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Homogenizing Swiss snow depth series - Impact on decadal trends and extremes

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Abstract. Our current knowledge on snow depth trends is based almost exclusively on these non-homogenized data.Long-term observations of deposited snow are well suited as indicator of climate change. However, like all other long-term observations, they are prone to inhomogeneities that can influence and change trends if not taken into account. We investigated the effects of removing inhomogeneities in the large network of Swiss snow depth observations on trends and extreme values of commonly used snow indices, such as snow days, seasonal averages or maximum snow depth in the period 1961-2021. For this task, three homogenization methods were applied: Climatol and HOMER, which use a median based adjustment method, and interpQM, which applies quantile based adjustments. All three were run using the same break points and input data. This allowed us to investigate and quantify the effects of these methods on the homogenization results. We found that all three methods agree well on trends in seasonal average snow depth, while differences are visible for seasonal maximum snow depth and the corresponding extreme values. Here, the quantile-based method performed slightly better than the two median-based methods, as it had the smallest number of stations outside the 95 % confidence interval for 50-year return periods of maximum snow depth. These differences are mainly caused by the way the reference series are selected. The combination of a high minimum correlation (>0.7) and restrictions in vertical (<300 m) and horizontal (<100 km) distances proved to be better suited than only using correlations or distances respectively as criteria. The adjustments removed all positive trends for snow days in the original data and strengthened the negative mean trend, especially for stations >1500 m. In addition, the number of significant negative stations was increased between 7 - 21 %, with the strongest changes at higher snow depths.

Climatol, HOMER, interpQM, trends, extreme values, Switzerland, Alps, snow, manual measurements

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1 Introduction

During winter in the northern hemisphere, more than 50 % of the earth‘s surface can be covered with snow. The thickness and duration of a snow cover play an important role for many animal and plant species (Johnston et al., 2019), but also have an important socio-economic dimension: For example, the timing and amount of snow melt are important for hydropower companies, the number of days with a certain minimum snow depth (e.g. 30 cm) is a metric widely used for the profitability of ski resorts (Abegg et al., 2020). Accurate and reliable measurements of solid precipitation, e.g. total height of fallen snow (snow depth) or the amount of freshly fallen snow (new snow height), are difficult to obtain but important (Nitu et al., 2018). They are used for various purposes, e.g. as ground evidence for large-scale grid-based forecasts of snow depth (Olefs et al., 2013) or the assessment of snow models used in the operational chain of avalanche hazard forecasting (Morin et al., 2020). Long-term measurements are key to climate monitoring and related analyses. They are not only used for climatological analyses (e.g. Matiu et al., 2021; Pulliainen et al., 2020), but also for creating and bias-correction gridded datasets (e.g. Cornes et al., 2018; Hersbach et al., 2020; Li et al., 2022).

The longer a time series, the more likely for it to contain inhomogeneities due to station relocation, changes in instruments, observers, the station environment, or a combination of the above factors (e.g. Auer et al., 2007). These inhomogeneities can significantly influence trends (Begert et al., 2005; Gubler et al., 2017; Resch et al., 2022) and extreme values (Kuglitsch et al., 2009). To address this problem, time series are usually homogenized in two steps: First, immanent break points or inhomogeneities are identified and then adjusted in the subsequent step. Homogeneity tests that are used for the identification of break points mostly assess ratios or differences between the station to be homogenized (candidate series) and highly correlated neighbouring stations (reference series) that are selected using several criteria, mostly the correlation and horizontal distances. In the second step, the reference series are used to calculate adjustments for the period before a break, which change the observations as if the current station environment had also existed in the past and the measurement technique had also been used in the past. This is a standard process for climate data like temperature and precipitation but has only recently been adopted for snow depth time series (Schöner et al., 2019; Resch et al., 2022).

Widespread used metrics to describe the snow pack include snow days and maximum and average snow depths. Snow days are relevant for ecology (e.g. Stone et al., 2002; Jonas et al., 2008) and climatology (e.g. Scherrer et al., 2004; Marty, 2008), whereas the average and maximum snow depths are particularly applicable to climatology and engineering applications. Trends and extreme value analyses of snow variables (e.g. Scherrer et al., 2013; Matiu et al., 2021) are commonly used methods in climate monitoring (Bocchiola et al., 2008; Marty and Blanchet, 2012; Buchmann et al., 2021a), model verification (e.g. Brown et al., 2003; Essery et al., 2013), whereas extreme value analysis is important for the definition of snow loads and limits for building-codes (e.g. Croce et al., 2021; Schellander et al., 2021; Al-Rubaye et al., 2022).

In spite of recent efforts of studying the homogenization of snow depth (Marcolini et al., 2019; Schöner et al., 2019; Buchmann et al., 2022; Resch et al., 2022), it is still an open question whether the use of one of the methods is more advantageous

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than the others, and how the methods impact trends and extreme values. So far, Swiss snow depth time series have not been homogenized and an impact assessment has not been carried out neither for Switzerland or any other region.

We are using the set of break points, recently identified by Buchmann et al. (2022) for manual Swiss snow series with a joint use of three state-of-the-art breakpoint-detection and homogenization methods: ACMANT (Domonkos, 2011), Climatol (Guijarro, 2018) and HOMER (Caussinus and Mestre, 2004; Domonkos, 2011; Picard et al., 2011; Guijarro, 2018). This break point set is then used as input for three homogenization methods to calculate and apply adjustments: Climatol, HOMER, and interpQM (Resch et al., 2022). The first two apply median based adjustments, the latter uses a quantile based approach. All three methods are then applied to the network of Swiss snow depth time series. This enables us to assess the impact of homogenization (dependent on the method used) on trends of seasonal mean and maximum snow depths, and days with snow on the ground as well as extreme values of maximum snow depths. To focus our study, our research questions are the following:

1. How do the homogenized series compare across the three methods applied?
2. What is the impact of homogenization on decadal trends of average and maximum snow depth?
3. How do the three homogenization methods influence widely used indices?
4. To what extent are maximum snow depths with a 50-year return period (as an example for snow metrics used by practitioners) affected by the various homogenization methods?

