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SPASS – new gridded climatological snow datasets for Switzerland: Potential and limitations

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Abstract: Gridded information on the past, present and future state of the surface snow cover is an indispensable climate service for any snow-dominated region like the Alps. Here, we present and evaluate the first long-term gridded datasets of modeled daily snow water equivalent and snow depth, which are available for the last 60+ years (since 1962) at 1 km spatial resolution over Switzerland. The comparison against a higher quality, but shorter model dataset shows on the one hand a good performance regarding bias and correlation and on the other hand acceptable absolute and relative errors except for ephemeral snow and for shorter time aggregations like weeks. The comparison against in-situ station data for yearly, monthly and weekly aggregated values at different elevation bands demonstrates only slightly better performance scores for the higher quality dataset, which demonstrates the good performance of the quantile-mapping method which was used to produce the long-term climatological from the higher quality dataset. A trend analysis of yearly mean snow depth from this gridded climatological- and from station-based data revealed a very good agreement on direction and significance at all elevations. However, at the lowest elevations the strength of the decreasing trend in snow depth is clearly overestimated by the gridded datasets. Moreover, a comparison of the trends between individual stations and the corresponding grid points revealed a few cases of larger disagreements in direction and strength of the trend. All these results imply that the performance of the new snow datasets is generally encouraging but can vary at low elevations, at single grid points or for short time windows. Therefore, despite some limitations, the new gridded snow products show promise as they provide high-quality and spatially high-resolution information of snow water equivalent and snow depth, which is of great value for typical climatological products like anomaly maps or elevation dependent long-term trend analysis.

1 Introduction

Snow cover is an integral and crucial component of the Earth's energy and water balance. It reacts sensitively to climate change due to its dependence on precipitation and temperatures below freezing. Climate changes lead to changes in the extent, thickness, density, optical and thermal properties of the snow cover and thus of the Earth's surface and the boundary layer between the Earth and the atmosphere (Abe, 2022). These changes have far-reaching consequences for glaciers, extreme events, natural hazards, ecosystems, biodiversity, forests and landscapes, as well as for winter sports and the tourism industry, both globally and regionally (Mote et al., 2018; López-Moreno et al., 2020; Bozzoli et al., 2024). This also includes the impact on water resources for irrigation, drinking water and hydropower (IPCC, 2019). Snow as frozen precipitation is of increasing importance globally in a world facing more frequent droughts on the one hand and more extreme precipitation events on the other, where snow can dampen immediate runoff but can also cause avalanches or flooding (Barnett et al., 2005). Accurate information about the past and current evolution of the snow cover is therefore of high importance (Van Ginkel et al., 2020).
In contrast to the hemispheric level (Mortimer et al., 2020) or other countries (Olefs et al., 2020), Switzerland so far provided long-term snow cover information based on in-situ data of snow depth (Marty and Blanchet, 2012; Scherrer et al., 2013; Schmucki et al., 2017) and water equivalent of the snow cover (SWE) from national monitoring networks (Marty et al., 2023), data of which are regularly published in the annual winter reports (Pielmeier et al., 2024) and in online repositories (Marty,

2020). Such point-based time series are very valuable because of their lengths and documented measurement history (Buchmann et al., 2022). However, even though Switzerland has a high density of snow measurement stations, their asymmetric distribution (especially in terms of altitude) and irregular temporal availability (some had to be abandoned, others recently started from scratch due to automation) limit their usefulness for many applications. For these reasons a recent study evaluated the usefulness of existing long-term and spatially gridded snow datasets for Switzerland (Scherrer et al., 2024). Among others, the authors state that most datasets, including the high-resolution ones, have problems correctly representing small SWE values at low elevations and they conclude that a km-scale model with assimilated snow measurement data is highly preferable. The only model in this investigation, which fulfilled these requirements, was a temperature-index model based on gridded temperature and precipitation input fields, as well as an algorithm for the fraction of snow-covered area and assimilated snow depth data from a time-invariant set of 350 in-situ snow stations assimilated using an Ensemble Kalman Filter (Magnusson et al., 2014). This model, which is operated by the operational snow hydrological service (OSHD) at WSL Institute for Snow and Avalanche Research SLF, is from now on referred to as OSHD-EKF and provides daily 1 km gridded information on SWE between 1999 and today (for details see Mott et al. 2023). The length of this dataset is limited back to 1999 because there are not enough high-elevation snow stations available for assimilation before that time. To overcome this limitation and make use of the full period of available gridded datasets (1962 to today), we developed within the project *SPAtial Snow climatology for Switzerland* (SPASS) a quantile mapping procedure (SnowQM). This method allows correcting the not data-assimilated full climatological SWE time series starting in the hydrological year 1962 (OSHD-CL) into a better quality dataset (OSHD-CLQM) which mimics the higher-quality model OSHD-EKF (Michel et al., 2024). For the development of OSHD-CLQM, the quantile mapping method SnowQM was calibrated and validated with SWE simulations between 1999 and 2021 using the OSHD-EKF data set as target and was then applied to the OSHD-CL data set over the period from the hydrological year 1962 to today.

Michel et al. (2024) concluded that the developed quantile-based correction can efficiently reduce the pronounced SWE bias at high elevations and that the average bias is always close to zero. Moreover, they stated that the mean absolute error can remain large even after correction and that SnowQM is not expected to do more than a climatological bias correction, meaning biases at short time scales, like on a single day or month, are not necessarily corrected. Additionally, they mentioned that such biases can also concern entire winters at low elevated regions. However, quantitative information on elevation-dependent uncertainties are not provided but are important in mountain regions (Switanek et al., 2024). Additionally, as SWE is an unusual and elusive variable for the non-scientific public (e.g. tourism, media), and many applications explicitly need snow depth (HS), Aschauer et al. (2023) developed the SWE2HS algorithm to convert daily SWE to HS, which is applied here for the first time on a gridded SWE dataset. This algorithm contains a multilayer densification model which uses daily SWE as the sole input. A constant new snow density is assumed, and densification is calculated via exponential settling functions. The maximum snow density of a single layer changes over time due to overburden and SWE losses.

As the knowledge of the uncertainties underlying such gridded datasets is crucial for any application, the aim of the current study is therefore to compare the new dataset to other gridded and station-based datasets and to investigate potential biases dependent on i) temporal aggregation, ii) elevation, iii) trend analysis to get a clearer picture on their potential and their limitations. In the next section (2), we first present the used gridded- and station data, as well as the evaluation methods applied. In section 3, we explain and discuss the results before we conclude our findings in section 4.

2 Data and methods

2.1 Spatial SWE and HS datasets

The main dataset of this study is the above mentioned OSHD-CLQM, which consists of 1 km daily gridded SWE data over the domain of Switzerland. Additionally, we also use the assimilated OSHD-EKF data as described in the former chapter and

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illustrated in Fig. 1. Both these datasets are converted into the corresponding gridded HS datasets by applying the SWE2HS algorithm (Aschauer et al., 2023). The analyses are performed for hydrological years, lasting from September of the previous year to August of the year of investigation. The hydrological year 2023, for instance, consists of the period 1 September 2022 to 31 August 2023. This definition is consistent with the settings of the OSHD models, which sets SWE to zero on 1 September of each year, to only represent seasonal snow, thus operating on an annual cycle starting in September. The time series under investigation therefore covers the hydrological years 1962 to 2023.

