewer. The discussion now reads as follows: *"We speculate that the better overall performance of MeMo compared to ESA-CCI$_{SWI}$ (Figs. 3a, 4, and 5) may be, at least partly, because ESA-CCI$_{SWI}$ incorporates ASCAT, which performed less well in the present evaluation, whereas MeMo incorporates SMAPL3E$_{SWI}$, which performed best among the single-sensor products (Figs. 3a and 4).*" We removed the second explanation provided in the original manuscript that ESA-CCI performed less because it uses only the soil moisture estimate from the 'best' sensor each day as this was incorrect. Note that the main developer of ESA-CCI is also co-author of the present study. Thanks for this comment.

9) MODERATE

Old comment:

Line 3 pag. 13. "and satellite-based GPCP V1.3 Daily Analysis (Huffman et al., 2001)" How a daily rainfall can provide 3-hourly estimates?

Answer by the authors:

Good question. This is explained in Section 2.1: *"Since the evaluation was performed at a 3-hourly resolution, we downscaled the two products with a daily temporal resolution (VIC-PGF and GLEAM) to a 3-hourly resolution using nearest neighbor resampling."* We realize that this is not ideal, but there was no other solution.

My reply:

Can you clarify it better? Do you downscale GPCP daily to 3 hourly data? So the daily value is divided by 8 to have consistent daily accumulations?

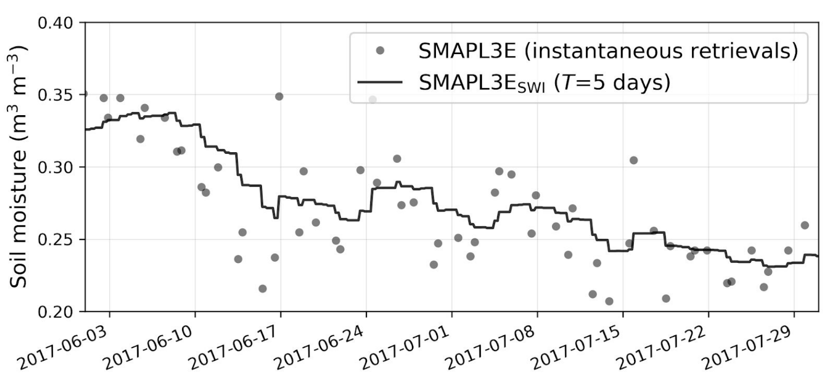
Apologies, we misread the question. Daily GPCP precipitation was disaggregated to 3-hourly using reanalysis data. The disaggregated precipitation data was subsequently used to force the Noah land surface model among others. For more information, see Rui et al. (2020).

In case the nearest neighbour resampling procedure used to downscale the daily VIC-PGF and GLEAM data to 3-hourly in our study was not clear, we added the following text: *"(resulting in replication of the daily value for all 3-hourly periods on each day)".*

10) MODERATE

I think it is important to provide some plots of the time series for instance for one/two locations (to put at least in the supplementary information) to better visualize the impact of the downscaling procedure and the visual comparison between the products.

Thank you for the suggestion. We have added the following figure (Fig. 1 of the revised manuscript) to illustrate the exponential SWI filter:



Evaluation of 18 satellite- and model-based soil moisture products using *in situ* measurements from 826 sensors

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Abstract. Information about the spatiotemporal variability of soil moisture is critical for many purposes, including monitoring of hydrologic extremes, irrigation scheduling, and prediction of agricultural yields. We evaluated the temporal dynamics of 18 state-of-the-art (quasi-)global near-surface soil moisture products, including six based on satellite retrievals, six based on models without satellite data assimilation (referred to hereafter as "open-loop" models), and six based on models that assimilate satellite soil moisture or brightness temperature data. Seven of the products are introduced for the first time in this study: one multi-sensor merged satellite product called MeMo and six estimates from the HBV model with three precipitation inputs (ERA5, IMERG, and MSWEP) and with and without assimilation of SMAPL3E satellite retrievals, respectively. As reference, we used *in situ* soil moisture measurements between 2015 and 2019 at 5-cm depth from 826 sensors, located primarily in the USA and Europe. The 3-hourly Pearson correlation (R) was chosen as the primary performance metric. Application of the Soil Wetness Index (SWI) smoothing filter resulted in improved performance for all satellite products. The best-to-worst performance ranking of the four single-sensor satellite products was $\text{SMAPL3E}_{\text{SWI}}$, SMOS_{SWI}, $\text{AMSR2}_{\text{SWI}}$, and $\text{ASCAT}_{\text{SWI}}$, with the L-band-based $\text{SMAPL3E}_{\text{SWI}}$ (median R of 0.72) outperforming the others at 50 % of the sites. Among the two multi-sensor satellite products (MeMo and $\text{ESA-CCI}_{\text{SWI}}$), MeMo performed better on average (median R of 0.72 versus 0.67), mainly due to the inclusion of $\text{SMAPL3E}_{\text{SWI}}$. The best-to-worst performance ranking of the six open-loop models was HBV-MSWEP, HBV-ERA5, ERA5-Land, HBV-IMERG, VIC-PGF, and GLDAS-Noah. This ranking largely reflects the quality of the precipitation forcing. HBV-MSWEP (median R of 0.78) performed best not just among the open-loop models but among all products. The calibration of HBV improved the median R by $+0.12$ on average compared to random parameters, highlighting the importance of model calibration. The best-to-worst performance ranking of the six models with satellite data assimilation

was HBV-MSWEP+SMAPL3E, HBV-ERA5+SMAPL3E, GLEAM, SMAPL4, HBV-IMERG+SMAPL3E, and ERA5. The assimilation of SMAPL3E retrievals into HBV-IMERG improved the median R by $+0.06$, suggesting that data assimilation yields significant benefits at the global scale.

1 Introduction

Accurate and timely information about soil moisture is valuable for many purposes, including drought monitoring, water resources management, irrigation scheduling, prediction of vegetation dynamics and agricultural yields, forecasting floods and heatwaves, and understanding climate change impacts (Wagner et al., 2007; Vereecken et al., 2008; Ochsner et al., 2013; Dorigo and de Jeu, 2016; Brocca et al., 2017; Miralles et al., 2019; Tian et al., 2019; Karthikeyan et al., 2020; Chawla et al., 2020). Over recent decades, numerous soil moisture products suitable for these purposes have been developed, each with strengths and weaknesses (see Table 1 for a non-exhaustive overview). The products differ in terms of design objective, spatiotemporal resolution and coverage, data sources, algorithm, and latency. They can be broadly classified into three major categories: (i) products directly derived from active- or passive-microwave satellite observations (Zhang and Zhou, 2016; Karthikeyan et al., 2017b), (ii) hydrological or land surface models without satellite data assimilation (referred to hereafter as "open-loop" models; Cammalleri et al., 2015; Bierkens, 2015; Kauffeldt et al., 2016; Chen and Yuan, 2020), and (iii) hydrological or land surface models that assimilate soil moisture retrievals or brightness temperature observations from microwave satellites (Moradkhani, 2008; Pan et al., 2009; Pan and Wood, 2010; Liu et al., 2012; Lahoz and De Lannoy, 2014; Reichle et al., 2017).

Numerous studies have evaluated these soil moisture products using *in situ* soil moisture measurements (e.g., Jackson et al., 2010; Bindlish et al., 2018), other independent soil moisture products (e.g., Chen et al., 2018; Dong et al., 2019), remotely-sensed vegetation greenness data (e.g., Tian et al., 2019), or precipitation data (e.g., Crow et al., 2010; Karthikeyan and Kumar, 2016). Pronounced differences in spatiotemporal dynamics and accuracy were found among the products, even among those derived from the same data source. However, most studies evaluated only one specific product or a small subset (≤ 3) of the available products (e.g., Martens et al., 2017; Liu et al., 2019; Zhang et al., 2019; Tavakol et al., 2019). Additionally, many had a regional (sub-continental) focus (e.g., Albergel et al., 2009; Gruhier et al., 2010; Griesfeller et al., 2016), potentially leading to conclusions with limited generalizability. Furthermore, several new or recently reprocessed products have not been thoroughly evaluated yet, such as ERA5 (Hersbach et al., 2020), ERA5-Land (C3S, 2019), and ESA-CCI V04.4 (Dorigo et al., 2017). There is also still uncertainty around, for example, the effectiveness of multi-sensor merging techniques (Petropoulos et al., 2015), the impact of model complexity on the accuracy of soil moisture simulations (Fatichi et al., 2016), the degree to which model deficiencies and precipitation data quality affect the added value of data assimilation (Xia et al., 2019), and the impact of smoothing filters such as the Soil Wetness index (SWI; Wagner et al., 1999; Albergel et al., 2008) on the performance ranking of products.

Our main objective was to undertake a comprehensive evaluation of 18 state-of-the-art (quasi-)global near-surface soil moisture products in terms of their temporal dynamics (Section 2.1). Our secondary objective was to introduce seven new soil moisture products (one multi-sensor merged satellite product called MeMo introduced in Section 2.2 and six HBV model-based products introduced in Sections 2.3 and 2.4). As reference for the evaluation, we used *in situ* soil moisture measurements between 2015 and 2019 from 826 sensors located primarily in the USA and Europe (Section 2.5). We aim to shed light on the advantages and disadvantages of different soil moisture products and on the merit of various technological and methodological innovations by addressing nine key questions frequently faced by researchers and end-users alike:

1. How do the ascending and descending retrievals perform (Section 3.1)?
2. What is the impact of the SWI smoothing filter (Section 3.2)?
3. What is the relative performance of the single-sensor satellite products (Section 3.3)?
4. How do the multi-sensor merged satellite products perform (Section 3.4)?
5. What is the relative performance of the open-loop models (Section 3.5)?
6. How do the models with satellite data assimilation perform (Section 3.6)?
7. What is the impact of model calibration (section 3.7)?
8. How do the major product categories compare (Section 3.8)?
9. To what extent are our results generalizable to other regions (Section 3.9)?