The article is structured as follows: Section 2 describes the data and Section 3 introduces the various methods used. Results are shown in Section 4 and discussed in Section 5. Conclusions are drawn in Section 6.

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2 Data

Daily manual snow depth measurements (HS) from 184 Swiss stations are used in this study. Seasonal (November to April) and monthly average (HSavg), maximum snow depths (HSmax), and the number of snow days >= 5 cm (dHS5) are calculated from the daily snow depth values measured at 07:00 each day. Figure 1 shows the station distribution. The stations, maintained by either the Federal Office of Meteorology and Climatology (MeteoSwiss) or the WSL Institute for Snow and Avalanche Research (SLF) provide data within the period from 1931 to 2021 and span from 200 to 2500 m a.s.l. Only stations with complete data coverage between November and April and at least 30 years of data are considered. For a detailed description of the data set, please see Buchmann et al. (2022).

2.1 Break points

We use 45 break points (found in 40 series), detected with a joint use of ACMANT (Domonkos, 2011), Climatol(Guijarro, 2018), and HOMER (Caussinus and Mestre, 2004; Domonkos, 2011; Picard et al., 2011; Guijarro, 2018), where break points are accepted as valid if they are at least identified by 2-out-of-3 methods within two years. For details, see Buchmann et al. (2022). Break points are detected using seasonal series. Available metadata was used to further verify break points where applicable. However, as our metadata is neither perfect nor complete, it is only used as an additional clue and not as stand-alone evidence. The analysis described in Buchmann et al. (2022) is re-run with the three additional Austrian data series along the eastern Swiss border to increase the number of available reference stations for Eastern Swiss series, thus increasing the valid break points to 45 (from the original 43 mentioned in Buchmann et al. (2022)). Figure 1 shows the location of all 184 series, the inhomogeneous ones are coloured pink. Two series (stations Bernina Hospiz and Gütsch) with insufficient data quality between 1961 and 2021 were removed from the subset of 42 series reported in Buchmann et al. (2022).

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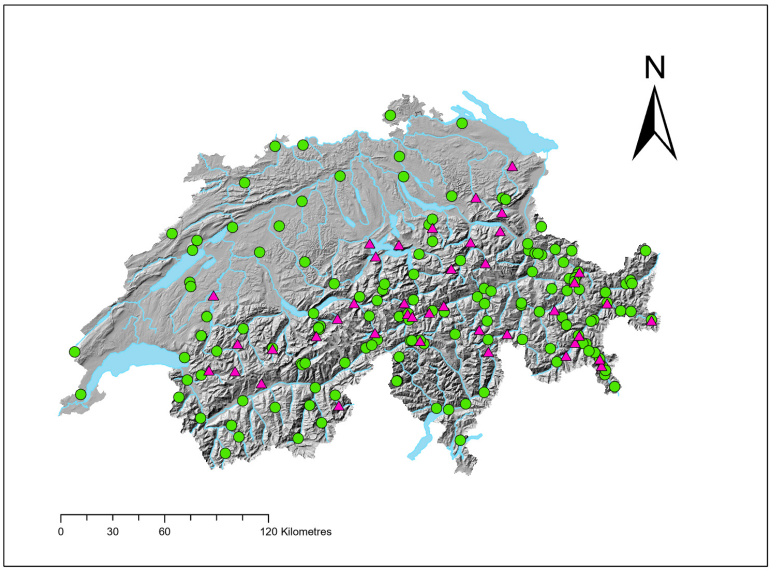

Figure 1. Map of Switzerland showing all 184 stations used in this study. The 42 inhomogeneous stations (identified in this study) with valid break points are highlighted in pink. Green circles are series considered homogeneous.

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3 Methods

3.1 Homogenization methods

Climatol (Guijarro, 2018) is a fully-automatic homogenization function based on SNHT (Alexandersson, 1986) and uses a step-wise detection of homogeneous sub-periods. It uses composite reference series that are constructed as a weighted mean, using the horizontal and vertical distance between suitable reference series and the candidate series as weight. It allows the use of a manually adjusted break file, which in our case is provided by Buchmann et al. (2022). Candidate series are adjusted stepwise backwards from the most recent homogeneous sub-period, by adjusting every detected break (sub-period between breaks) with an annual adjustment factor (see (Guijarro, 2018) for details).

HOMER (Caussinus and Mestre, 2004; Domonkos, 2011; Picard et al., 2011; Guijarro, 2018) is a toolbox which provides several methods for break detection and adjustments, like pairwise comparison (Caussinus and Mestre, 2004), joint-segmentation (Picard et al., 2011) and ACMANT-detection (Domonkos, 2011). Like Climatol, HOMER can be run with an independently derived break file and also uses a manual added metadata-file. In HOMER, series are adjusted with a single annual factor for the entire period before a break point. The adjustment factor is determined by means of variance analysis ANOVA (Caussinus and Mestre, 2004; Mestre et al., 2013) based on the reference sub-networks, which in our case have a minimum correlation of 0.8 with the candidate.