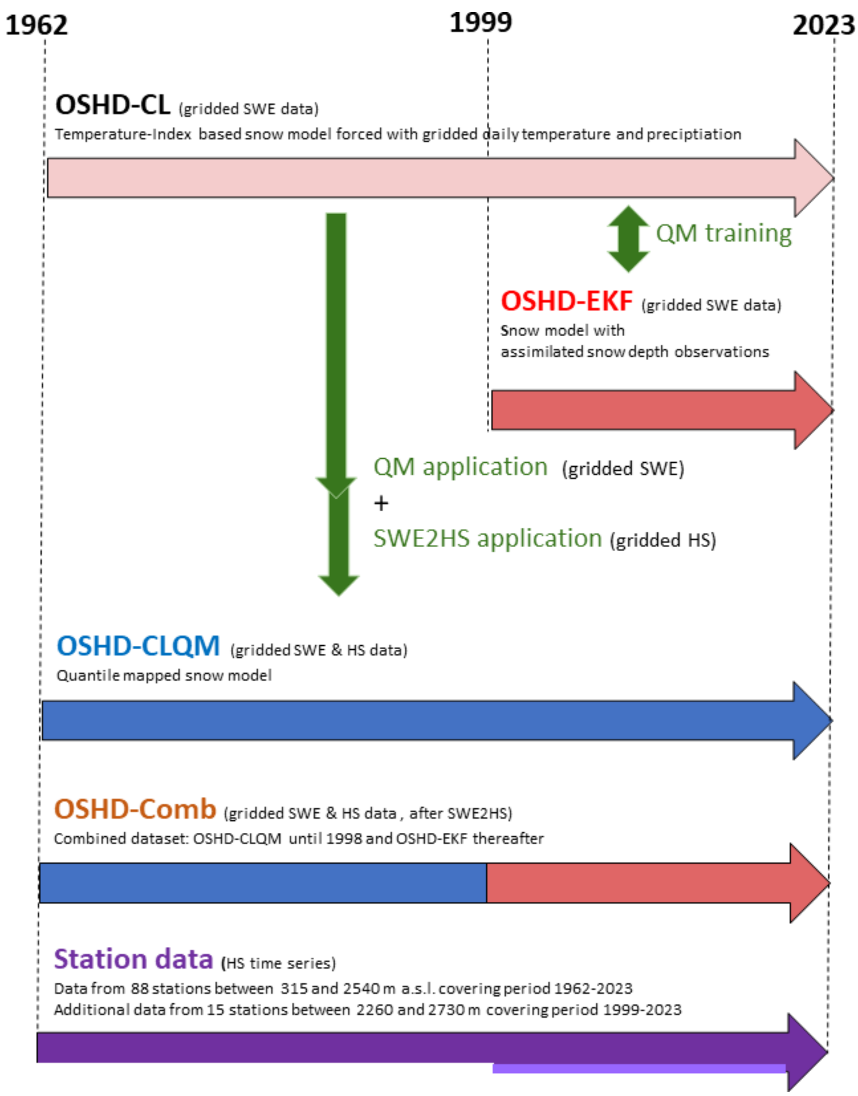

Figure 1: Conceptual view of the workflow of the different model- and station-datasets used as well as for which period they are available.

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2.2 Reference datasets

To evaluate the performance of the long-term OSHD-CLQM dataset, we use as two references: (1) the higher-quality OSHD-EKF dataset, which limits the comparison to the 1999-2023 period and (2) daily in-situ station data, which limits the comparison to snow depth.

It is important to mention that OSHD-CLQM is not independent of the first reference as OSHD-EKF was used in the above-described quantile mapping step to produce OSHD-CLQM. Additionally, some bias is expected when comparing HS data, as this variable is only available for both datasets through the conversion using the SWE2HS algorithm.

When comparing to in-situ data (second reference) we have to take into account the common grid-to-point mismatch problem. In this regard, it is important to know that both datasets (CLQM and EKF) are both based on the OSHD temperature index model, which was run in its default mode, where the SWE values represent spatial mean of the respective grid cells, considering its predominant land cover types and terrain characteristics. This is in-line with the OSHD-EKF's objective of conducting a comprehensive assessment of snow and water resources in Switzerland, but it entails issues when comparing to in-situ data which represent snow conditions at flat, non-forested, sheltered field sites. Indeed, the monitoring sites have been reported to often systematically overrepresent snow depth (Grünewald and Lehning, 2015), hence negative biases of OSHD-EKF relative to station data are expected and intentional, which must be kept in mind when interpreting respective results. Moreover, elevations above 3000 m are not analyzed as grid points above this elevation are sometimes affected by too much snow accumulation in the model due to the lack of high-elevation station data for assimilation into the model (Michel et al., 2024).

As daily in-situ snow depth time-series, we use on the one hand data of 103 stations (Table S1), which have already been used in the assimilation procedure of OSHD-EKF (Fig. 1) and are therefore complete between 1999-2023. On the other hand, for an independent analysis (Fig. 6), we use data of 79 independent stations, which have not been used in the data assimilation step, because they cover only part of the time between 1999-2023. All stations are all located between 200 and 2800 m a.s.l. (Fig. 2), whereas stations below 2000 m consist of manual measurements only and stations above 2000 m mostly consist of automatic measurements. The data of these stations have been carefully quality-controlled and gap-filled in separate steps. Technically, each station is compared with its most representative grid point, which was determined based on the selection of the grid cell that contains the station of interest as well as the eight surrounding grid cells. The grid cell with the smallest elevation difference to the station was chosen for the comparison. The median elevation difference between the station and the selected grid cell over all stations is 10 m with a standard deviation of 23 m; the largest elevation difference is 105 m. The digital elevation model to determine the grid point elevation was provided by swisstopo (2017).

2.3 Spatial and temporal aggregations

Michel et al. 2024 demonstrated that the SWE bias of OSHD-CLQM is not remarkably different between north and south of the Alps, which are the two main climatic regions in Switzerland. We here focus on elevation dependent biases, as the existence of snow in the Alps strongly depends on the elevation above sea level. For this purpose, we use elevation bands with a width of ±250 m which are centered at 500, 1000, 1500, 2000 and 2500 m. Therefore, we also pool the above-mentioned station data into these elevations bands with the goal to compare all grid points in an elevation band to all stations in this elevation band (Table S1 and Table S2).

These elevation bands imply that grid points below 250 m and above 2750 m were not evaluated when comparing with station data, because there are hardly any stations for assimilation or validation available (>2750 m). Additionally, there are hardly any grid points below 250 m in the domain of Switzerland.

To assess time aggregation dependent biases, we use aggregations of the daily data to weekly, monthly and yearly mean values. Yearly mean values are based on the 6-month period between November and April, which we will refer to as 'yearly' from now on, because it's the period where snow cover is predominant in most of the regions in the country and because it's the period where manual snow depth measurements are available completely.

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Moreover, we evaluate time aggregation- and elevation-dependent biases of commonly used climatological anomalies. For this purpose, the 30-year average between 1991 and 2020 (standard 30-year reference period) is calculated for every grid point and the ratio between the weekly, monthly or yearly mean values and its reference period is determined. For these comparisons we focus on the period 1999-2023 to also be able to investigate performance differences between OSHD-CLQM and OSHD-EKF, as well as to have enough in-situ data (Fig. 2, Table S2) available in the different elevation bands (mean per elevation band is 20 stations, minimum 14 stations, maximum 34 stations).

2.4 Merging gridded datasets for trend analysis

It is not surprising and there are clear indications that the climatology of OSHD-CLQM and OSHD-EKF are not that different (Fig. S1). Hence, we also constructed a new "combined" time series OSHD-Comb (Fig. 1), by concatenating the first part of OSHD-CLQM (1962-1998) with OSHD-EKF (1999 and 2023). This approach allows investigating the impact on trends when merging the best available datasets for each period.