2 Data and methods

2.1 Soil moisture products

We evaluated in total 18 near-surface soil moisture products, including six based on satellite observations, six based on open-loop models, and six based on models that assimilate satellite data (Table 1). We evaluated six products per category, which was sufficient to compare the performance among and within product categories and address the questions posed in the introduction. We only considered widely used products with (quasi-)global coverage and we attempted to keep the selection of products in each category as diverse as possible. For example, we considered products based on several major satellite missions used for global soil moisture mapping (AMSR2, ASCAT, SMAP, and SMOS), models of various type and complexity (with and without calibration), different sources of precipitation data (satellites, reanalyses, gauges, and combinations thereof), and various data merging and assimilation techniques (with different inputs).

The units differed among the products; some are provided in volumetric water content (typically expressed in m^3 m^{-3}; e.g., ERA5) and others in degree of saturation (typically expressed in %; e.g., ASCAT). We did not harmonize the units among the products, because the Pearson correlation coefficient — the performance metric used in the current study (Section 2.6) — is insensitive to the units. Since the evaluation was performed at a 3-hourly resolution, we downscaled the two products with a daily temporal resolution (VIC-PGF and GLEAM) to a 3-hourly resolution using nearest neighbor resampling (resulting in

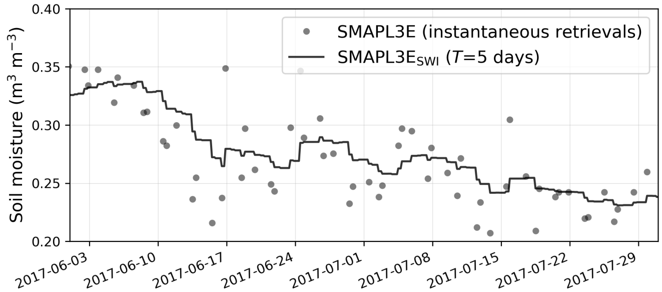

Figure 1. To illustrate the SWI filter, SMAPL3E instantaneous volumetric soil moisture retrievals (from both ascending and descending overpasses) and 3-hourly SMAPL3E$_{\mathrm{SWI}}$ time series obtained by application of the SWI filter (with the time lag constant T set to 5 days) for a 2-month period at 34.82°N, 89.44°W.

replication of the daily value for all 3-hourly periods on each day). In contrast to the model products, the satellite products (with the exception of ASCAT) often do not provide retrievals when the soil is frozen or snow-covered (Supplement Fig. S1). To keep the evaluation consistent (Gruber et al., 2020), we used ERA5 (Hersbach et al., 2020) to discard the estimates of all 18 products when the near-surface soil temperature of layer 1 (0–7 cm) was < 4°C and/or the snow depth was > 1 mm.

To deepen the vertical support of the superficial satellite observations and suppress noise, we also evaluated 3-hourly versions of the satellite products processed using the SWI exponential smoothing filter (Wagner et al., 1999; Albergel et al., 2008). MeMo was not processed as it was derived from SWI-filtered products. The SWI filter is defined according to:

$$\mathrm{SWI}(t) = \frac{\sum\limits_i \mathrm{SM_{sat}}(t_i) e^{-\frac{t-t_i}{T}}}{\sum\limits_i e^{-\frac{t-t_i}{T}}}, \tag{1}$$

where SM$_{\mathrm{sat}}$ (units depend on the product) is the soil moisture retrieval at time t_i, T (days) represents the time lag constant, and t represents the 3-hourly time step. T was set to 5 days for all products, as the performance did not change markedly using different values, as also reported in previous studies (Albergel et al., 2008; Beck et al., 2009; Ford et al., 2014; Pablos et al., 2018). Following Pellarin et al. (2006), ~~the~~ SWI at time t was only calculated if ≥ 1 retrievals were available in the interval $(t - T,\, t]$ and ≥ 3 retrievals were available in the interval $[t - 3T,\, t - T]$. Fig. 1 illustrates the filter for the SMAPL3 product.

The vertical support is physically consistent with *in situ* soil moisture measurements at 5-cm depth for most models. The average depth of the soil layer (i.e., half the depth of the lower boundary) is 2.5 cm for SMAPL4, 3.5 cm for ERA5 and ERA5-Land, 5 cm for GLEAM, 8.5 cm for HBV-ERA5, 6.6 cm for HBV-IMERG, 7.3 cm for HBV-MSWEP, and 15 cm for VIC-PGF (Table 1; Supplement Table S1). The soil layers of HBV may seem too deep, especially since they represent conceptual “buckets” that can be fully filled with water, in contrast to the soil layers of the other models which additionally consist of mineral and organic matter. However, the soil layer depths of HBV were calibrated (see Section 2.3) and are thus empirically consistent with *in situ* measurements at 5-cm depth.

2.2 Merged soil Moisture (MeMo) product

Merged soil Moisture (MeMo) is a new 3-hourly soil moisture product derived by merging the soil moisture anomalies of three single-sensor passive-microwave satellite products with SWI filter ($\mathrm{AMSR2_{SWI}}$, $\mathrm{SMAPL3E_{SWI}}$, and $\mathrm{SMOS_{SWI}}$; Table 1). MeMo was produced for 2015–2019 (the period with data for all three products) as follows:

1. Three-hourly soil moisture time series of $\mathrm{AMSR2_{SWI}}$, $\mathrm{SMAPL3E_{SWI}}$, $\mathrm{SMOS_{SWI}}$, the active-microwave satellite product $\mathrm{ASCAT_{SWI}}$, and the open-loop model HBV-MSWEP were normalized by subtracting the long-term means and dividing by the long-term standard deviations of the respective products (calculated for the period of overlap).

2. Three-hourly anomalies were calculated for the five products by subtracting their respective seasonal averages. The seasonal climatology was calculated by taking the multi-year mean for each day of the year, after which we applied a 30-day central moving mean to eliminate noise. The moving mean was only calculated if > 21 days with values were present in the 30-day window. Due to the large number of missing values in winter (Supplement Fig. S1), we were not able to compute the seasonality and, in turn, the anomalies in winter for some satellite products.

3. Time-invariant merging weights for $\mathrm{AMSR2_{SWI}}$, $\mathrm{SMAPL3E_{SWI}}$, and $\mathrm{SMOS_{SWI}}$ were calculated using extended triple collocation (McColl et al., 2014), a technique to estimate Pearson correlation coefficients (R) for independent products with respect to an unknown truth. The R values for the respective products were determined using the triplet consisting of the product in question in combination with ASCAT and HBV-MSWEP, which are independent from each other and from the passive products. The R values were only calculated if > 200 coincident anomalies were available. The weights were calculated by squaring the R values.

4. For each 3-hourly time step, we calculated the weighted mean of the available anomalies of $\mathrm{AMSR2_{SWI}}$, $\mathrm{SMAPL3E_{SWI}}$, and $\mathrm{SMOS_{SWI}}$. If only one anomaly was available, this value was used and no averaging was performed. The climatology of SMAPL3E — the best-performing product in our evaluation — was added to the result, to yield the MeMo soil moisture estimates.

2.3 HBV hydrological model

Six new 3-hourly soil moisture products were produced using the Hydrologiska Byr Vattenbalansavdelning (HBV) conceptual hydrological model (Bergström, 1976, 1992) forced with three different precipitation datasets and with and without assimilation of SMAPL3E soil moisture estimates, respectively (Table 1). HBV was selected because of its low complexity, high agility, computational efficiency, and succesful application used in numerous studies spanning a wide range of climate and physiographic conditions (e.g., Steele-Dunne et al., 2008; Driessen et al., 2010; Beck et al., 2013; Vetter et al., 2015; Jódar et al., 2018). The model has one soil moisture store, two groundwater stores, and 12 free parameters. Among the 12 free parameters, 7 are relevant for simulating soil moisture as they pertain to the snow or soil routines, while 5 are irrelevant for this study as they pertain to runoff generation or deep percolation. The soil moisture store has two inputs (precipitation and snowmelt) and two outputs (evaporation and recharge). The model was run twice for 2010–2019; the first time to initialize the soil moisture store, and the second time to obtain the final outputs.

HBV requires time series of precipitation, potential evaporation, and air temperature as input. For precipitation, we used three different datasets: (i) the reanalysis ERA5 (hourly $0.28°$ resolution; Hersbach et al., 2020); (ii) the satellite-based IMERG dataset (Late Run V06; 30-minutes $0.1°$ resolution; Huffman et al., 2014, 2018); and (iii) the gauge-, satellite-, and reanalysis-based MSWEP dataset (V2.4; 3-hourly $0.1°$ resolution; Beck et al., 2017b, 2019b). For the ERA5 and IMERG datasets, we calculated 3-hourly precipitation accumulations. Daily potential evaporation was estimated using the Hargreaves (1994) equation from daily minimum and maximum air temperature. The daily potential evaporation data were downscaled to 3-hourly using nearest neighbour resampling. Air temperature estimates were taken from ERA5. To improve the representation of mountainous regions and ameliorate potential biases, the ERA5 air temperature data were matched on a monthly climatological basis using an additive (as opposed to multiplicative) approach to the comprehensive station-based WorldClim climatology (V2; 1-km resolution; Fick and Hijmans, 2017).