InterpQM (Resch et al., 2022) is an extension of INTERP (Vincent et al., 2002), using quantile matching to improve the adjustments, considering frequency distribution of adjustment factors. It yields daily homogenized data, which then allows the analysis of subsequently derived snow indicators. For this, the daily measurements of candidate and reference series are split into several interquantile ranges (IQR), which are then compared. An adjustment factor is calculated for each IQR and then linearly interpolated between neighbouring IQR's to avoid artificial jumps. Reference series can either be selected manually or calculated using a weighted mean of a network of selected stations (< 100 km horizontal and < 300 m vertical distance, > 0.7 correlation, no detected breaks), which can be manually refined and optimized by making use of local knowledge and experience. The distribution of the weighting between the stations of a network can either be exponential or linear. For reducing the strong impact of single highly correlated stations on the result, linear distribution of the weighting was chosen. Identified breaks from a break file were used.

3.2 Detection of trends and changes in snow depth series

The use of homogenization techniques that adjust daily values allows the analysis of the impact on derived parameters (indicators) which require daily data for their calculation, e.g. snow days. These common used indicators are defined as the number of days within a time period with a snow depth greater or equal to a specified threshold, typically between 1 - 50 cm. (e.g. Abegg et al., 2020; Schmucki et al., 2017). Since Climatol and HOMER calculate either seasonal or monthly parameter values, only interpQM could be used for their analysis. Since it was decided that interpQM does not change the total number of snow days ($HS > 0$), the thresholds of 5, 30 and 50 cm (dHS5, dHS30, dHS50) were used and summed up for each hydrological year between November and April.

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Trends are detected using the non-parametric Mann-Kendall trend test (Mann, 1945; Kendall, 1975). As we are working with seasonal (November-April) values, the large auto-correlation of daily snow depth does not apply here. Trends are treated significant if their corresponding p-values are less than 0.05 and not significant if greater or equal to 0.05 (5 % assumption).

Theil-Sen slopes (Theil, 1950; Sen, 1968) are used to estimate the strength of the trends. Decadal trends are expressed as change in [cm/decade]. To compare the homogenized subsets of 40 stations, we focus on the period from 1961 to 2021 since most stations have data within this period. Trends for all available decades are provided in the supplement (Figure A1).

To study the impact of homogenization on extreme snow depths, return levels for seasonal maximum snow depth (HSmax) (Marty and Blanchet, 2012) are calculated for a fixed return period of 50 years based on original and homogenized data (R50HSmax). Calculations are done with the R package extRemes (Gilleland and Katz, 2016) run in standard settings (GEV, estimation method MLE, and 95 % confidence intervals). To assess the significance of the homogenization performed, a Kolmogorov-Smirnov test was conducted with seasonal data.

3.3 Intercomparison experiment of homogenization methods

We use the subset of 40 stations with identified breaks as input and homogenize it. Both Climatol and HOMER use monthly values as input and are therefore run with monthly HSavg as well as HSmax values. InterpQM works with daily snow depth values, from which the analysed seasonal HSavg and HSmax are then derived after the successful homogenization. Decadal trends are calculated for seasonal HSavg, aggregated either from monthly HSavg (HOMER and Climatol) or daily HS (interpQM). Furthermore, trends for snow days are compared for original and interpQM. The largest HSmax value per station, calculated over the entire period, (absolute maximum snow depth, maxHSmax) is compared for homogenized and original values. Return levels for seasonal HSmax with a 50-year return period (R50HSmax) are retrieved from either daily homogenized HS aggregated into seasonal HSmax (interpQM) or monthly homogenized HSmax (HOMER and Climatol). Trends and R50HSmax for the subset are then compared across the methods. Climatol automatically fills in missing values, thus artificially increasing the length of the series. However, for the trend analysis, only the time period available in the original series are considered for the homogenized data in order to make it comparable. ACMANT, being fully automatic, does not allow for manual break point input and was therefore not used for our analyses. We are using Climatol v3.1.2 (Guijarro, 2019), and InterpQM (Resch et al., 2022) on R 4.2 (R Core Team, 2022) and HOMER v2.6 on R 2.15 (R Core Team, 2012). To evaluate the differences between the used homogenization methods, a Kolmogorov-Smirnov test was performed with seasonal data.

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4 Results

In the following section, the impact of the performed homogenization on indices of snow depth series is shown. The figures and tables demonstrate that it mostly lowered the original snow depths and increased the number of time series with a significant negative trend in the time period studied. The differences between homogenization methods were more pronounced for R50HSmax than for trends of HSavg. The Kolmogorov-Smirnov test performed with seasonal values showed that the homogenized data was significantly different from the original in five stations for HSmax and eight stations for HSavg. While there were no significant differences between the methods for HSmax, there were for four stations for HSavg.

4.1 Trends of snow days

Table 1. Statistics for snow days (dHS) for the period 1961 to 2021 on a seasonal basis with thresholds of 5, 30 and 50 cm for both original (Orig) and interpQM-homogenized data (iQM).

	dHS5				**dHS30**				**dHS50**			
	<1500 m		**>1500 m**		**<1500 m**		**>1500 m**		**<1500 m**		**>1500 m**	
	Orig	iQM	Orig	iQM	Orig	iQM	Orig	iQM	Orig	iQM	Orig	iQM
Median trend [days/decade]	-4.8	-6	-2.4	-2.8	-5.7	-5.5	-3.3	-3.7	-3.2	-2.5	-4	-5.5
Mean trend [days/decade]	-5.6	-5.8	-3.3	-3.4	-5.7	-4.9	-4.3	-4.7	-4.7	-3.5	-5.4	-5.8
Positive [%]	0	0	0	0	4	0	14	0	4	0	7	0
Negative [%]	100	100	93	93	77	81	86	100	54	65	93	100
Significant Positive* [%]	0	0	0	0	0	0	0	0	0	0	0	0
Significant Negative* [%]	81	85	69	77	70	67	33	43	86	53	31	50
Positive to Negative [%]	-	0	-	0	-	7	-	14	-	7	-	7
Negative to Positive [%]	-	0	-	0	-	0	-	0	-	0	-	0
Significant to not significant [%]	-	4	-	0	-	12	-	0	-	15	-	0
Not significant to significant [%]	-	8	-	7	-	15	-	7	-	12	-	21

Percentages for significant negative and significant positive, indicated with an asterisk, are calculated based on the total number of negative/positive values respectively.