Long-term trends of all the above mentioned time series are evaluated based on yearly values with the Theil-Sen slope (Theil, 1950; Sen, 1968) and the Mann-Kendall (MK) trend test (Mann, 1945). A positive standardized MK value indicates an increasing trend, while a negative value demonstrates a decreasing one. Confidence levels of 95% are used as a threshold to classify a significant trend ($p < 0.05$). The Theil-Sen slope estimator provides a measure of the strength of a trend based on a robust simple non-parametric linear regression. Absolute trends were always calculated as change per decade and relative trends were calculated for the entire 62-year period as percentage changes between 1962 and 2023 based on the Theil-Sen slope. Please keep in mind that a direct comparison of percentage changes is only meaningful between indicators of the same unit and similar absolute values. The thus calculated trends of the model datasets are also compared to the trends from in-situ station data. The stations available for this comparison cover all elevation levels quite well. The same stations are available for each elevation band as for the 1999-2023 comparison, except for the highest elevation band (2250-2750 m a.s.l.), where only one station covers the required full period between 1962 and 2023.

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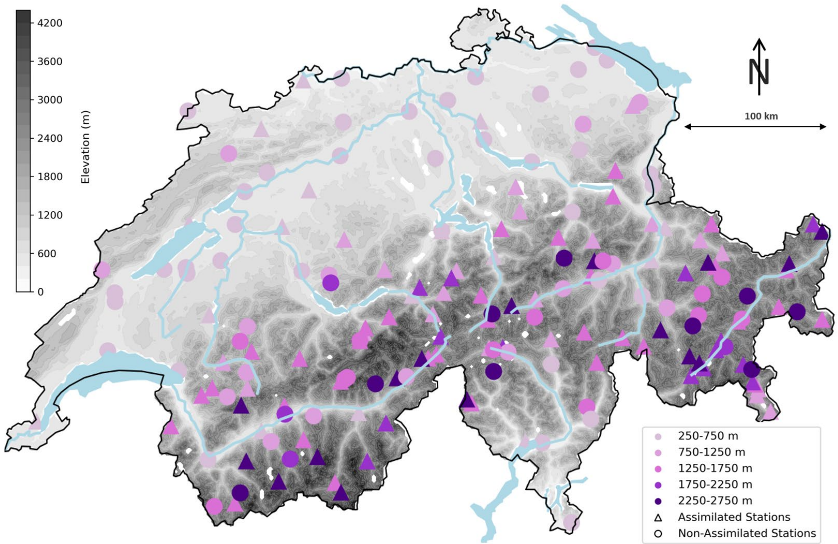

Figure 2: Map of Switzerland with the elevation of the individual grid points and the distribution of stations used to validate the gridded datasets. Stations are colored by elevation band; assimilated stations (OSHD-EKF) are shown as triangles and non-assimilated stations as circles.

2.5 Evaluation metrics

The analyses are mainly based on the two variables describing the mass and depth of snow cover: SWE in millimeters and HS in cm. Moreover, we also analyze the number of snow days. A snow day is defined as day with snow cover of at least 5, 30 or 50 cm of snow depth, which implies that we have three different classes of snow days.

We use four statistical evaluation scores to compare the various datasets: Root mean squared error (RMSE), mean bias (BIAS), correlation coefficient (R) and mean arctangent absolute percentage error (MAAPE) to evaluate the gridded snow products.

MAAPE (Kim and Kim, 2016) is an adaptation of the mean absolute percentage error (MAPE), to mitigate large percentage errors occurring only due to small reference values. To get MAAPE, first, like in the case of MAPE, the absolute relative difference between the target value ($\hat{y}$) and the reference value (y_i) is calculated.

$$MAAPE = \frac{1}{n}\sum_{i=1}^{n} \arctan\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right)$$

But then the arctan of this relative difference is taken, which maps large values to [0; π/2] and hence limits the maximum relative error to 157 %. When we write about relative errors in the results section, we always refer to MAAPE values for better readability.

For each data set to be compared we calculated the four metrics for each elevation band. and averaged the resulting scores for each temporal aggregation unit (hydrological year, month, and week respectively). This resulted in the creation of arrays with temporal dimensions corresponding to the number of hydrological years (e.g. 25, when using OSHD-EKF as reference), months (150), or weeks (668). These arrays of scores finally provide the base for calculating boxplots of RMSE, BIAS, R and MAAPE for each temporal aggregation with each elevation band (500, 1000, 1500, 2000, 2500 m) as running variable.

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3 Results and Discussion

3.1 Analysis of performance scores based on gridded reference dataset

In order to quantify time and elevation dependent uncertainties arising from the quantile mapping, we first evaluated the OSHD-CLQM model simulation against the OSHD-EKF model simulations used as target dataset (Fig. 3). As expected from the quantile mapping procedure, BIAS for SWE is close to zero for all temporal aggregations and all elevation bands. HS, however, reveals a slightly negative BIAS (ca. -2 cm) for the highest elevation band, because HS has been derived from SWE and therefore not been directly mapped to match the quantile distributions of the observed snow depth measurements. For both variables SWE and HS, RMSE and MAAPE demonstrate a moderate worsening of the score performance for all elevations with temporal aggregation over smaller periods, illustrated e.g. by RMSE values at 1500 m increasing from 21 to 31 mm SWE or 7 to 11 cm HS going from yearly to weekly aggregation. Regarding elevation dependence, both MAAPE and R reveal a clear improvement in score performance when going from low to high elevations. Indeed, MAAPE scores demonstrate for SWE and HS at 500 m values of about 37 % for yearly resolution and increases to about 58% at monthly and 65% at weekly resolution. At the same time, at 2500 m MAAPE is about 8 % at yearly resolution and increases to 11 % at monthly and 13 % at weekly resolution. The poorer performance at low altitudes is easily explained by the fact that quantile mapping is not really suitable for time series with many zero values, i.e. for regions with a snow cover of only a few days per winter (Michel et al. 2024). RMSE also shows better performance with higher elevations, but the scores improve clearly only between 500 and 1500 m and are more or less stable above. Generally, the performance increases with elevation in all of the four evaluation metrics. High elevations show larger absolute (RMSE) but smaller relative errors (MAAPE).