We calibrated the 7 relevant parameters of HBV using *in situ* soil moisture measurements from 177 independent sensors from the International Soil Moisture Network (ISMN) archive (Section 2.5; Supplement Fig. S2). These sensors did not have enough measurements during the evaluation period (March 31, 2015, to September 16, 2019) and thus were available for an independent calibration exercise. The parameter space was explored by generating $N = 500$ candidate parameter sets using Latin hypercube sampling (McKay et al., 1979), which splits the parameter space up into N equal intervals and generates parameter sets by sampling each interval once in a random manner. The model was subsequently run for all candidate parameter sets, after which we selected the parameter set with the best overall performance across the 177 sites (Supplement Table S1). As objective function, we used the median Pearson correlation coefficient (R) calculated between 3-hourly *in situ* and simulated soil moisture time series. To avoid giving one of the precipitation datasets an unfair advantage, we recalibrated the model for each of the three precipitation datasets (ERA5, IMERG, and MSWEP).

2.4 Soil moisture data assimilation

Instantaneous soil moisture retrievals (without SWI filter) from SMAPL3E (Table 1) were assimilated into the HBV model forced with the three above-mentioned precipitation datasets (ERA5, IMERG, and MSWEP). Previous regional studies that successfully used HBV to assess the value of data assimilation include Parajka et al. (2006), Montero et al. (2016), and Lü et al. (2016). We used the simple Newtonian nudging technique of Houser et al. (1998) that drives the soil moisture state of the model towards the satellite observations. Nudging techniques are computationally efficient and easy to implement, and have therefore been used in several studies (e.g., Brocca et al., 2010b; Dharssi et al., 2011; Capecchi and Brocca, 2014; Laiolo et al., 2016; Cenci et al., 2016; Martens et al., 2016). For each grid-cell, the soil moisture state of the model was updated when a satellite observation was available according to:

$$\mathrm{SM}^{+}_{\mathrm{mod}}(t) = \mathrm{SM}^{-}_{\mathrm{mod}}(t) + kG\left[\mathrm{SM}^{\mathrm{sc}}_{\mathrm{sat}}(t) - \mathrm{SM}^{-}_{\mathrm{mod}}(t)\right], \quad (2)$$

where SM_{mod}^{+} and SM_{mod}^{-} (mm) are the updated and *a priori* soil moisture states of the model, respectively, SM_{sat}^{sc} (mm) are the rescaled satellite observations, and t is the 3-hourly time step. The satellite observations were rescaled to the open-loop model space using cumulative distribution function (CDF) matching (Reichle and Koster, 2004).

The nudging factor k $(-)$ was set to 0.1 as this gave satisfactory results. The gain parameter G $(-)$ determines the magnitude of the updates and ranges from 0 to 1. G is generally calculated based on relative quality of the satellite retrievals and the open-loop model. Most previous studies used a spatially and temporally uniform G (e.g., Brocca et al., 2010b; Dharssi et al., 2011; Capecchi and Brocca, 2014; Laiolo et al., 2016; Cenci et al., 2016). Conversely, Martens et al. (2016) used the triple collocation technique (Scipal et al., 2008) to obtain spatially variable G values. Here we calculated G in a similar fashion according to:

$$G = \frac{R_{sat}^2}{R_{sat}^2 + R_{mod}^2}, \tag{3}$$

where R_{sat} and R_{mod} $(-)$ are Pearson correlation coefficients with respect to an unknown truth for SMAPL3E and HBV, respectively, calculated using extended triple collocation (Section 2.2). R_{sat} was determined using 3-hourly anomalies of the triplet SMAPL3E, $ASCAT_{SWI}$, and HBV-MSWEP (Table 1) which are based on passive microwaves, active microwaves, and an open-loop model, respectively. R_{mod} was determined using 3-hourly anomalies of the triplet HBV (forced with either ERA5, IMERG, or MSWEP), $ASCAT_{SWI}$, and $SMAPL3E_{SWI}$. The anomalies were calculated by subtracting the seasonal averages of the respective products. The seasonal averages were determined as described in Section 2.2. The R_{sat} and R_{mod} values were only calculated if > 200 coincident anomalies were available. The resulting G values vary in space but are constant in time.

2.5 *In situ* soil moisture measurements

As reference for the evaluation, we used harmonized and quality-controlled *in situ* volumetric soil moisture measurements (m^3 m^{-3}) from the ISMN archive (Dorigo et al., 2011, 2013; Appendix Table A1). The measurements were performed using various types of sensors, including time-domain reflectometry sensors, frequency-domain reflectometry sensors, capacitance sensors, and cosmic-ray neutron sensors, among others. Similar to numerous previous evaluations (e.g., Albergel et al., 2009; Champagne et al., 2010; Albergel et al., 2012; Wu et al., 2016), we selected measurements from sensors at a depth of 5 cm ($\pm$2 cm). Since the evaluation was performed at a 3-hourly resolution, the measurements in the ISMN archive, which have a hourly resolution, were resampled to a 3-hourly resolution. We only used sensors with a 3-hourly record length > 1 year (not necessarily consecutive) during the evaluation period from March 31, 2015, to September 16, 2019. We did not average the measurements of sites with multiple sensors to avoid potentially introducing discontinuities in the time series. In total 826 sensors, located in the USA (692), Europe (117), and Australia (17), were available for evaluation (Fig. 2). The median record length was 3.0 years.

2.6 Evaluation approach

We evaluated the 18 near-surface soil moisture products (Table 1) for the 4.5-year long period from March 31, 2015 (the date on which SMAP data became available), to September 16, 2019 (the date on which we started processing the products). As

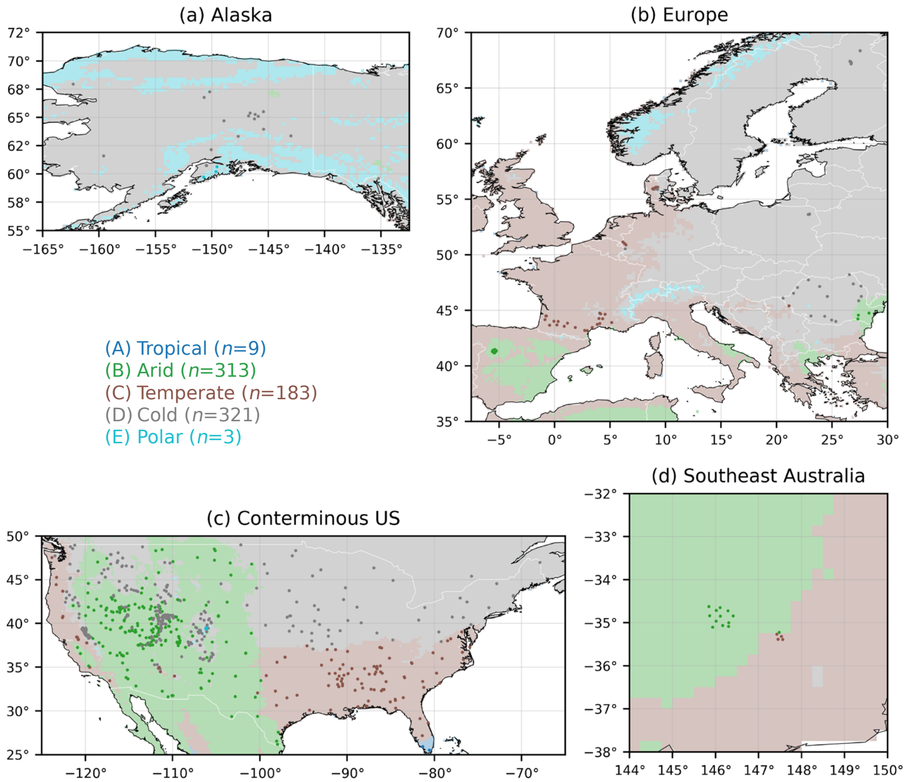

Figure 2. Major Köppen-Geiger climate class (Beck et al., 2018) of the 826 sensors used as reference. n denotes the number of sensors in each class.

performance metric, we used the Pearson correlation coefficient (R) calculated between 3-hourly soil moisture time series from the *in situ* sensors and the products, similar to numerous previous studies (e.g., Karthikeyan et al., 2017a; Al-Yaari et al., 2017; Kim et al., 2018). R measures how well the *in situ* and product time series correspond in terms of temporal variability, and thus evaluates the most important aspect of soil moisture time series for the majority of applications (Entekhabi et al., 2010; Gruber et al., 2020). It is insensitive to systematic differences in mean and variance, which can be substantial due to: (i) the use of different soil property maps as input to the retrieval algorithms and hydrological models (Teuling et al., 2009; Koster et al., 2009); and (ii) the inherent scale discrepancy between *in situ* point measurements and satellite footprints or model grid-cells (Miralles et al., 2010; Crow et al., 2012; Gruber et al., 2020).

Additionally, to quantify the performance of the products at different time scales, we calculated Pearson correlation coefficients for the low-frequency fluctuations (i.e., the slow variability at monthly and longer time scales; R_{lo}) and the high-frequency fluctuations (i.e., the fast variability at 3-hourly to monthly time scales; R_{hi}). The low-frequency fluctuations were isolated using a 30-day central moving mean, similar to previous studies (e.g., Albergel et al., 2009; Al-Yaari et al., 2014; Su et al., 2016).