The snow days of each season were examined in two subsets of stations below and above 1500 m, in this chapter called "lower altitude" and "higher altitude" stations. This altitude was chosen as the dividing line because the area above it is currently normally covered with snow in winter. A strong decrease in snow depth in the altitude range from 1500 to 2500 m has been identified for the coming decades (e.g. Marke et al., 2015; Marty et al., 2017), which makes this altitude interesting for the analysis of the changes that have already occurred. Thresholds of 5, 30 and 50 cm (dHS5, dHS30, dHS50) where analyzed for the original and homogenized data. As shown in Table 1, the number of snow days per season is declining for the vast majority of stations for all analyzed thresholds and altitude levels.

In the original data, no station has a positive trend for dHS5, but between 4 - 14 % of stations for dHS30 and dHS50. The homogenization with interpQM removed all positive snow day trends. Due to the warmer temperatures at lower elevations, the

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smaller thresholds of dHS5 and dHS30 show a stronger decline there. In the original data, the mean trend for stations at lower elevations is -5.6 days/decade for dHS5 and -5.7 for dHS30. For stations >1500 m it is -3.3 days/decade for dHS5 and -4.3 for dHS30. The percentage of stations with a significant negative trend for dHS5 and dHS30 is also higher for lower elevations: 81 % of the lower and 69 % of the higher altitude stations for dHS5 and 70 %, respectively 33 % for dHS30. This is the other way round for the 50 cm threshold: The mean trend for lower elevations is -4.7 days/decade and -5.4 for higher situated stations. Only 54 % of lower stations have a negative trend for dHS50, but 93 % of stations at higher elevations. This may be irritating, but it has several reasons: Firstly, the variability of greater snow depths is strong. Secondly, days with a snow depth of >50 cm are possible at lower altitudes, but generally rare. Therefore, 89 % of stations <1000 m and 18 % of stations between 1000 - 1500 m show no trend for dHS50. With the exception of Ilios, all other stations below 1500 m show a strong mean decrease between -2.9 to -14.7 days/decade.

As mentioned above, no station in the original data shows a positive trend for dHS5. For dHS30, one lower station at 1340 m (Iltios) shows a small positive trend of +0.9 days/decade, and two at higher elevations (Mürren at 1650 m with +0.3 and St.Moritz at 1850 m with +1.7 days/decade). For dHS50, the stations Iltios (+1.2) and St.Moritz (+1.1) are positive. Due to the warmer temperature at lower altitudes, the smaller threshold values dHS5 and dHS30 show stronger negative trends there. The mean trend for dHS5 is -5.6 days/decade for low and -3.3 for higher elevations. For dHS30 it is -5.7 and -4.3, respectively. Both the colder temperature and the greater amount of precipitation lead to more frequent greater snow depths at higher elevations. The trend for dHS50 is stronger at higher (-5.4 days/decade) than at lower elevations (-4.7). Also, the percentage of stations with decreasing dHS50 is almost twice as high for larger altitudes (93 % at >1500 m and 54 % for <1500 m).

Homogenization with interpQM removed all positive trends and increased the percentage of stations with a decline in snow days for both dHS30 and dHS50. The mean trends for lower altitudes changed from -5.6 to -5.8 days/decade for dHS5, weakened from -5.7 to -4.9 for dHS30 and from -3.7 to -3.5 for dHS50. For higher altitudes it changed from -3.3 to -3.4 for dHS5, strengthened from -4.3 to -4.7 for dHS30 and -5.4 to -5.8 for dHS50.

All analysed stations above 1500 m show a decrease in days per season with snow depths of more than 30 or 50 cm after the adjustments made. It reinforced the negative trend for dHS5 in both altitude subgroups. The mean trend of dHS30 at lower altitudes got weakened from -5.7 to -4.9 days/decade, while it strengthened from -4.3 to -4.7 at higher altitudes. For dHS50, the negative trend weakened from -4.7 to -3.5 days/decade at lower elevations, but strengthened at higher elevations (from -5.4 to -5.8). The percentage of stations, whose negative trend was significant was increased for all stations for dHS5, but only at higher altitudes for dHS30. For dHS50, it decreased sharply from 86 % to 54 % for the lower altitudes but increased from 31 % to 50 % for the higher altitudes. The stronger impact of the homogenization with interpQM to larger thresholds is also shown in Fig. 2, with changes between -11 to +4 days/decade for dHS30 and -10 to +5 days/decade for dHS50. In contrast, the changes from homogenization for dHS5 were minor, between -1 to +3 days/decade. All in all, interpQM weakened the dHS5-trends for 35 % of all stations, strengthened it for 30 % and did not change it for 35 %. For dHS30, 38 % of all stations had weaker trends after the adjustments, 40 % had a stronger one and for 22 % it did not change. For dHS50, the trend was weakened for 30 %, strengthened for 38 % and did not change for 32 % of all stations.