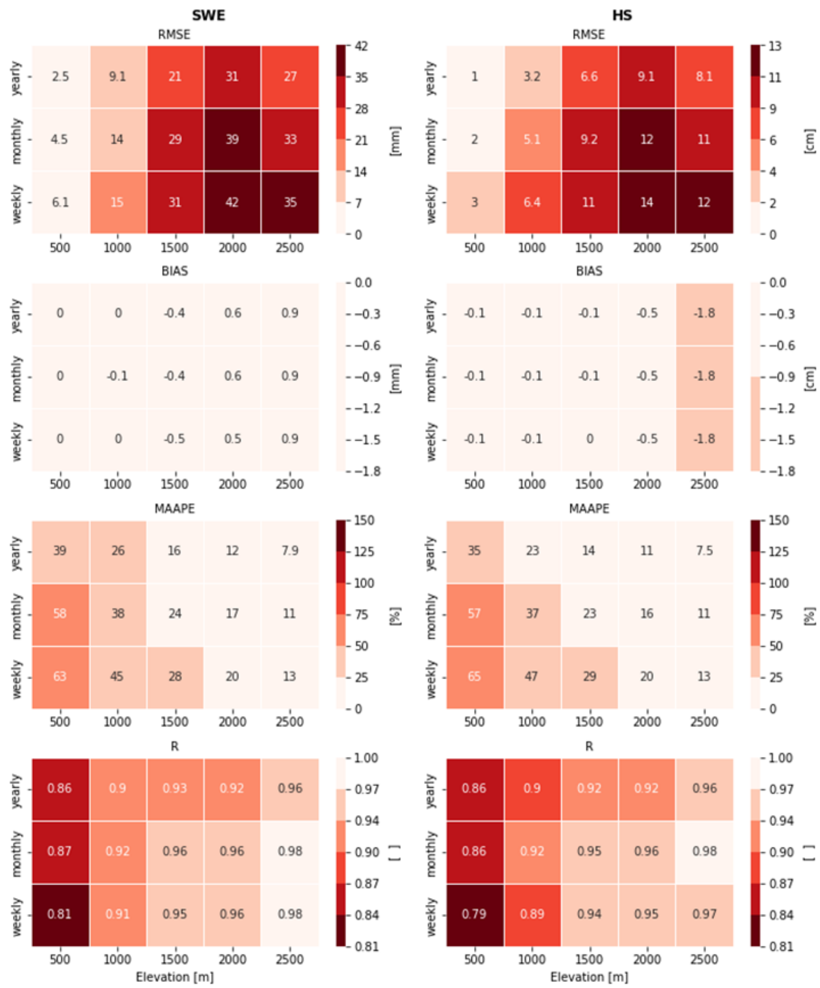

Figure 3: Heatmap of mean SWE (left) and HS (right) evaluation scores for the gridded OSHD-CLQM dataset in the period 1999-2023 using the OSHD-EKF dataset as reference. Darker shades of red indicate worse scores.

In a second step, we investigated the distribution of the performance scores with the help of boxplots for the same temporal aggregations and elevation bands. Figure 4 shows the corresponding boxplots consisting of the 25 yearly values (1999-2023) for both snow variables. While mean values of BIAS are close to zero for all elevations bands, whiskers and outliers demonstrate a clear increase of variability of the yearly values with increasing elevation. Larger BIAS can occur above 2750 m (not shown), where no in-situ data for assimilation is available, but where such differences are still small in relative terms. This can also be seen by the low MAAPE values in the highest elevation band. In contrast, at 500 m MAAPE values demonstrate that in 90% of all years (see whiskers) the relative error is about 40 % but can be as high as 70 % in rare cases. Similarly, R values show a clear increase in the spread with decreasing elevation.

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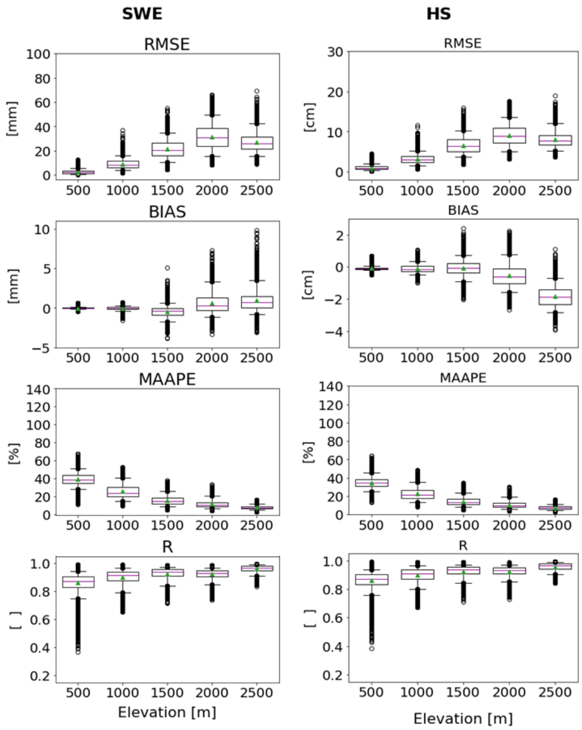

Figure 4: Score comparison between models OSHD-CLQM and OSHD-EKF ('reference') on a yearly resolution at respective elevation bands (m) for SWE (left) and HS (right). Boxplots were generated from these performance scores to illustrate the distribution, outliers, mean (green triangle) and median (purple line). The box reflects the 50 % of data between the lower quartile and upper quartile. The whiskers extend from the boxes' edges and illustrate the data range between the 5th and 95th percentile. Outliers are represented as individual dots.

The same analysis has been undertaken for monthly and weekly performance scores (Fig. S2). Monthly scores reveal the highest RMSE values at 2000 m of about 20 to 50 mm SWE (based on whiskers) or 8 to 13 cm HS, which according to MAAPE corresponds to a relative error range of 5 to 20 % for HS and SWE. However, in extremes cases (outliers) this error can be as high as 35 %. At 500 m MAAPE whisker range goes from 30 to 50% for both snow variables but can go up to about 70 % in extreme cases. This low performance in these extreme cases in this elevation band is also illustrated by accordingly low R scores of less than 0.6 for both variables. Weekly scores demonstrate a similar pattern but slightly higher values for RMSE and MAAPE for both variables SWE and HS. Highest relative errors scores (but on the same small absolute errors) can again be seen in the lowest elevation band with a MAAPE whisker range demonstrating values between 50 to 70%.

3.2 Analysis of performance scores based on in-situ station data as reference

After investigating differences between the OSHD-CLQM and OSHD-EKF models, we here now compare HS simulations of the two gridded models with HS observations at the stations. Note, that point observations do not necessarily represent spatial means over large grid cells, particularly in complex and steep terrain, and a comparison to results from a model that represents the existing subgrid variability is hence confounded.

Figure 5 illustrates that the yearly scores between the stations and the respective model grid points of OSHD-CLQM and OSHD-EKF show remarkable similarity overall. However, R values of OSHD-EKF stand out as being more consistent and are found to be higher in all elevation bands, especially at lower elevations. As expected for a model that assimilates snow

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observations, OSHD-EKF demonstrates slightly better comparison statistics, but the differences are minor which attests to the good performance of the quantile mapping procedure. Both models show larger BIAS values at higher elevations, peaking in the highest elevation band with median values of about -20 cm, which indicates that, as expected, the two models feature less snow at the highest elevations compared to the station values. There are several reasons for these BIAS values. First, data from flat field observations at high elevation often show larger values than the surrounding area (Grünewald and Lehning, 2015). Second, the SWE2HS algorithm sometimes tends to underestimate HS at these elevations (Aschauer et al., 2023). And third, there is lack of stations for assimilation at thigh elevation (Mott et al., 2023). In relative term this bias, which is reflected in the MAAPE score, reveals errors between 15 and 25 % at the elevation band 1500 m and above. This is in strong contrast to the values of about 80 % at the 500 m elevation band, owing to the very low mean snow depths at these elevations.

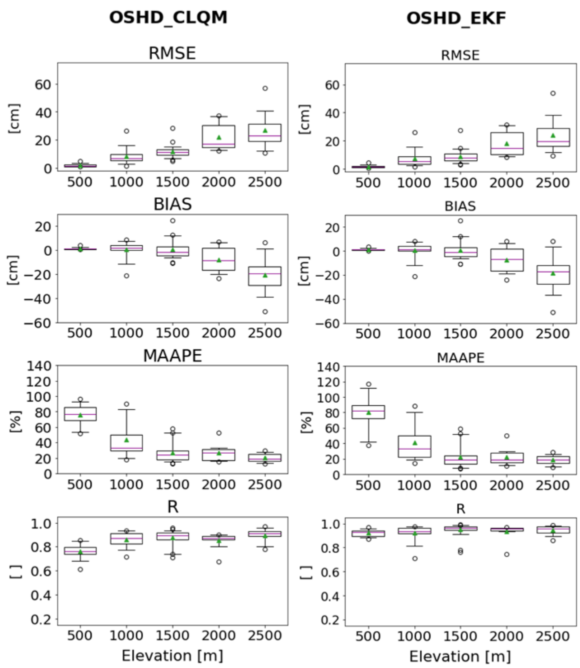

Figure 5: Score comparison between station data and OSHD-CLQM (left) as well as OSHD-EKF (right) in the respective elevation bands for yearly snow depth values. Median value is illustrated as purple line and mean value as green triangle.