The moving mean was calculated only if > 21 days with estimates were present in the 30-day window. The high-frequency fluctuations were isolated by subtracting the low-frequency fluctuations from the original 3-hourly time series.

To ensure a fair evaluation, we discarded the estimates of all products when the near-surface soil temperature was $< 4°C$ and/or the snow depth was > 1 mm (both determined using ERA5; Hersbach et al., 2020). For the satellite products without SWI filter, we matched the instantaneous soil moisture retrievals with coincident 3-hourly *in situ* measurements to compute the R values. Since the evaluation was performed at a 3-hourly resolution, we downscaled the two products with a daily temporal resolution (VIC-PGF and GLEAM; Table 1) to a 3-hourly resolution using nearest neighbor resampling. To ensure reliable R values, we only calculated R, R_{hi}, or R_{lo} values if > 200 coincident soil moisture estimates from the sensor and the product were available. The final number of R, R_{hi}, and R_{lo} values thus varied depending on the product.

To derive insights into the reasons for the differences in performance, median R values were calculated separately for different Köppen-Geiger climate classes, leaf area index (LAI) values, and topographic slopes. To determine the Köppen-Geiger climate classes, we used the 1-km Köppen-Geiger climate classification map of Beck et al. (2018; Fig. 2), which represents the period 1980–2016. To determine LAI, we used the 1-km Copernicus LAI dataset derived from SPOT-VGT and PROBA-V data (V2; Baret et al., 2016; mean over 1999–2019). To determine the topographic slope, we used the 90-m MERIT DEM (Yamazaki et al., 2017). To reduce the scale mismatch between point locations and satellite sensor footprints or model grid-cells, we upscaled the Köppen-Geiger, LAI, and topographic slope maps to 0.25° using majority, average, and average resampling, respectively.

3 Results and discussion

3.1 How do the ascending and descending retrievals perform?

Microwave soil moisture retrievals from ascending and descending overpasses may exhibit performance differences due to diurnal variations in land surface conditions (Lei et al., 2015) and radio-frequency interference (RFI; Aksoy and Johnson, 2013). Table 2 presents R values for the instantaneous ascending and descending retrievals of the four single-sensor products (AMSR2, ASCAT, SMAPL3E, and SMOS; Table 1). Descending (local night) retrievals were more reliable for the passive microwave-based AMSR2, in agreement with several previous studies (Lei et al., 2015; Griesfeller et al., 2016; Bindlish et al., 2018), and consistent with the notion that soil-vegetation temperature differences during day-time interfere with passive microwave soil moisture retrieval (Parinussa et al., 2011). Descending (local morning) retrievals were more reliable for the active microwave-based ASCAT (Table 2), in agreement with Lei et al. (2015). The ascending and descending retrievals performed similarly for the passive microwave-based SMAPL3E and SMOS (Table 2). For the remainder of this analysis, we will use only descending retrievals of AMSR2. We did not discard the ascending retrievals of ASCAT as they helped to improve the performance of $\text{ASCAT}_{\text{SWI}}$.

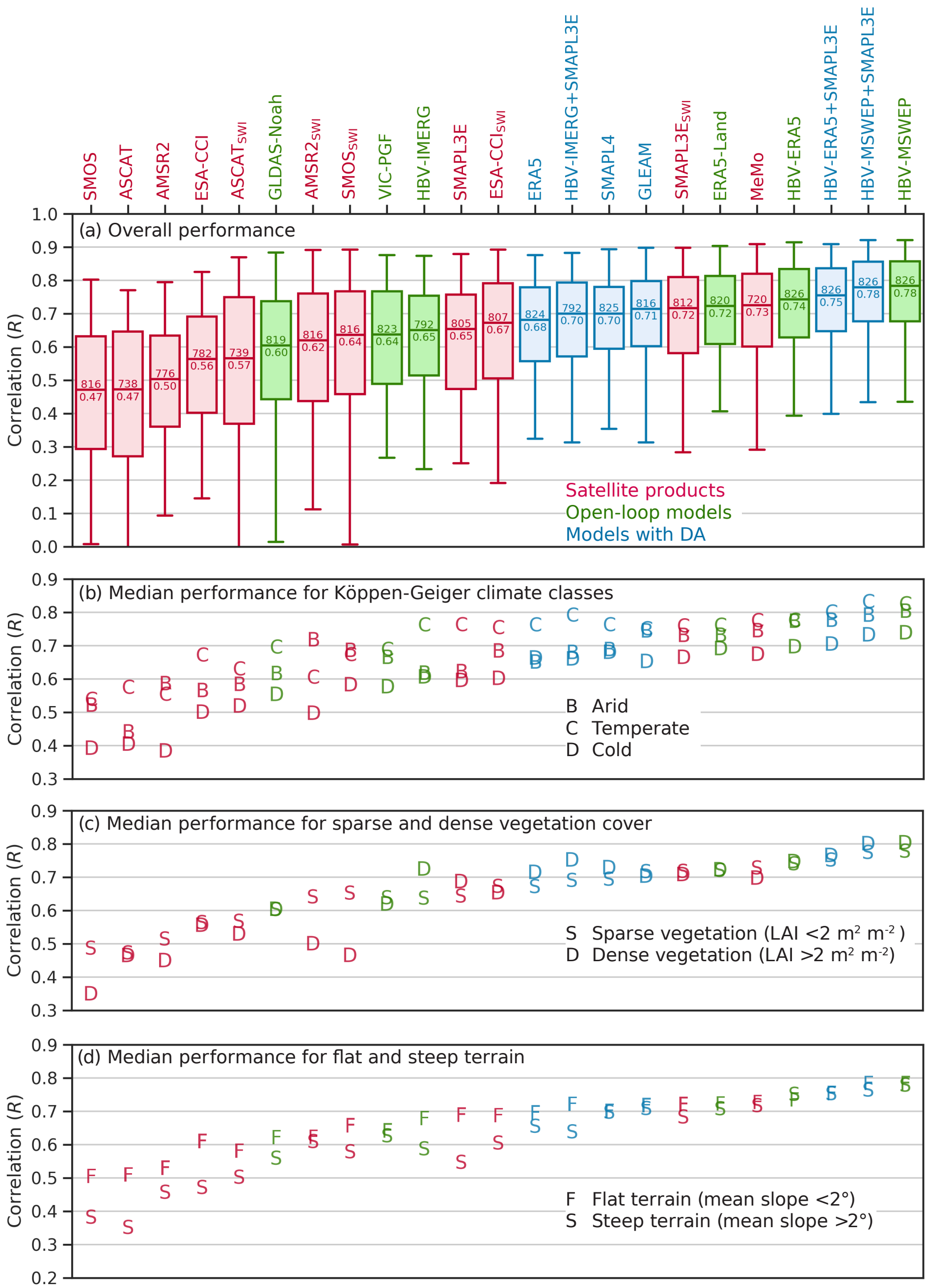

Figure 3. (a) Performance of the soil moisture products in terms of 3-hourly Pearson correlation (R). The products were sorted in ascending order of median R. Outliers are not shown. The number above the median line in each box represents the number of sites with R values and the number below the median line represents the median R value. Also shown are median R values for different (b) major Köppen-Geiger climate classes, (c) mean leaf area index (LAI) values, and (d) mean topographic slopes.