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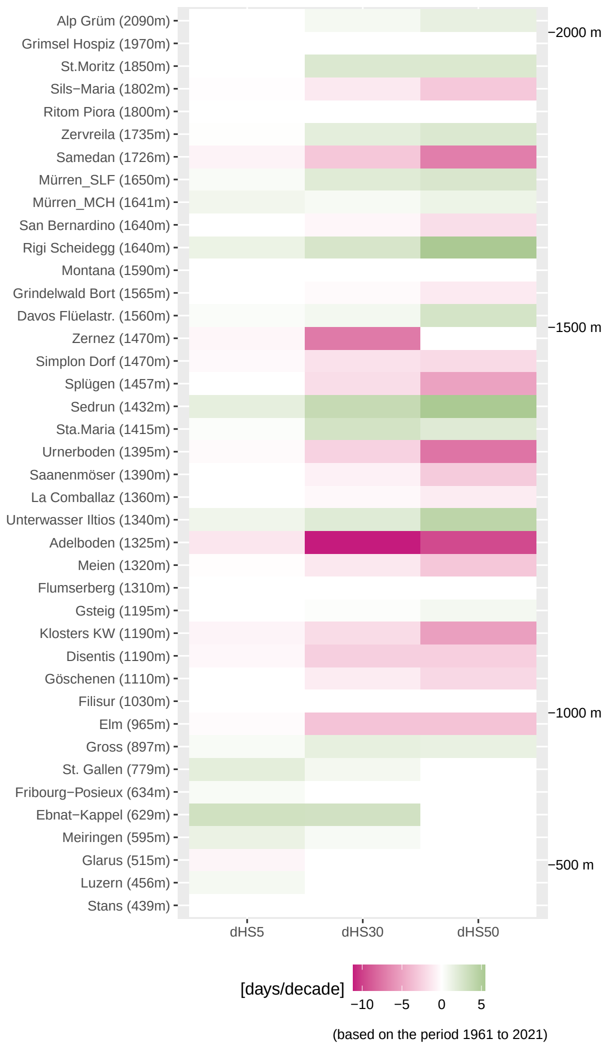

Figure 2. Difference of trends for snow days between Original and interpQM for 5, 30 and 50 cm thresholds (dHS5, dHS30 and dHS50).

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4.2 Trends of mean and maximum snow depth

To assess the impact of homogenization on trends of HSavg and HSmax of snow depth series, decadal trends are calculated for each homogenization method and the original data respectively. Figure 3 shows the trends for HSavg in the left and for HSmax in the right panel. Trends are expressed as cm/decade for the period from 1961 to 2021 for each method and station of the inhomogeneous subset, black dots indicate significant trends. For HSavg, we found an overall similar pattern across the methods. Figure A2 shows the trends as differences between original and homogenized values for Climatol, HOMER, and interpQM for both HSavg and HSmax. Two original series (St. Moritz and Iltios) show positive trends, whereas HOMER displays positive trends for Simplon and Glarus. No trends are positive with interpQM or Climatol. Except Glarus (HOMER), none of the positive trends are significant. Table 2 describes the mean and median trends across all stations, as well as the change from positive to negative and significant to not significant and vice-versa for both HSavg and HSmax. The mean trends of HSavg for Climatol and HOMER appear to be weaker than for the original and interpQM homogenised.

Figure 3 further reveals that the homogenized trends for HSavg mimic the pattern of the original trends, which shows almost zero trends for stations below 500 m, strong negative and significant trends for the group between 1000 and 1400 m, followed by mostly not significant trends for stations between 1500 and 1600 m a.s.l. This suggests that the various intrinsic ways of building reference series and sub-networks of the underlying homogenization methods do not have a significant impact on decadal trends of HSavg.

When focusing on trends of HSmax, the vast majority of series show negative trends. However, in contrast to HSavg, some are positive across the methods, see right side of Table 2 for details. The number of significant trends is about 20 % lower than for HSavg. The order of the methods is maintained with interpQM still showing the largest and HOMER the lowest number of significant trends. The most striking difference between the pattern in panel (a) and (b) of Fig. 3 is the area with no significant trends. For HSavg, this is located between 1500 and 1600 m a.s.l., whereas for HSmax it concerns stations below 1000 m a.s.l. The exception is interpQM which shows significant trends for stations below 1000 m a.s.l. There seems to be no particular altitudinal pattern other than that trends below 1000 m a.s.l. are weak across the methods and increase in strength from 1200 to 1400 m a.s.l. This suggests that in contrast to HSavg, trends for HSmax seem to be more sensitive to the underlying homogenization methods.