The same analysis has been undertaken for monthly and weekly performance scores (Fig. S3) and generally reveals the same pattern (lower performance for smaller time aggregations) as found when intercomparing the two models, with the difference that the performance decrease going from yearly to monthly or weekly time-windows is now much weaker. OSHD-EKF stands out again with higher R values, especially at lower elevations. MAAPE median values are again largest at 500 m, with median values reaching 100% for monthly and 110% for weekly aggregations. These values decrease to 40% and less for elevations above 1500 m for monthly and weekly time-windows.

The above shown station-based comparisons are not independent as the same station data is used in the assimilation step of OSHD-EKF, which then also indirectly influences OSHD-CLQM through the quantile-mapping step. In separate step, we therefore additionally analyzed also non-assimilated stations with respect to the OSHD-CLQM model (Fig. 6). The result demonstrates that the BIAS for non-assimilated and assimilated stations is very similar. This indicates that the assimilation of stations within OSHD-EKF transfers well to unobserved locations, while the quantile mapping is capable of inheriting this

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asset to OSHD-CLQM. As expected, we see generally higher BIAS values above 2000 m, which (as explained above) is due to the fact flat field observations at high elevation often show larger values than the surrounding area. As shown in Fig. 5 these BIAS values are only about 20% in relative terms. Moreover, above 2000 m the errors for the non-assimilated stations are in general only about 5 cm larger, which corroborates the performance of the quantile mapping step for this independent dataset.

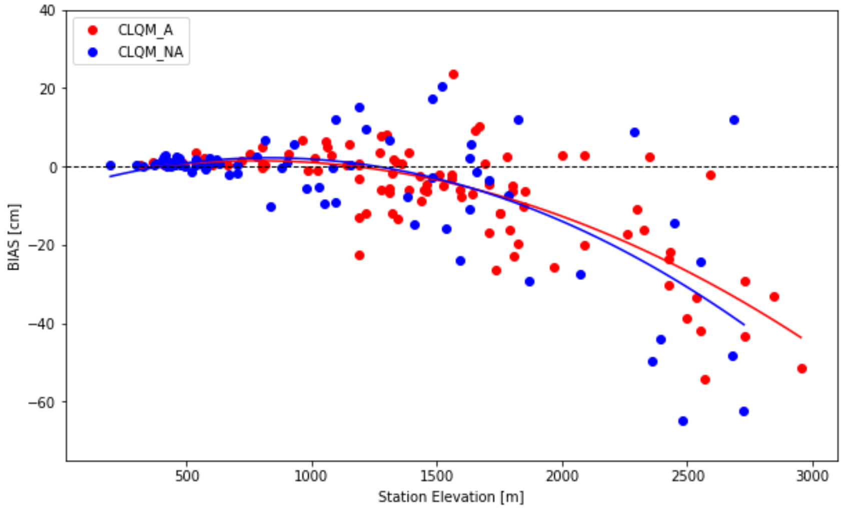

Figure 6: BIAS of yearly mean snow depth [cm] vs elevation [m] for the comparison of assimilated (red) and non-assimilated (blue) stations value with respect to the OSHD-CLQM model. The curves are polynomials fits of first degree.

When looking at the entire country, i.e. all grid points across Switzerland, the analysis reveals for yearly mean values a median RMSE of about 10 cm (Fig. S4). At shorter time aggregations the median RMSE is only slightly increasing. This good performance when averaging over all grid points gives confidence in typical climatological analysis like the comparison of the annual snow depth evolution between different climate periods (e.g. 1962-1990 with 1991-2020). The corresponding plot (Fig. S5) demonstrates a clear decrease of snow depth in recent decades, which is mainly driven by less accumulation in spring and an earlier snow disappearance in summer. This finding is not new as it has been described with station data and explained with higher temperatures (Klein et al., 2016; Marty et al., 2023), but can now also be demonstrated with gridded data.

3.3 Evaluation of impact on trends

3.3.1 Elevation dependent snow depth trends

Here, we investigate how long-term HS trends of OSHD-CLQM and OSHD-Comb compare to trends observed at stations in the different elevation bands. Already Fig. 5 demonstrated that compared to station data, median performance scores of OSHD-CLQM and OSHD-EKF are generally (except R) very similar, demonstrating the good performance of the quantile mapping step. However, focusing on the whiskers of the boxplots, it is obvious that with OSHD-EKF smaller errors (outliers) are achieved. Therefore, using OSHD-EKF data instead of OSHD-CLQM data, when possible, i.e. OSHD-Comb, can be a gain. A typical application case, where the benefit of using OSHD-Comb can be nicely demonstrated, is the use of climatological anomaly maps (Fig. 7). In the shown example of winter 2018 (Nov-Apr) we see that the relative snow depth anomaly for this season with respect to the long-term mean (1991-2020) was clearly above average in the Alps (see high elevations in Fig. 2) and in the south for OSHD-CLQM and OSHD-EKF, but less consistent patterns appear at low elevations in the north. A visual comparison to the station values (marked in Fig. 7 as well) demonstrates that OSHD-EKF provides the more accurate results

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regarding these regional differences revealing that the Swiss Plateau experienced clearly below average snow depth in the 2018 winter season. Moreover, OSHD-EKF in this case appears to exhibit greater spatial uniformity. This result is not surprising as already Fig. 3 and Fig. 4 demonstrated that the performance of quantile mapping approach used in OSHD-CLQM is limited in case of low-snow environments.