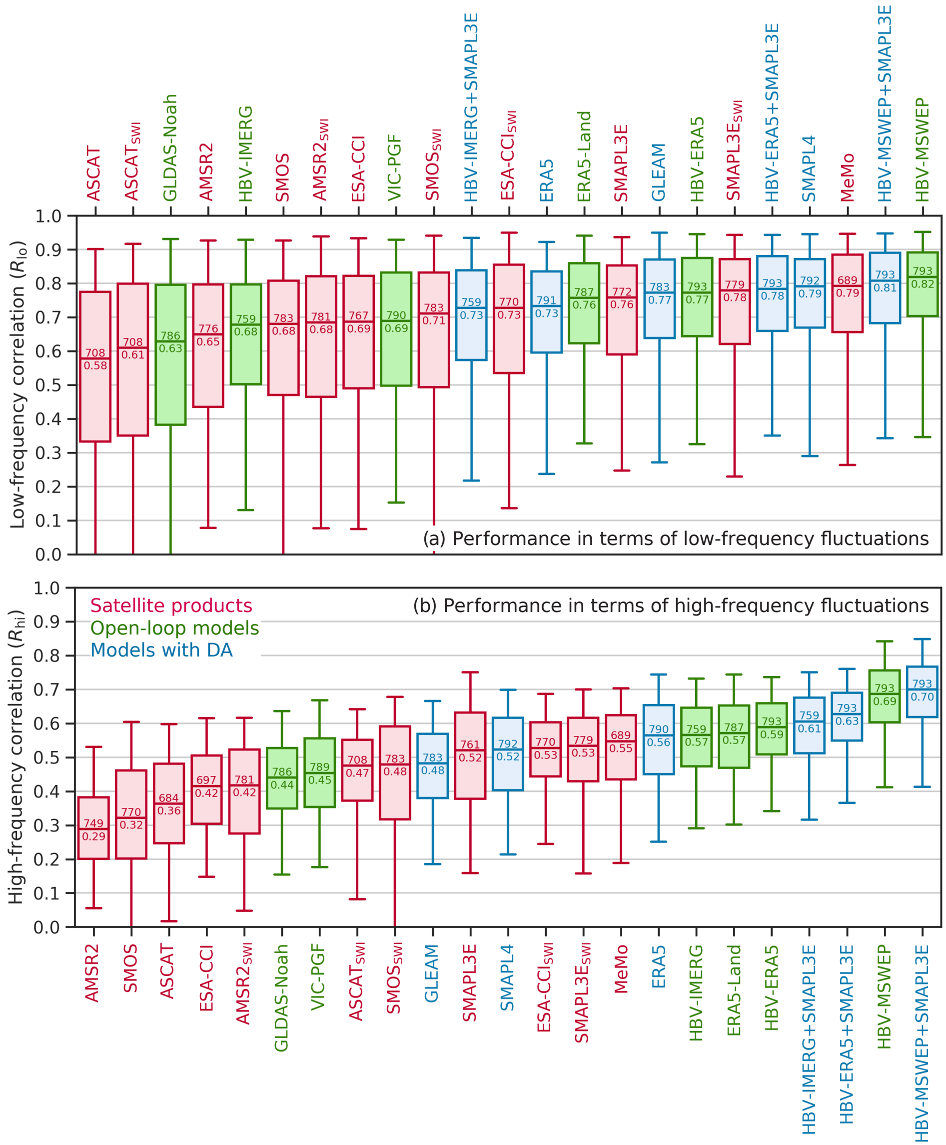

Figure 4. Performance of the soil moisture products in terms of 3-hourly Pearson correlation for (a) low-frequency fluctuations (R_{lo}) and (b) high-frequency fluctuations (R_{hi}). The products were sorted in ascending order of the median. The number above the median line in each box represents the number of sites with R_{lo} or R_{hi} values and the number below the median line represents the median R_{lo} or R_{hi} value. Outliers are not shown.

3.2 What is the impact of the Soil Wetness Index (SWI) smoothing filter?

The application of the SWI filter resulted in higher median R, R_{hi}, and R_{lo} values for all satellite products (Figs. 3a and 4; Table 1). The median R improvement was $+0.12$ for AMSR2, $+0.10$ for ASCAT, $+0.07$ for SMAPL3E, $+0.17$ for SMOS, and $+0.11$ for ESA-CCI (Fig. 3a). The improvements are probably mainly because the SWI filter reduces the impact of random errors and potential differences between ascending and descending overpasses (Su et al., 2015; Bogoslovskiy et al., 2015). Additionally, since the SWI filter simulates the slower variability of soil moisture at deeper layers (Wagner et al., 1999; Albergel et al., 2008; Brocca et al., 2010a), it improves the consistency between the *in situ* measurements at 5-cm depth and the microwave signals, which often have a penetration depth of just 1–2 cm depending on the observation frequency and the land surface conditions (Long and Ulaby, 2015; Shellito et al., 2016a; Rondinelli et al., 2015; Lv et al., 2018). Our results suggests that previous near-surface soil moisture product assessments (e.g., Zhang et al., 2017; Karthikeyan et al., 2017a; Cui et al., 2018; Al-Yaari et al., 2019; Ma et al., 2019), which generally did not use smoothing filters, may have underestimated the true skill of the products.

3.3 What is the relative performance of the single-sensor satellite products?

Among the four single-sensor products with SWI filter ($\text{AMSR2}_{\text{SWI}}$, $\text{ASCAT}_{\text{SWI}}$, $\text{SMAPL3E}_{\text{SWI}}$, and SMOS_{SWI}; Table 1), $\text{SMAPL3E}_{\text{SWI}}$ performed best in terms of median R, R_{lo}, and R_{hi} by a wide margin (Figs. 3a and 4), in agreement with previous studies using triple collocation (Chen et al., 2018) and *in situ* measurements from the USA (Karthikeyan et al., 2017a; Zhang et al., 2017; Cui et al., 2018; Al-Yaari et al., 2019), the Tibetan Plateau (Chen et al., 2017), the Iberian Peninsula (Cui et al., 2018), and across the globe (Al-Yaari et al., 2017; Kim et al., 2018; Ma et al., 2019). The good performance of $\text{SMAPL3E}_{\text{SWI}}$ is likely attributable to the deeper ground penetration of L-band signals (Lv et al., 2018), the sensor's higher radiometric accuracy (Entekhabi et al., 2010), and the application of an RFI mitigation algorithm (Piepmeier et al., 2014). SMOS_{SWI} is also an L-band product, while the $\text{AMSR2}_{\text{SWI}}$ product used here was derived from X-band observations, which have a shallower penetration depth (Long and Ulaby, 2015). Both $\text{AMSR2}_{\text{SWI}}$ and SMOS_{SWI} are more vulnerable to RFI, which may have reduced their overall performance (Njoku et al., 2005; Oliva et al., 2012). The active microwave-based $\text{ASCAT}_{\text{SWI}}$ performed significantly better in terms of high-frequency than low-frequency fluctuations (Fig. 4), likely due to the presence of seasonal vegetation-related biases (Wagner et al., 2013). $\text{ASCAT}_{\text{SWI}}$ showed a relatively small spread in R_{hi} values (Fig. 4b), although it showed the largest spread in R and R_{lo} values not just among the single-sensor products but among all products (Figs. 3a and 4a).

All single-sensor satellite products achieved lower R values in cold climates (Figs. 2 and 3b), in agreement with other global evaluations using ISMN data (Kim et al., 2018; Al-Yaari et al., 2019; Zhang et al., 2019; Ma et al., 2019), and previously attributed to the confounding influence of dense vegetation cover (de Rosnay et al., 2006; Gruhier et al., 2008; Dorigo et al., 2010), highly organic soils (Zhang et al., 2019), and standing water (Ye et al., 2015; Du et al., 2018) on soil moisture retrievals. However, since the models also tend to exhibit lower R values in cold regions (Fig. 3b), it could also be that the *in situ* measurements are of lower quality or less representative of satellite footprints or model grid-cells, or that our procedure to screen for frozen or snow-covered soils is imperfect. AMSR2 and particularly $\mathrm{AMSR2_{SWI}}$ performed noticeably better in terms of R in arid climates (Figs. 2 and 3b), as reported in previous studies (Wu et al., 2016; Cho et al., 2017), and likely due to the availability of coincident Ka-band brightness temperature observations which are used as input to the LPRM retrieval algorithm (Parinussa et al., 2011). AMSR2 and SMOS (with and without SWI filter) showed markedly lower R values for sites with mean leaf area index > 2 m^2 m^{-2} (Fig. 3c), confirming that their retrievals are affected by dense vegetation cover (Al-Yaari et al., 2014; Wu et al., 2016; Cui et al., 2018). Most satellite products performed worse in terms of R in areas of steep terrain (Fig. 3d), consistent with previous evaluations (Paulik et al., 2014; Karthikeyan et al., 2017a; Ma et al., 2019), and attributed to the confounding effects of relief on the upwelling microwave brightness temperature observed by the radiometer (Mialon et al., 2008; Pulvirenti et al., 2011; Guo et al., 2011).

3.4 How do the multi-sensor merged satellite products perform?

The multi-sensor merged product MeMo (based on $\mathrm{AMSR2_{SWI}}$, $\mathrm{SMAPL3E_{SWI}}$, and $\mathrm{SMOS_{SWI}}$) performed better than the four single-sensor products for all three metrics (R, R_{lo}, and R_{hi}; Figs. 3a and 4; Table 1). These results highlight the value of multi-sensor merging techniques, in line with prior studies that merged satellite retrievals (Gruber et al., 2017; Kim et al., 2018), model outputs (Guo et al., 2007; Liu and Xie, 2013; Cammalleri et al., 2015), and satellite retrievals with model outputs (Yilmaz et al., 2012; Anderson et al., 2012; Tobin et al., 2019; Vergopolan et al., 2020). However, MeMo performed only marginally better in terms of median R than the best-performing single-sensor product $\mathrm{SMAPL3E_{SWI}}$ (which was incorporated in MeMo; Fig. 3a). The most likely reason for this is that triple collocation-based merging techniques rely on several assumptions (linearity, stationarity, error orthogonality, and zero cross-correlation) which are generally difficult to fully satisfy in practice, affecting the optimality of the merging procedure (Yilmaz and Crow, 2014; Gruber et al., 2016).