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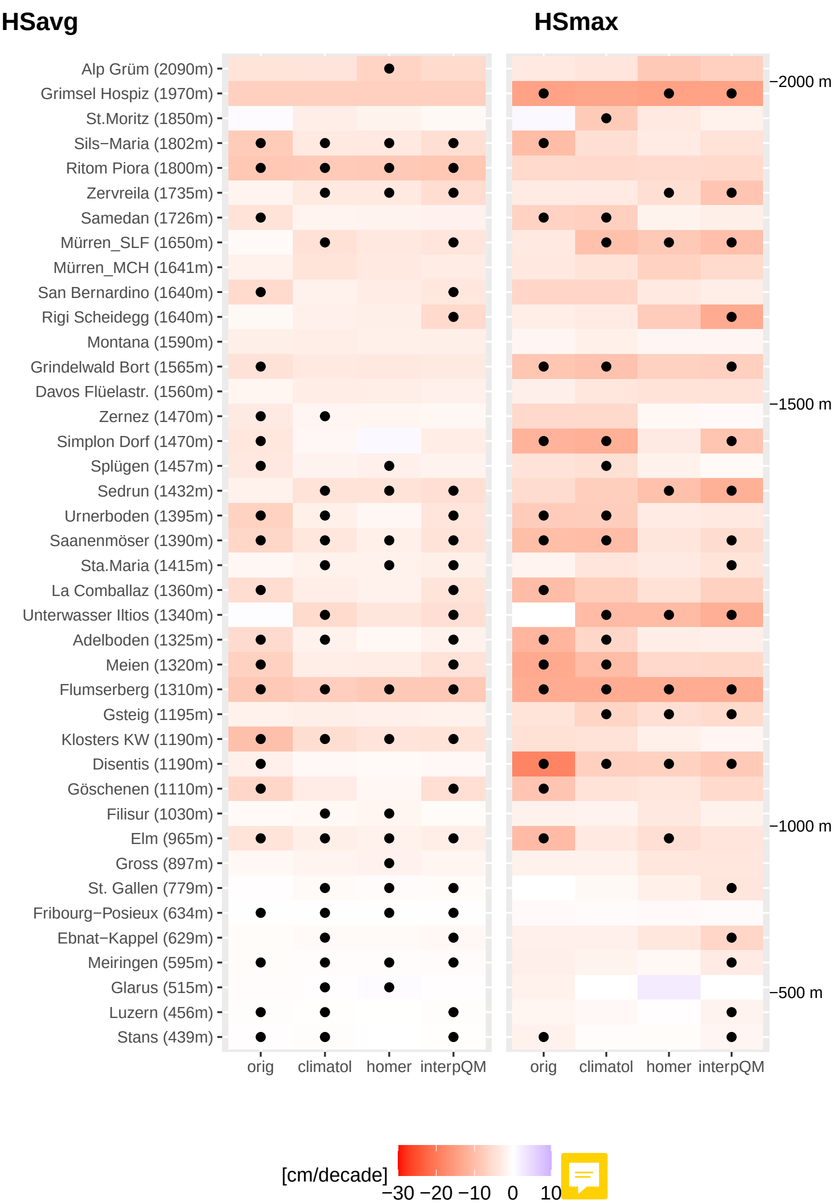

Figure 3. Comparison of trends calculated with original and homogenized data (Climatol, HOMER, and interpQM) for the period 1961-2021 for HSavg (left side) and HSmax (right side). Stations are ordered according to elevation. Black dots indicate statistical significance with p-values below 0.05.

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Table 2. Statistics for trends of HSavg and HSmax for the period 1961 to 2021.

	HSavg				HSmax			
	Original	Climatol	HOMER	interpQM	Original	Climatol	HOMER	interpQM
Median trend [cm/decade]	-2.4	-2.5	-2.3	-2.7	-4.3	-4.9	-3.8	-4.5
Mean trend [cm/decade]	-3.7	-2.8	-2.6	-3.2	-5.8	-5.6	-4.6	-5.4
Positive [%]	5	0	5	0	8	3	3	3
Negative [%]	95	100	95	100	98	98	98	98
Significant [%]	55	55	43	60	38	35	23	45
Significant negative* [%]	58	55	42	60	41	36	23	46
Significant positive* [%]	0	0	50	0	0	0	0	0
Positive to Negative [%]	-	5	8	5	-	5	5	5
Negative to Positive [%]	-	0	5	0	-	0	5	0
Significant to not significant [%]	-	23	33	15	-	15	25	20
Not significant to significant [%]	-	23	20	20	-	13	13	28

Percentages for significant negative and significant positive, indicated with an asterisk, are calculated based on the total number of negative/positive values respectively.

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4.3 Impact on maximum snow depth

To investigate a possible influence of the homogenization procedure on absolute maximum snow depths (maxHSmax) recorded at each station over the entire period, the year with the absolute maximum snow depth, as well as the difference between original and homogenized maxHSmax are plotted for each station and homogenization method. Figure 4 shows the results. Here we found that for the majority of series, the differences are 0. The differences are generally left-skewed, except for the largest differences observed with Climatol (Fig. 4d). This again suggests that, in contrast to the trends of HSavg, differences across the methods are more visible for HSmax. Furthermore, Fig. 4c clearly highlights the four known snow-rich winters of 1951, 1968, 1975, and 1999.

Return levels for 50-year return periods of maximum snow depth (R50HSmax) are calculated from homogenized data and compared to values obtained from the original data including the 95 % confidence intervals. Figure 5 shows the original values in grey with their associated 95 % confidence intervals and the homogenized values in colour. Here we found a similar pattern for a majority of stations across the methods. However, between six (interpQM) and 13 (Climatol), with HOMER in-between with 11, stations have R50HSmax outside the 95 % confidence intervals of the original values. For Climatol, seven are above and six below, HOMER shows four above and seven below, whereas for interpQM the numbers are three above and three below, see Table 3 for details. This again suggests that the differences between the homogenization methods are more pronounced for R50HSmax than for trends of HSavg, with interpQM performing slightly better than Climatol or HOMER. An additional analysis (not shown here) of the change of the 95 % confidence intervals reveals that the 95 % confidence intervals of the homogenized values are smaller than the original. Mean values over all 40 stations range from 89 cm for the original to 75 cm (HOMER) with Climatol (87 cm) and interpQM (83 cm) in-between.