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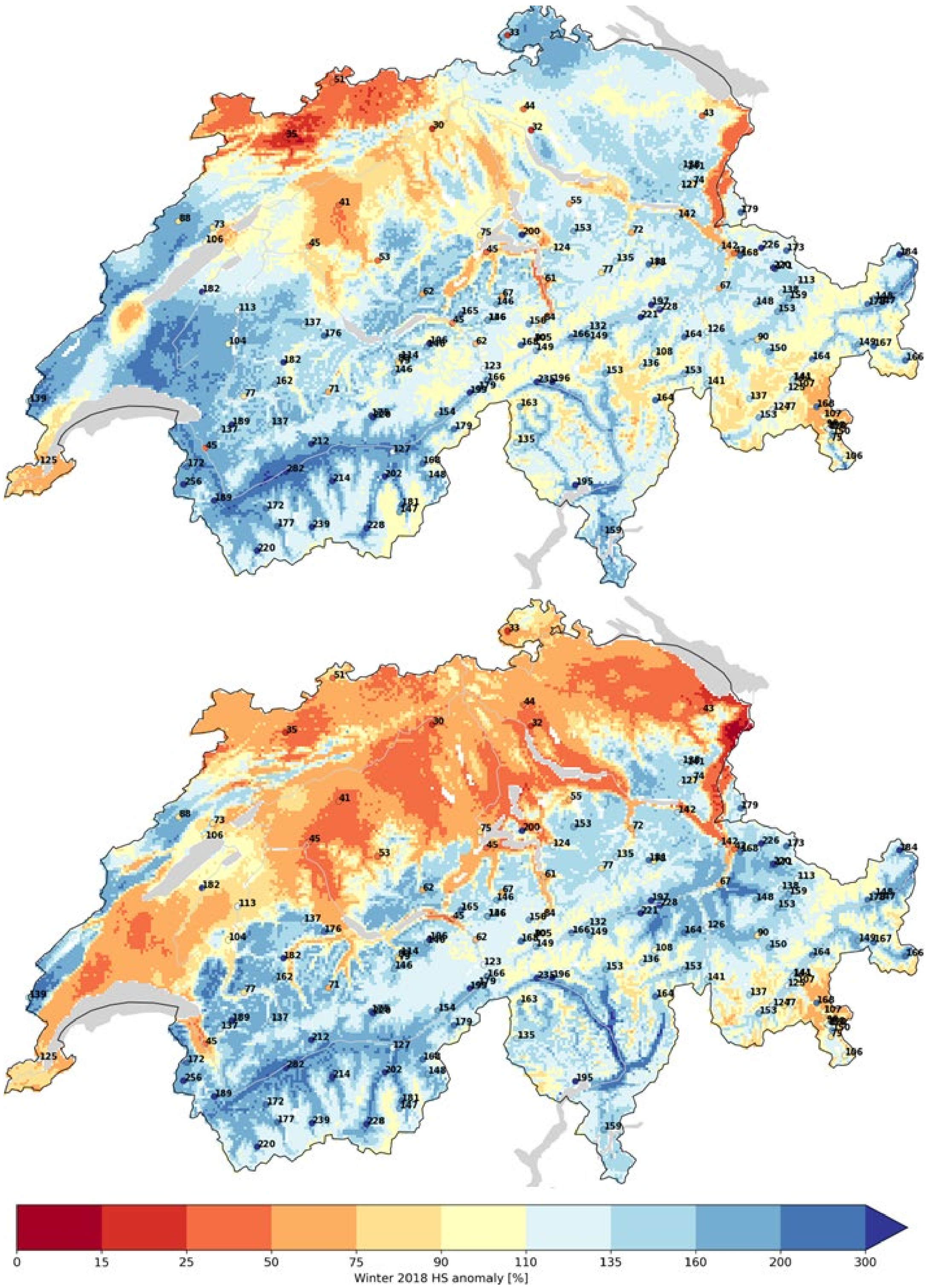

Figure 7: Relative snow depth anomaly (%) of winter 2018 (Nov-Apr) with respect to the long-term mean (1991-2020) for OSHD-CLQM (top) and OSHD-EKF (bottom). Red indicates below-average, yellow average, and blue signifies above-average snow depth. The colored dots and numbers indicate station anomalies.

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The combined model OSHD-Comb utilizes the OSHD-EKF from 1999 onwards, which helps capturing short-term variations more accurately. Meanwhile, OSHD-CLQM originates from quantile mapping of the climatological model OSHD-CL onto OSHD-EKF aiming to reduce systematic differences in the simulation of OSHD-CL. On the other hand, using OSHD-Comb could introduce temporal inconsistencies at the point in time when OSHD-CLQM and OSHD-EKF are combined (1998/1999; see Fig. 1), which we investigated by analyzing the involved trends in Fig. 8. Examining the plots in this figure reveals that the interannual variability in the modelled long-term snow depth time series (OSHD-CLQM and OSHD-Comb) agree very well, especially when comparing all elevations (Fig. 8f). But both datasets also align well with the long-term station data, particularly at elevations of 1000, 1500, 2000 and 2500 m, which demonstrates the performance of the quantile mapping step in these elevation bands. The OSHD-Comb trend magnitude is marginally weaker than the OSHD-CLQM trend magnitude and thus closer to the station-based trend magnitude for all investigated elevations with the exception of the 2000 m band. The largest differences between station-based and model-based trends appears, again, in the lowest elevation band, which corroborates the findings of Michel et al. (2024) and Fig. 5 with large relative errors at low elevation. On a closer look at this low elevation band (Fig. 8a), we see that largest differences occur during snow-rich winters in the first 20 years. These differences are similar when using OSHD-CL, which indicates that not the QM step, but either the meteorological input data and/or the temperature-index model are the main reason for the large biases in the first two decades in the lowest elevation band. Focusing on the significance of the decreasing trends we see that the level of significance agrees well for all data sets and elevation bands, which is also in agreements with other studies analyzing station-based trends.

Notice, there is only one long-term station available in the 2500 m elevation band, which strongly limits the informative value of this elevation band. Therefore, an additional analysis for this elevation band has been undertaken for the shorter 24-year period 2000-2023 (Fig. S6), where data from 14 stations are available. This figure corroborates the findings of Fig. 8e by confirming the magnitude of the absolute snow depth values as well as the similarity and the non-significance of the found trends in this elevation band. The above results agree well with other recent studies analyzing station-based trends with mostly significant decreasing trends below about 2000 m (Matiu et al., 2021; Marty et al., 2023).

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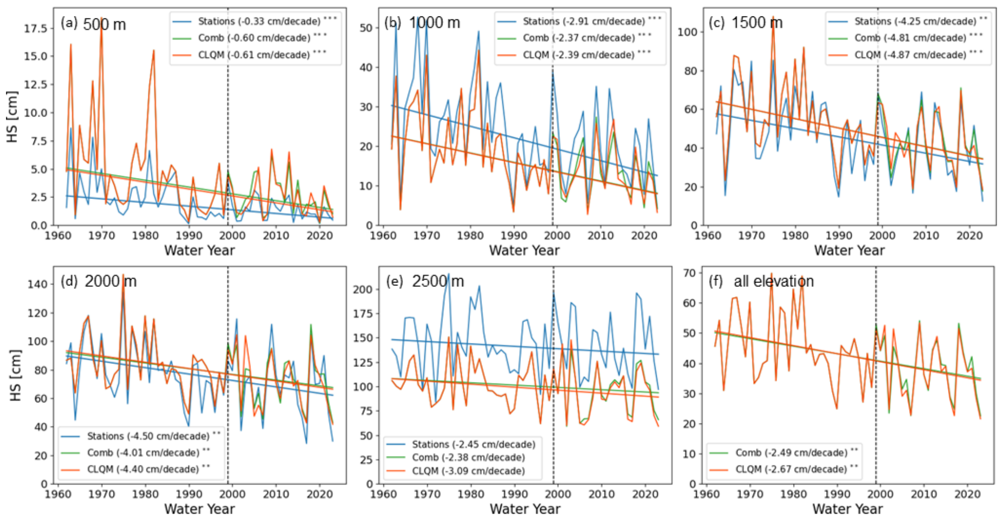

Figure 8: Trends of yearly snow depth[cm / decade] calculated using Theil-Sen slopes for the OSHD-CLQM and the combined model data series (OSHD-Comb), as well as for station measurements for the five elevation bands: (a) 500, (b) 1000, (c) 1500, (d) 2000, (e) 2500 m and (f) entire Switzerland (0-3000 m). Significance is indicated with * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The dashed line indicates the year 1999, before which the yearly values of OSHD-CLQM and OSHD-comb are the same.

3.3.2 Snow depth trends at individual stations

We also conducted a trend comparison based on single grid points, since having available a gridded datasets makes it tempting to fill missing snow information at a specific location with the data from the corresponding grid point. We compared the Theil-Sen slopes of the yearly means of stations with those of the closest grid point from both the OSHD-CLQM and the OSHD-Comb model. The corresponding plot (Fig. 9) reveals that in the large majority of the cases the trends well align between models and stations. Moreover, there seems to be almost no performance difference between the two model chains. However, we can also observe that the bias (difference between station and model trend) is large for a small set of station at elevations between 1200 and 2000 m. Both, OSHD-CLQM and OSHD-Comb show the same eight stations that differ by more than ± 4 cm/decade in their trends. Out of these eight stations, there are 5 stations, which show a considerably weaker trend, and 3 stations which show a stronger trend in the modeled time series compared to those of the respective stations.