Additionally, MeMo performed better than the multi-sensor merged product $\mathrm{ESA\text{-}CCI_{SWI}}$ (based on AMSR2, ASCAT, and SMOS) for all three metrics (Figs. 3a and 4). MeMo performed better in terms of R at 68 % of the sites, and performed particularly well across the central Rocky Mountains, although $\mathrm{ESA\text{-}CCI_{SWI}}$ performed better in eastern Europe (Fig. 5). The two products performed similarly in terms of high-frequency fluctuations (median R_{hi} of 0.55 for MeMo versus 0.53 for $\mathrm{ESA\text{-}CCI_{SWI}}$; Fig. 4b). ~~The~~ We speculate that the better overall performance of MeMo compared to $\mathrm{ESA\text{-}CCI_{SWI}}$ (Figs. 3a, 4, and 5) ~~is probably due to two factors. First,~~ may be, at least partly, because $\mathrm{ESA\text{-}CCI_{SWI}}$ incorporates ASCAT, which performed less well in the present evaluation, whereas MeMo incorporates $\mathrm{SMAPL3E_{SWI}}$, which performed best among the single-sensor products (Figs. 3a and 4). ~~The median R of MeMo dropped by 0.04 after excluding $\mathrm{SMAPL3E_{SWI}}$ (data not shown), which supports this explanation. The next version of ESA-CCI (V5) is anticipated to incorporate SMAP soil moisture estimates, and is therefore expected to perform better (Gruber et al., 2019). Secondly, MeMo merges soil moisture estimates from multiple sensors each day, whereas $\mathrm{ESA\text{-}CCI_{SWI}}$ uses only the soil moisture estimate from the 'best' sensor each day, resulting in a loss of information.~~

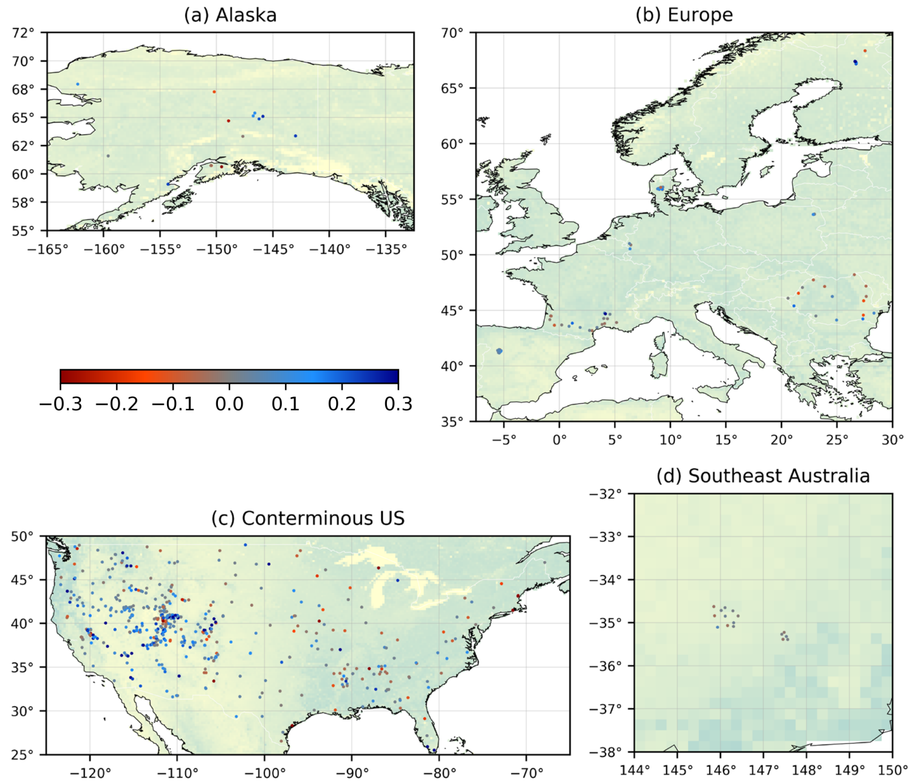

Figure 5. Three-hourly Pearson correlations (R) obtained by MeMo minus those obtained by ESA-CCI. Blue indicates that MeMo performs better, whereas red indicates that ESA-CCI performs better. A map of long-term mean LAI (Baret et al., 2016) is plotted in the background.

3.5 What is the relative performance of the open-loop models?

The ranking of the six open-loop models in terms of median R (from best to worst) was (i) HBV-MSWEP, (ii) HBV-ERA5, (iii) ERA5-Land, (iv) HBV-IMERG, (v) VIC-PGF, and (vi) GLDAS-Noah (Fig. 3a; Table 1). The models were forced with precipitation from, respectively: (i) the gauge-, satellite-, and reanalysis-based MSWEP V2.4 (Beck et al., 2017b, 2019b), (ii) and (iii) the ERA5 reanalysis (Hersbach et al., 2020), (iv) the satellite-based IMERGHHE V06 (Huffman et al., 2014, 2018), (v) the gauge- and reanalysis-based PGF (Sheffield et al., 2006), and (vi) the gauge- and satellite-based GPCP V1.3 Daily Analysis (Huffman et al., 2001). This order matches the overall performance ranking of precipitation datasets in a comprehensive evaluation over the conterminous USA carried out by Beck et al. (2019a). Furthermore, the performance of HBV-ERA5 did not depend on the terrain slope, while HBV-IMERG performed worse in steep terrain (Fig. 3d), which is also consistent with the evaluation of Beck et al. (2019a). HBV-IMERG performed worse for low-frequency than for high-frequency fluctuations (Fig. 4), which likely reflects the presence of seasonal biases in IMERG (Beck et al., 2017c; Wang and Yong, 2020). Overall, these results confirm that precipitation is by far the most important determinant of soil moisture simulation performance (Gottschalck et al., 2005; Liu et al., 2011; Beck et al., 2017c; Dong et al., 2019; Chen and Yuan, 2020). The superior performance of MSWEP is primarily attributable to the inclusion of daily gauge observations (Beck et al., 2019b).

Among the three soil moisture products derived from ERA5 precipitation (ERA5, ERA5-Land, and HBV-ERA5), and among the three products forced with daily gauge-corrected precipitation (GLEAM, HBV-MSWEP+SMAPL3E, and SMAPL4; Table 1), the ones based on HBV performed better overall in terms of all three metrics (R, R_{lo}, and R_{hi}; Figs. 3a and 4). This demonstrates that soil moisture estimates from complex, data-intensive models (H-TESSEL underlying ERA5 and ERA5-Land, GLEAM, and the Catchment model underlying SMAPL4) are not necessarily more accurate than those from relatively simple, calibrated models (HBV). This is in line with several previous multi-model evaluations focusing on soil moisture (e.g., Guswa et al., 2002; Cammalleri et al., 2015; Orth et al., 2015), the surface energy balance (e.g., Best et al., 2015), evaporation (e.g., McCabe et al., 2016), runoff (e.g., Beck et al., 2017a), and river discharge (e.g., Gharari et al., 2020).

3.6 How do the models with satellite data assimilation perform?

The performance ranking of the models with satellite data assimilation in terms of median R (from best to worst) was HBV-MSWEP+SMAPL3E, HBV-ERA5+SMAPL3E, GLEAM, SMAPL4, HBV-IMERG+SMAPL3E, and ERA5 (Fig. 3a; Table 1). The assimilation of SMAPL3E retrievals resulted in a substantial improvement in median R of $+0.06$ for HBV-IMERG, a minor improvement of $+0.01$ for HBV-ERA5, and no change for HBV-MSWEP (Fig. 3a). Improvements in R were obtained for 90 %, 65 %, and 56 % of the sites for HBV-IMERG, HBV-ERA5, and HBV-MSWEP, respectively. For HBV-IMERG, the greatest improvements were found over the central Rocky Mountains (Fig. 6), where IMERG performs relatively poorly (Beck et al., 2019a). Overall, these results suggest that data assimilation provides greater benefits when the precipitation forcing is more uncertain. Since rain gauge observations are not available over the large majority of the globe (Kidd et al., 2017), we expect data assimilation to provide significant added value at the global scale, as also concluded by Bolten et al. (2010), Dong et al. (2019), and Tian et al. (2019). The lack of improvement for HBV-ERA5+SMAPL3E and HBV-MSWEP+SMAPL3E suggests that the gain parameter G (Eq. 3), which quantifies the relative quality of the satellite and model soil moisture estimates, can be refined further.

The ERA5 reanalysis, which assimilates ASCAT soil moisture (Hersbach et al., 2020), obtained a lower overall performance (median $R = 0.68$) than the open-loop models ERA5-Land (median $R = 0.72$) and HBV-ERA5 (median $R = 0.74$), which were both forced with ERA5 precipitation (Fig. 3a). This suggests that assimilating satellite soil moisture estimates (ERA5) was less beneficial than either increasing the model resolution (ERA5-Land) or improving the soil moisture simulation efficiency (HBV). In line with these results, Muñoz Sabater et al. (2019) found that the joint assimilation of ASCAT soil moisture retrievals and SMOS brightness temperatures into an experimental version of the Integrated Forecast System (IFS) model underlying ERA5 did not improve the soil moisture simulations. They attributed this to the adverse impact of simultaneously assimilated screen-level temperature and relative humidity observations on the soil moisture estimates.

In line with our results for HBV-MSWEP+SMAPL3E, Kumar et al. (2014) did not obtain improved soil moisture estimates after the assimilation of ESA-CCI and AMSR-E retrievals into Noah forced with highly accurate NLDAS2 meteorological data for the conterminous USA. Conversely, several other studies obtained substantial performance improvements after data