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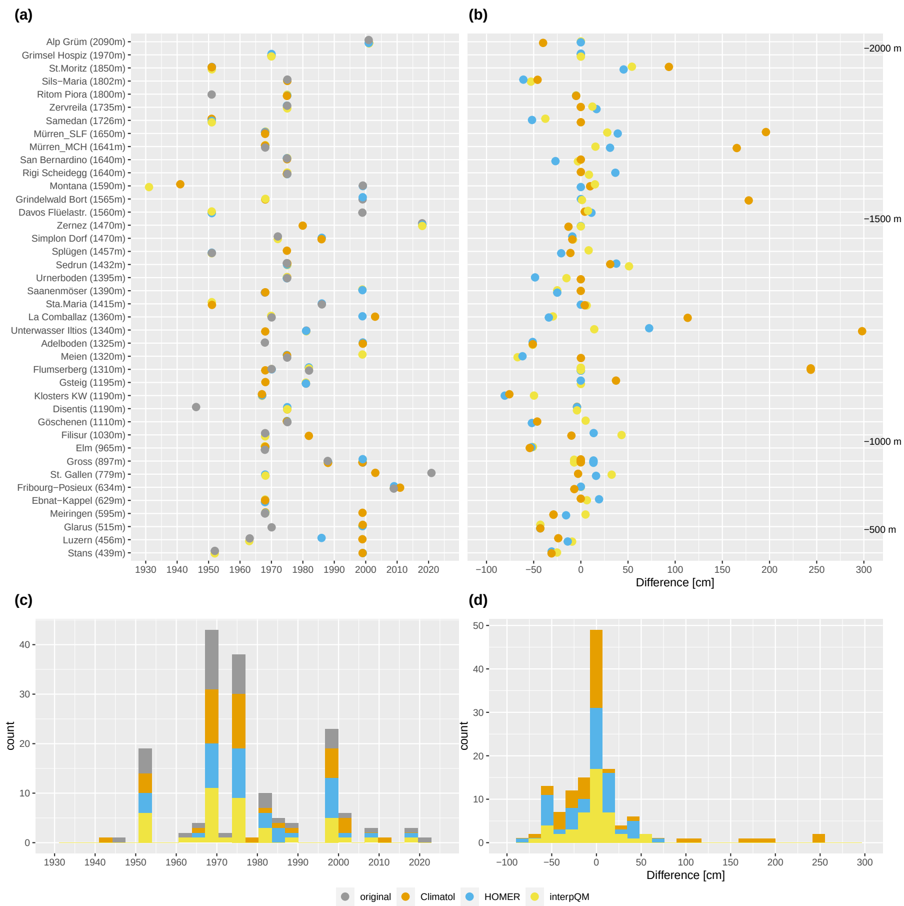

Figure 4. Maximum values of HSmax recorded for each station and method over the entire period (1961-2021). (a) shows the year for which the absolute maximum snow depth is recorded, (b) displays the differences between original and homogenized values, (c) and (d) are the corresponding histograms.

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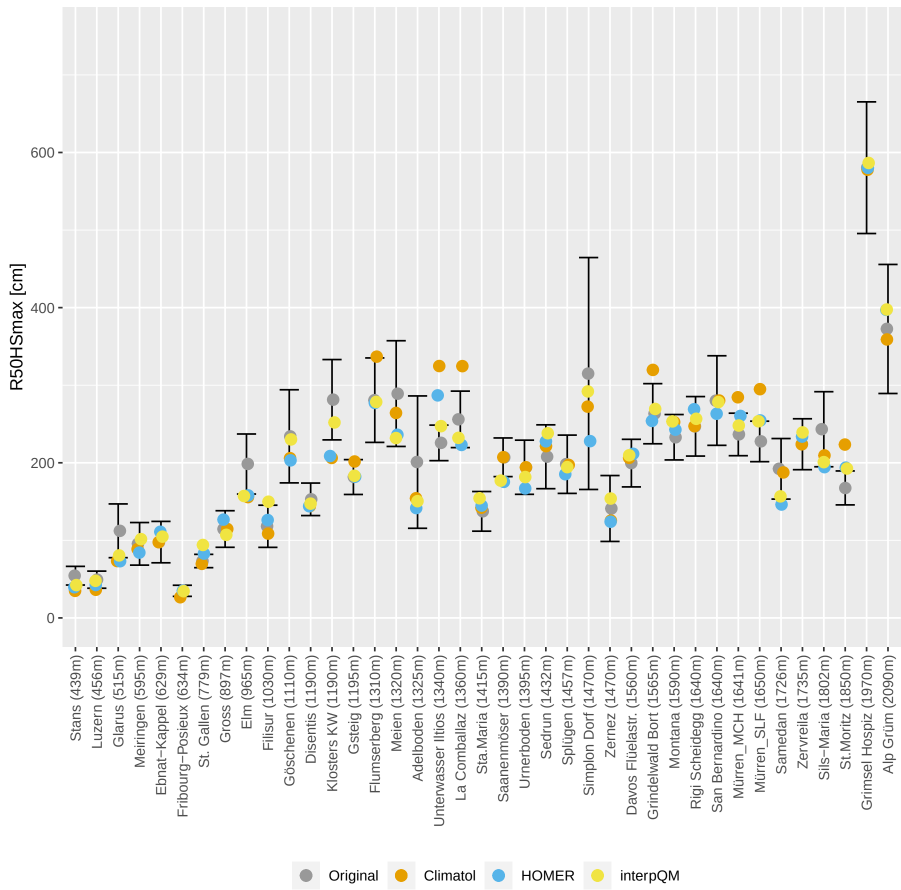

Figure 5. HSmax with 50-year return periods and 95 % confidence intervals for both original (grey) and homogenized data using Climatol (orange), HOMER (blue), and interpQM (yellow). The whiskers represent the 95 % confidence interval for the original values. Stations are ordered left to right according to elevation.

Table 3. Statistics for R50HSmax: Number and percentage of stations that are outside the origininal's 95 % confidence intervals for each homogenization method.