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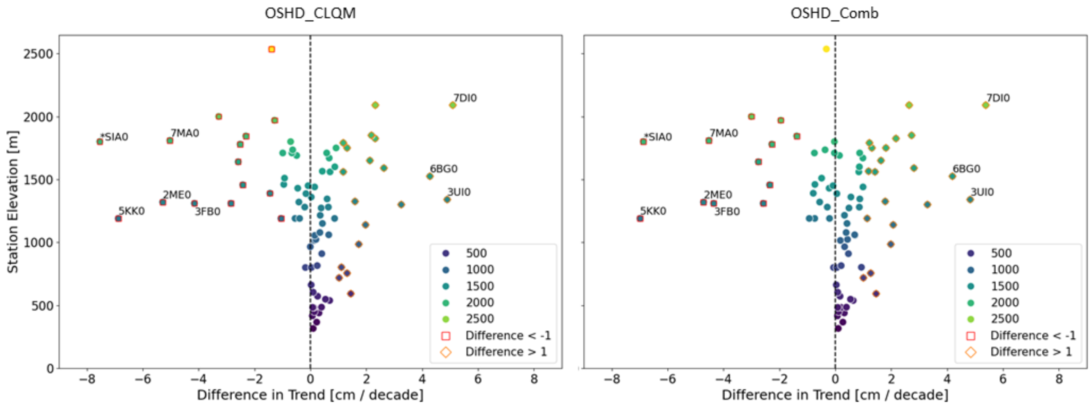

Figure 9: Scatter plots of station elevation [m] vs difference (station minus model) of the snow depth trend [cm / decade] for yearly values in the period 1962-2023, for OSHD-CLQM (left) and OSHD-Comb (right). Differences larger than 1 and smaller than -1 are depicted with an orange diamond and red square respectively. Stations that show a difference greater than ± 4 cm/decade are labeled.

Upon closer examination of these stations, we find that one station (7DI0) is located above the tree line and heavily wind influenced and subject to several relocations during the investigated period. Moreover, three stations (3UI0, 5KK0, 2ME0) are known as inhomogeneous series, due to major shifts in location (Buchmann et al., 2022). These findings reveal that the new gridded datasets have some potential to find indications of potential inhomogeneities in station time series. However, there are also larger differences for four other stations, which compared to trends at neighboring stations and neighboring grid points are probably caused by station inhomogenities (3FB0) or problems with the gridded meteorological input data (6BG0, 7MA0, SIA0). Interestingly the former three stations are all in southern regions with steep topography and only few precipitation time series available as input. These examples also indicate that when comparing station data to model values, we should sometimes rather use multiple grid points of a larger area for comparison instead of only one single grid cell (see 3.4 and Michel et. al. 2024).

Such exceptions do not impact the informative value of the gridded trend results on a larger spatial scale. Indeed, a map illustrating of the OSHD-CLQM trends for each grid point in Switzerland separately (Fig. 10) reveals significant trends at almost all low and mid elevated regions, which corroborates the results of Figure 8. Elevations above 2000 m along the main alpine ridge and in adjacent inner-alpine dry regions show mostly non-significant decreasing trends, except a small area near the southwestern border (Saas Valley) with non-significant increasing trends. The only non-significant region in the lowest elevation band is located in the Rhone valley southeast of the lake of Geneva (southwestern corner of Switzerland). Moreover, Fig. 10 generally confirms the known weaker absolute trends at lower elevations (Schöner et al., 2019) by the easy visual recognizability of the alpine valleys. Finally, Fig. 10 also demonstrates a good agreement with a similar analysis, but a different model, for Austria (Olefs et al., 2020), in which also partly non-significant trends for the Austrian region (Tirol), which is adjacent just east of south-eastern Switzerland, were found.

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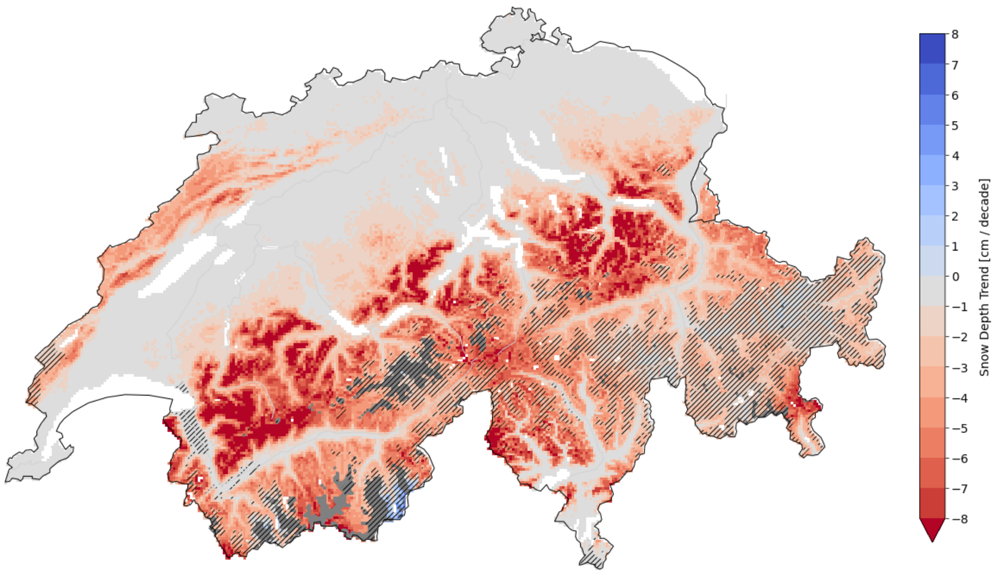

Figure 10: Trends of yearly mean snow depth (cm/decade) for the period 1962 - 2023 based on Theil-Sen slopes for each 1-km grid point of the OSHD-CLQM model in Switzerland. Water bodies appear white, elevations above 3000 m are colored in grey and non-hatched areas indicate significant trends at 95% confidence level, p < 0.05.

3.3.3 Elevation dependent snow day trends

The number of snow cover days during a season is a useful additional metric as it reflects not only the quantity of snow in the Alps but also the duration. The duration of snow covers holds important implications for various sectors, including ecology, winter tourism or hydropower. Comparing the different datasets in Fig. S7 across the five elevation bands reveals on the one hand that the direction of the trends (mostly decreasing) is the same in all analyses. No trend could be detected in those elevation bands where the number of snow days is bounded due to our November to April season definition (low HS threshold at high elevation) or where the number of snow days was mostly zero (high HS threshold at low elevation).

There is generally less agreement in the magnitude of the trends compared to corresponding analysis of mean snow depth. Such a disagreement is not uncommon, as threshold analyses in general are known for their high sensitivity and limitations of the input data do likely also contribute (see 3.4). At 500 m and with a 5 cm threshold, models predict over double the decrease compared to stations. This matches the result observed in the mean HS trend analysis at 500 m (see Fig. 8).