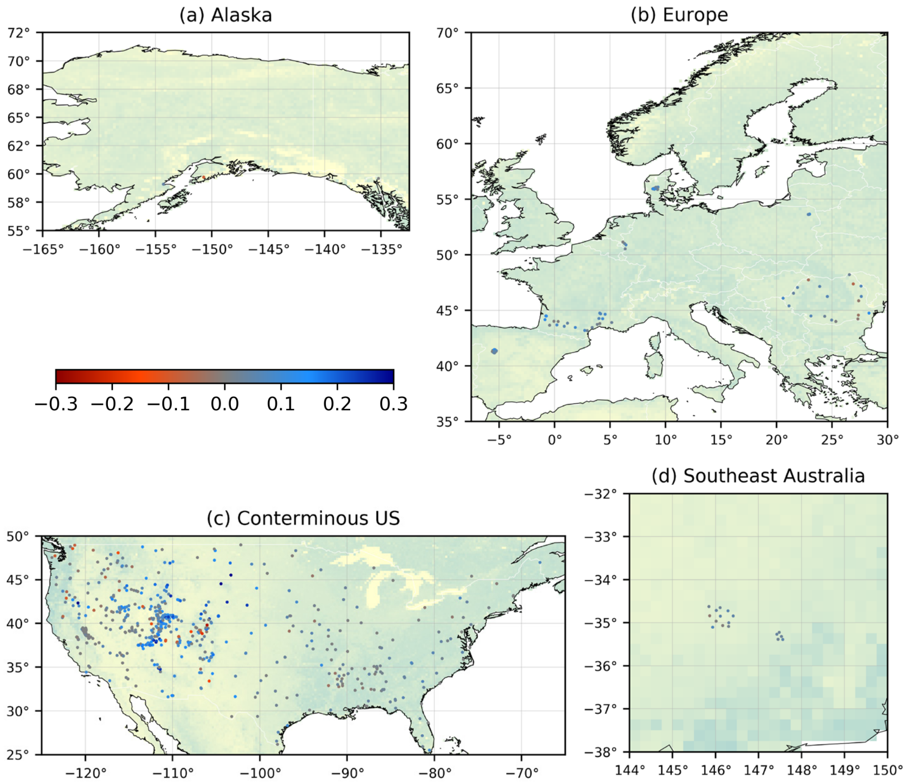

Figure 6. Three-hourly Pearson correlations (R) obtained by HBV-IMERG+SMAPL3E minus those obtained by HBV-IMERG. Blue indicates improved performance after data assimilation, whereas red indicates degraded performance after data assimilation. The sites in Alaska and Finland are not shown as IMERG does not cover high latitudes. A map of long-term mean LAI (Baret et al., 2016) is plotted in the background.

assimilation despite the use of high-quality precipitation forcings (Liu et al., 2011; Koster et al., 2018; Tian et al., 2019). We suspect that this discrepancy might reflect the lower performance of their open-loop models compared to ours. Using different (but overlapping) *in situ* datasets, Koster et al. (2018) and Tian et al. (2019) obtained mean daily open-loop R values of 0.64 and 0.59, respectively, while we obtained a mean daily open-loop R of 0.75 (slightly lower than the 3-hourly median value shown in Fig. 3a). Overall, it appears that the benefits of data assimilation are greater for models that exhibit structural or parameterization deficiencies.

3.7 What is the impact of model calibration?

Among the models evaluated in this study, only HBV and the Catchment model underlying SMAPL4 have been calibrated against *in situ* soil moisture measurements, although only a single parameter out of more than 100 was calibrated for the Catchment model (Reichle et al., 2019b). HBV-ERA5, HBV-IMERG, and HBV-MSWEP with calibrated parameters obtained median R values of 0.74, 0.65, and 0.78, respectively (Fig. 3a), whereas the same three models with randomly generated (uncalibrated) parameters obtained mean median R values of 0.59, 0.53, and 0.62, respectively (standard deviations 0.17, 0.16, and 0.16, respectively; data not shown). The calibration thus resulted in mean increases in median R of $+0.15$, $+0.12$, and $+0.16$, respectively, for the three models, which represent substantial improvements in performance. These results are in line with previous studies calibrating different models using soil moisture from *in situ* sensors (e.g., Koren et al., 2008; Shellito et al., 2016b; Thorstensen et al., 2016; Reichle et al., 2019b) or remote sensing (e.g., Zhang et al., 2011; Wanders et al., 2014; López López et al., 2016; Koster et al., 2018).

The mean improvements in median R obtained for HBV-ERA5, HBV-IMERG, and HBV-MSWEP after calibration ($+0.15$, $+0.12$, and $+0.16$, respectively) were significantly greater than the improvements obtained for the same three models after satellite data assimilation ($+0.01$, $+0.06$, and -0.00, respectively; Fig. 3a; Section 3.6), which suggests that model calibration results in more benefit overall than data assimilation. Additionally, model calibration benefits regions with both sparse and dense rain gauge networks, whereas data assimilation mainly benefits regions with sparse rain gauge networks (Section 3.6). Conversely, only data assimilation is capable of ameliorating potential deficiencies in the meteorological forcing data (e.g., undetected precipitation).

Our calibration approach was relatively simple and yielded only a single spatially uniform parameter set (Section 2.3). Previous studies focusing on runoff have demonstrated the value of more sophisticated calibration approaches yielding ensembles of parameters that vary according to climate and landscape characteristics (Samaniego et al., 2010; Beck et al., 2016, 2020). Whether these approaches have value for soil moisture estimation as well warrants further investigation. It should be noted, however, that many current models have rigid structures, insufficient free parameters, and/or a high computational cost which makes them less amenable to calibration (Mendoza et al., 2015). Moreover, the validity of calibrated parameters may be compromised when the model is subjected to climate conditions it has never experienced before (Knutti, 2008). Care should also be taken that calibration of one aspect of the model does not degrade another aspect and that we get "the right answers for the right reasons" (Kirchner, 2006).

3.8 How do the major product categories compare?

The median $R \pm$ interquartile range across all sites and products in each category was 0.53 ± 0.32 for the satellite soil moisture products without SWI filter, 0.66 ± 0.30 for the satellite soil moisture products with SWI filter including MeMo, 0.69 ± 0.25 for the open-loop models, and 0.72 ± 0.22 for the models with satellite data assimilation (Fig. 3a; Table 1). The satellite products thus provided the least reliable soil moisture estimates and exhibited the largest regional performance differences on average, whereas the models with satellite data assimilation provided the most reliable soil moisture estimates and exhibited the smallest regional performance differences on average. Our performance ranking of the major product categories is consistent with previous studies for the conterminous USA (Liu et al., 2011; Kumar et al., 2014; Fang et al., 2016; Dong et al., 2020), Europe (Naz et al., 2019), and the globe (Albergel et al., 2012; Tian et al., 2019; Dong et al., 2019). It should be kept in mind, however, that these studies, including the present one, used *in situ* soil moisture measurements from regions with dense rain gauge networks, and hence likely overestimate model performance (Dong et al., 2019).

The large spread in performance across the satellite products reflects the large number of factors that affect soil moisture retrieval, including, among others, vegetation cover, surface roughness, soil composition, diurnal variations in land surface conditions, and RFI (Zhang and Zhou, 2016; Karthikeyan et al., 2017b). The spread in performance across the open-loop models is lower as it depends primarily on the precipitation data quality, which, in turn, depends mostly on a combination of gauge network density and prevailing precipitation type (convective versus ~~stratiform~~frontal; Gottschalck et al., 2005; Liu et al., 2011; Beck et al., 2017c; Dong et al., 2019). The smaller spread in performance across the models with satellite data assimilation is due to the fact that individual errors in satellite retrievals and model estimates are cancelled out, to a certain degree, when they are combined, confirming the effectiveness of the data assimilation procedures (Moradkhani, 2008; Liu et al., 2012; Reichle et al., 2017).

3.9 To what extent are our results generalizable to other regions?

The large majority (98 %) of the *in situ* soil moisture measurements used as reference in the current study were from dense monitoring networks in the USA and Europe (Fig. 2) and therefore our results will be most applicable to these regions. We speculate that our results for the models (with and without data assimilation; Figs. 3, 4, and 6) apply to other regions with dense rain gauge networks and broadly similar climates (e.g., parts of China and Australia, and other parts of Europe; Kidd et al., 2017). The calibrated models (HBV and the Catchment model underlying SMAPL4) may, however, perform slightly worse in regions with climatic and physiographic conditions dissimilar to the *in situ* sensors used for calibration (but likely still better than the uncalibrated models). In sparsely gauged areas the four model products based on precipitation forcings that incorporate daily gauge observations (GLEAM, HBV-MSWEP, HBV-MSWEP+SMAPL3E, and SMAPL4; Table 1) will inevitably exhibit lower performance (but not necessarily lower than the other model products). In convection-dominated regions models driven by precipitation from satellite datasets such as IMERG may well outperform those driven by precipitation from reanalyses such as ERA5 (Massari et al., 2017; Beck et al., 2017c, 2019b). Conversely, in mountainous and snow-dominated regions models driven by precipitation from reanalyses are likely to outperform those driven by precipitation from satellites (Ebert et al., 2007; Beck et al., 2019b, a).

Our results for the satellite soil moisture products may be less generalizable, given the large spread in performance across different regions and products revealed in the current study (Figs. 3 and 4) and in previous quasi-global studies using triple collocation (Al-Yaari et al., 2014; Chen et al., 2018; Miyaoka et al., 2017). Outside developed regions we expect the lower prevalence of RFI to lead to more reliable retrievals for those satellite products susceptible to it (Njoku et al., 2005; Oliva et al., 2012; Aksoy and Johnson, 2013; Ticconi et al., 2017). At low latitudes the lower satellite revisit frequency will inevitably increase the sampling uncertainty and reduce the overall value of satellite products relative to models. In tropical forest regions passive products often do not provide soil moisture retrievals, and when they do, the retrievals are typically less reliable than those from active products due to the dense vegetation cover (Al-Yaari et al., 2014; Chen et al., 2018; Miyaoka et al., 2017; Kim et al., 2018). Shedding more light on the strengths and weaknesses of soil moisture products in regions without dense measurement networks — for example using independent soil moisture products (Chen et al., 2018; Dong et al., 2019) or by expanding measurement networks (Kang et al., 2016; Singh et al., 2019) — should be a key priority for future research (Ochsner et al., 2013; Myeni et al., 2019).