Having a closer look, we can detect that in most instances OSHD-Comb generally demonstrates better agreement with the year-to-year station fluctuations. Below the elevation band of 2000 m, both models demonstrate a significantly decreasing trend. At the 2000 m elevation, the models only show significance with $p > 0.05$ at a threshold of 30 cm. However, significance is observed at all other thresholds and elevation bands up to 2500 m. The elevation-dependent pattern agrees well with that seen for snow day trends in Fig. A1 in Buchmann et al. (2023). The largest decrease in number of snow cover days (about 9 days per decade) is found at 1000 m for the 5 cm threshold, which can be explained by the fact that this elevation band is where the current mean snow fall limit is located (Scherrer et al., 2021).

3.4 Limitations regarding input data and involved models

When utilizing the investigated gridded snow dataset for climatological analyses, the involved uncertainties of the underlying input data and methods used to derive SWE and HS should always be considered. They include the following issues.

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The gridded temperature and precipitation datasets used as input for the snow model are not perfectly consistent over time as the number of stations available for the spatial analysis on the 1 km grid can vary over time and elevation (Frei, 2014). It is important to keep this fact in mind when using the gridded snow datasets for trend analysis. This potential inhomogeneity further increases when using OSHD-Comb, because it combines two datasets of different quality. Our analysis demonstrates that the impact is small when using data of the entire country on the current time series length. But this does not need to be the case for smaller regions or shorter time periods.

Furthermore, there are unresolved small-scale effects in these gridded input datasets. Regarding temperature, among these are all kinds of land cover effects (e.g. lakes and urban heat islands) and the influence of local topography. As a result, it must be expected that spatial variations are underestimated (too smooth), particularly at the scale of the grid-point spacing, and small-scale patterns may display with considerable uncertainty in extent and amplitude. This is particularly true for valley cold pools: Their reproduction by the analysis critically depends on the existence of in-situ measurements within these pools. Hence cold air pools may be missing completely in un-instrumented valleys (see Frei et al. (2014)). Regarding precipitation, possible undetected station and time dependent measurement errors can always be an issue and the interpolation is limited by small-scale variability of precipitation. The provider of the datasets (MeteoSwiss) expects that the effective resolution of the daily gridded precipitation product is in the order of 10 to 20 km, likely even coarser in the high mountains. Additionally, measurements by rain gauges are subject to systematic errors, like gauge under-catch, which causes an underestimation of precipitation, particularly during days with snowfall and at wind-exposed locations (Yang et al., 1999). However, the problem should be, at least partially, mitigated by the QM step, which constrains the model by assimilation of snow depth observations (OSHD-EKF) and thereby indirectly also corrects for under-catch issues in the gridded precipitation dataset.

When these two gridded datasets (temperature and precipitation) are used as input for the temperature-index based snow model, we must be aware that the temperature data represents the daily average from midnight-to-midnight UTC, whereas the precipitation data represents the daily average from 06:00 UTC of day D to 06:00 UTC of day D+1. This temporal mismatch is another reason for possible biases in gridded snow data, especially at shorter time scales.

These limitations of the atmospheric input data are the reason why the assimilation of snow measurements is an important step and that the corresponding OSHD-EKF datasets has a better quality. Also, the OSHD-EKF modelling chain contributes to the overall uncertainties, being a conceptual model with one parameter set applied over the entire period of 6 decades. A particularly relevant contributing factor is the use of daily average temperatures to partition precipitation into snowfall and rain. Uncertainties arise every time a precipitation event happens at times that are colder (nights) or warmer (days) than the 24h average temperature, which is a generic limitation of models that use input data at daily rather than hourly resolution. This is also one of the reasons that we deliberately not analyzed daily values in this study. The other reason is the fact that the quantile mapping method can be associated with substantial uncertainties at the daily scale and that an interpretation of the results at this scale is not recommended (Michel et al., 2024).

Furthermore, it is important to keep in mind, that the OSHD datasets provide SWE values, which are then converted to HS. This conversion has a RMSE of about 1.5 cm and a BIAS of 1 cm (Aschauer et al., 2023). Therefore, HS has always a slightly higher uncertainty than SWE.

4 Conclusions

We analyzed the potential and limitations of newly developed spatially gridded datasets of snow water equivalent and snow depth for climatological applications in Switzerland spanning over 6 decades from 1962 to 2023. Our results demonstrate that the use of a long-term gridded snow data has a high potential for climatological analysis, albeit with some limitations. Our analysis corroborates the findings of Michel et al. (2024), that the quantile-mapping approach generally achieves good results in producing long-term climatological timeseries of snow. In addition, we could for the first time demonstrate in a quantitative manner how the uncertainty of new gridded climatological snow depth datasets increases with shorter analysis time scales and especially for low elevations.

More specifically, a comparison of the 60+ year-long datasets to station measurements for yearly mean snow depth values revealed in general a good performance of the new gridded datasets. We also evaluated how well station-based trends were captured in the modelled gridded datasets. In general, the results demonstrated a very good agreement between station- and model-based trends, i.e. clear decreasing trends for mean snow depth and the snow cover duration (based on snow days) for the different elevation bands. Yearly mean snow depth demonstrated an excellent agreement with respect to the decrease per decade and the significance of this decrease for the different elevation bands, except for the lowest elevation band, where snow is generally scarce. There, the modeled trend was much stronger as the station trend. The same trend overestimation in the lowest elevation band was also found when analyzing trends of the number of snow days. However, as often with count data, the agreement between model- and station-trends was not as good and depended also on the threshold of the snow day definition.

Moreover, a comparison between long-term trends of mean snow depth calculated using in-situ data from individual stations and gridded data with the closest grid points revealed a generally good agreement. However, for about 20 % of all stations, the disagreement between the trends was larger than 1 cm /decade and sometimes even had the opposite direction, owing to either inhomogeneities in the observations or modeling / input data issues. Therefore, we generally recommend using the new SPASS datasets for trend analysis with at least some level of spatial aggregation and for elevation above 1000 m, while caution is needed for interpretation of data at the pixel level and/or in low-snow regions. Furthermore, we urge caution when using maximum values, for reasons already mentioned in (Michel et al., 2024).

On the other hand, the generally good performance of the new datasets allows for the first time to produce e.g. high resolution (1 km), high quality country-wide SWE and snow depth maps of climatological mean values or monthly/seasonal anomaly graphs for different regions/elevations. Moreover, except for low elevations, the data provide a reliable basis to analysis elevation dependent trends of SWE and snow depth. Hence, these datasets are an important basis for applied research (Troxler et al., 2023) in an alpine country like Switzerland. For these reasons the two involved institutions (SLF and MeteoSwiss) will use the new datasets to regularly provide maps (WMO, 2024; SLF, 2025) and graphs on the current snow status in Switzerland as a climate service for interested public or businesses.

Our results also reveal that especially at low elevations and for shorter time aggregations like month or week it may be worth to make use of the higher-quality, but shorter-term OSHD-EKF dataset, which assimilates in-situ snow depth data. This fact also demonstrates that long-term station measurements are still indispensable, as they are still needed to produce long-term, high-quality gridded snow datasets.

5 Data Availability

Model data of SWE and HS is available on envidat.ch (*URL will be provided*). In-situ snow depth data from SLF stations can be freely downloaded from: https://www.slf.ch/en/services-and-products/slf-data-service. In-situ snow depth data from MeteoSwiss are available on request.

6 Author Contributions

CM: Conceptualization, Formal analysis, Data curation, Methodology, Software, Writing – original draft. AM: Methodology, Resources, Software, Writing – review & editing. CS: Software, Visualization. TJ: Resources, Data curation, Reviewing. RM: Resources, Writing – review & editing. SK: Conceptualization, Formal analysis, Methodology, Writing – review & editing.

7 Conflict of Interest

The authors declare that they have no conflict of interest.

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