4 Conclusions

To shed light on the advantages and disadvantages of different soil moisture products and on the merit of various technological and methodological innovations, we evaluated 18 state-of-the-art (sub-)daily (quasi-)global near-surface soil moisture products using *in situ* measurements from 826 sensors located primarily in the USA and Europe. Our main findings related to the nine questions posed in the introduction can be summarized as follows:

1. Local night retrievals from descending overpasses were more reliable overall for AMSR2, whereas local morning retrievals from descending overpasses were more reliable overall for ASCAT. The ascending and descending retrievals of SMAPL3E and SMOS performed similarly.

2. Application of the SWI smoothing filter resulted in improved performance for all satellite products. Previous near-surface soil moisture product assessments generally did not apply smoothing filters and therefore may have underestimated the true skill of the products.

3. $\mathrm{SMAPL3E_{SWI}}$ performed best overall among the four single-sensor satellite products with SWI filter. $\mathrm{ASCAT_{SWI}}$ performed markedly better in terms of high-frequency than low-frequency fluctuations. All satellite products tended to perform worse in cold climates.

4. The multi-sensor merged satellite product MeMo performed best among the satellite products, highlighting the value of multi-sensor merging techniques. MeMo also outperformed the multi-sensor merged satellite product $\mathrm{ESA\text{-}CCI_{SWI}}$, likely due to the inclusion of $\mathrm{SMAPL3E_{SWI}}$.

5. The performance of the open-loop models depended primarily on the precipitation data quality. The superior performance of HBV-MSWEP is due to the calibration of HBV and the daily gauge corrections of MSWEP. Soil moisture simulation performance did not improve with model complexity.

6. In the absence of model structural or parameterization deficiencies, satellite data assimilation yields substantial performance improvements mainly when the precipitation forcing is of relatively low quality. This suggests that data assimilation provides significant benefits at the global scale.

7. The calibration of HBV against *in situ* soil moisture measurements resulted in substantial performance improvements. The improvement due to model calibration tends to exceed the improvement due to satellite data assimilation and is not limited to regions of low quality precipitation.

8. The satellite products provided the least reliable soil moisture estimates and exhibited the largest regional performance differences on average, whereas the models with satellite data assimilation provided the most reliable soil moisture estimates and exhibited the smallest regional performance differences on average.

9. We speculate that our results for the models (with and without data assimilation) apply to other regions with dense rain gauge networks and broadly similar climates. Our results for the satellite products may be less generalizable due to the large number of factors that affect retrievals.

Appendix: *In situ* soil moisture measurement networks

Table A1 lists the measurement networks part of the ISMN archive from which we have used *in situ* soil moisture data.

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Table 1. The 18 soil moisture products evaluated in this study. For the single-sensor satellite products, the spatial sampling represents the footprint size and the temporal sampling the average revisit time. Acronyms: A = ascending; D = descending; PMW = passive microwave; AMW = active microwave; P = precipitation; DA = data assimilation.

Acronym	Details	Spatial sampling	Temporal sampling	Temporal coverage	Latency	Reference(s)
Satellite products						
AMSR2[a]	AMSR2/GCOM-W1 LPRM L3 V001 (soil_moisture_x); single-sensor PMW product; only D passes	∼47 km	1–3 days	2012–present	∼1.5 days	Parinussa et al. (2015)
ASCAT[a]	Combination of H115 and H116; single-sensor AMW product; A and D passes	∼30 km	1–2 days	2007–present	2–4 months	Wagner et al. (2013); H SAF (2019a, b)
SMAPL3E[a]	SPL3SMP_E.003 L3 Enhanced Radiometer EASE-Grid V3; single-sensor PMW product; A and D passes	∼30 km	1–3 days	2015–present	∼2 days	Entekhabi et al. (2010); Chan et al. (2018); O'Neill et al. (2019)
SMOS[a]	L2 User Data Product (MIR_SMUDP2) V650; single-sensor PMW product; A and D passes	∼40 km	1–3 days	2010–present	∼12 hours	Kerr et al. (2012)
ESA-CCI[a]	ESA-CCI SM V04.4 COMBINED; multi-sensor merged AMW- and PMW-based product derived from AMSR2, ASCAT, and SMOS	0.25°	Daily	1978–2018	About a year	Dorigo et al. (2017); Gruber et al. (2019)
MeMo	Multi-sensor merged PMW product derived from AMSR2, SMAPL3E, and SMOS with SWI filter	0.1°	3-hourly	2015–present	∼12 hours	This study (Section 2.2)
Open-loop models (i.e., without data assimilation)						
ERA5-Land	Volumetric soil water layer 1 (0–7 cm); H-TESSEL model; forced with ERA5 P (Hersbach et al., 2020)	0.1°	Hourly	1979–2020	2–3 months	C3S (2019)
GLDAS-Noah	GLDAS_NOAH025_3H.2.1 (SoilMoi0_10cm_inst) forced with GPCP V1.3 Daily Analysis P (Huffman et al., 2001)	0.25°	3-hourly	1948–2020	∼4 months	Rodell et al. (2004); Rui et al. (2020)
HBV-ERA5	HBV forced with ERA5 P (Hersbach et al., 2020)	0.28°	3-hourly	1979–2020	∼6 days	This study (Section 2.3)
HBV-IMERG	HBV forced with IMERGHHE V06 P (Huffman et al., 2014, 2018)	0.1°	3-hourly	2000–present	∼3 hours	This study (Section 2.3)
HBV-MSWEP	HBV forced with MSWEP V2.4 P (Beck et al., 2019b)	0.1°	3-hourly	2000–present	∼3 hours[b]	This study (Section 2.3)
VIC-PGF	Layer 1 (0–30 cm) of VIC forced with PGF (Sheffield et al., 2006)	0.25°	Daily	1950–2016	Several years	He et al. (2020)
Models with satellite data assimilation						
ERA5	ECMWF ERA5-HRES reanalysis layer 1 (0–7 cm); ASCAT soil moisture DA	0.28°	Hourly	1979–2020	∼6 days	Hersbach et al. (2020)
GLEAM	GLEAM V3.3a surface layer (0–10 cm); MSWEP V2.2 P forcing; ESA-CCI DA	0.25°	Daily	1980–2018	6–12 months	Martens et al. (2017)
HBV-ERA5+SMAPL3E	HBV forced with ERA5 P; SMAPL3E DA	0.1°	3-hourly	2015–2020	∼6 days	This study (Section 2.4)
HBV-IMERG+SMAPL3E	HBV forced with IMERG P; SMAPL3E DA	0.1°	3-hourly	2015–present	∼2 days	This study (Section 2.4)
HBV-MSWEP+SMAPL3E	HBV forced with MSWEP P; SMAPL3E DA	0.1°	3-hourly	2015–present	∼2 days	This study (Section 2.4)
SMAPL4	SMAP L4 V4 surface layer (0–5 cm); NASA Catchment model forced with GEOS P corrected using CPC Unified (Chen et al., 2008); SMAP brightness temperature DA	9 km	3-hourly	2015–present	∼2 days	Reichle et al. (2019b); Reichle et al. (2019a)

[a] We also evaluated versions of these products with Soil Wetness Index (SWI) filter (Wagner et al., 1999; Albergel et al., 2008) with the time lag constant T set to 5 days.

[b] At a latency of hours, MSWEP does not include daily gauge corrections and is therefore of lower quality. The data evaluated here have an effective latency of several days.

Table 2. Median Pearson correlations (R) between *in situ* measurements and retrievals from ascending and descending overpasses for the single-sensor soil moisture products (Table 1). The approximate local solar time (LST) of the overpasses is reported in parentheses. Probability (p) values were determined using the Kruskal and Wallis (1952) test. A small p-value indicates that the difference in median R is unlikely to be due to chance.

	Correlation (R)		
Product	Ascending (LST)	Descending (LST)	p-value
AMSR2	0.40 (13:30)	0.50 (01:30)	0.000
ASCAT	0.41 (21:30)	0.47 (09:30)	0.000
SMAPL3E	0.65 (18:00)	0.65 (06:00)	0.643
SMOS	0.49 (06:00)	0.48 (18:00)	0.271

Table A1. The measurement networks part of the ISMN archive from which we have used *in situ* soil moisture data.

Network	Reference(s) or website
ARM	www.arm.gov
BIEBRZA	www.igik.edu.pl
BNZ-LTER	Van Cleve et al. (2015)
COSMOS	Zreda et al. (2008, 2012)
CTP	Yang et al. (2013)
DAHRA	Tagesson et al. (2015)
FMI	http://fmiarc.fmi.fi
FR	www.inrae.fr
HOBE	Kang et al. (2014); Jin et al. (2014)
HYDROL-NET	Morbidelli et al. (2014)
iRON	Osenga et al. (2019)
LAB-net	Mattar et al. (2014)
MySMNet	Kang et al. (2016)
ORACLE	https://gisoracle.inrae.fr
OZNET	Smith et al. (2012)
REMEDHUS	http://campus.usal.es/~hidrus/
RISMA	Ojo et al. (2015)
RSMN	http://assimo.meteoromania.ro
SCAN	www.wcc.nrcs.usda.gov
SMOSMANIA	Calvet et al. (2007); Albergel et al. (2008)
SNOTEL	www.wcc.nrcs.usda.gov
SOILSCAPE	Moghaddam et al. (2010); Moghaddam et al. (2016)
SWEX	Marczewski et al. (2010)
TERENO	Zacharias et al. (2011)
UDC	Loew et al. (2009)
USCRN	Bell et al. (2013)
VAS	http://nimbus.uv.es
WSMN	Petropoulos and McCalmont (2017)