	R50HSmax		
	Climatol	HOMER	interpQM
Outside 95 % conf interv	13 (32.5 %)	11 (27.5 %)	6 (15 %)
Above	7 (17.5 %)	4 (10 %)	3 (7.5 %)
Below	6 (15 %)	7 (17.5 %)	3 (7.5 %)

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5 Discussion

The analysis of dHS5, which shows almost no differences between the original and the homogenized series, confirms the stability of this metric as reported in Buchmann et al. (2021b). The altitude pattern for dHS30 and dHS50 can be explained by the fact that at stations below 1000 m a.s.l. hardly any dHS30 and dHS50 occur and therefore small changes can have a strong influence. Those high-elevation stations that show large differences between trends before and after the homogenization in Fig. 2 (SIA, x.Sam, 6SB, ZNZ, 4SM, and 5SP) are all located at location highly influenced by southern flows. Especially the Engadin, a high-elevated, inner alpine valley with its dry and cold climate, is normally not associated with large snow depths or many days with dHS30 or dHS50. Furthermore, these large positive differences occur either from (a) a change of trend from positive to negative after homogenization or (b) from no trend to negative. Moreover, the size of the adjustment factor is not directly responsible for these large differences, as the impact on the trends is more sensitive on the length and location of the adjusted sub-period than the magnitude. Even more so, as the actual adjustment factors for x.SAM, SIA, ZNZ, anf ABO are all smaller than 1, and are not among the largest adjustment factors in the subset, even when considering absolute values.

All but two of the trends for HSavg (both in original and homogenized data) are negative, corresponding to findings from previous snow studies (e.g. Laternser and Schneebeli, 2003; Marty, 2008; Scherrer et al., 2013; Fontrodona Bach et al., 2018; Matiu et al., 2021). Marcolini et al. (2019) report an increase in series showing significant trends for HSavg after homogenization (40 to 44 %). We can see the same effect for interpQM, but not for Climatol (no change) and HOMER, which shows a decrease of significant trends after homogenization (Table 2). The same increase can be observed for trends in snow days and HSmax. There are no striking differences across the homogenization method for HSavg, whereas for HSmax, the results from the various homogenization methods differ for stations below 1000 m a.s.l. with interpQM having stronger and more significant trends. A performed Kolmogorov-Smirnov-Test showed no significant differences for the results of three homogenization methods for HSavg except 4 of the 40 stations (GLA, GRA, LUZ, SNS).

For the majority of stations, R50HSmax from homogenized data are still within the 95 % confidence intervals of the original values. However, depending on the homogenization method, between 3 to 7 (see Table 3) stations show R50HSmax exceeding the original values beyond the 95 % confidence intervals, with potential implications for engineering applications and building codes. Values well above the 95 % intervals are predominantly from Climatol. The reference networks in Climatol are built with the help of Euclidean distances between candidate and reference series, with an optional scale-factor for the vertical component. We set this threshold to $wz = 100$, as in that configuration, the station pair Davos (1570 m a.s.l.) and Weissfluhjoch (2535 m a.s.l.) cannot be selected. However, it maybe the case that this threshold is just not low enough to inhibit further station combinations with a similarly large gradient. Unfortunately, Climatol does not allow the user to see which series have been used as references for a given station. The decrease of the 95 % confidence intervals across the methods after the homogenization indicates a decrease in variation and an increase in confidence in the results.

The observed differences across the methods can be explained by the various intrinsic means of handling the construction of the sub-networks of reference series and the adjustments. HOMER adjusts the entire period before an identified break point with a single factor, whereas Climatol uses multiple factors dependent on the reference series constructed using homogenized

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sub-periods. InterpQM on the other hand, uses multiple adjustment factors based on quantile matching. The range of the applied adjustments for interpQM is shown in Appendix A3.

The selection of suitable reference series is the crucial part of the homogenization procedure, for the detection of breaks as well as for the adjustment step. HOMER can either be run in correlation or distance mode, meaning sub-networks are built based on thresholds for either correlation or horizontal distances. In Climatol, the sub-networks are built using the Euclidean distance between series with a scale parameter for the vertical component. InterpQM allows the user to choose correlation and both horizontal and vertical distance thresholds. For an elevation dependent variable such as snow depth, the possibility to select the sub-networks by means of setting thresholds for vertical and horizontal distances separately proves invaluable. It is possible, albeit cumbersome, to manually define the sub-networks and use them as input for HOMER. The possibility in HOMER to visually scrutinize the set of reference series used for each candidate station can give a useful hint of how accurately the reference series reflect local climatic or topographic characteristics; e.g. is a majority of the reference series drawn from a completely different micro-climate? This is especially important for a study area with a complex Alpine topography, where neighbouring valleys can have completely different climates: North/South, inner-Alpine, or pre-Alps. Furthermore, these lists of reference series can also be used to identify stations with suspicious reference series that are probably not suited for homogenization.

The analysis of the sub-networks for HOMER and interpQM shows that due to the distance constraint in interpQM, reference series are drawn from a more similar region, whereas for HOMER, distant stations with high correlations are frequently included. To avoid selecting close-by, but unsuitable reference series due to local-scale climatic variations, the correlation criterion in interpQM works well.

6 Conclusions

This study is the first in-depth comparison of different homogenization methods applied to a large network of snow depth series. The focus is their influence on extreme snow depths, decadal trends in the number of snow days of different thresholds (5, 30 and 50 cm), and seasonal mean and maximum snow depths (HSavg, HSmax). The results confirm the significant importance of homogenizing long time series (e.g. Auer et al., 2007; Venema et al., 2020). Due to the impact on derived trends, this is especially true for conclusions drawn from single series. For the long-term trends of HSavg and dHS5, the overall picture does not change with homogenized or original data. However, it becomes clearer when a quantile based homogenization approach (interpQM) is applied, which shows the strongest effect with exclusively negative trends for HSavg and, as expected, a slight increase in the number of significant trends. The differences between the methods become clearer when considering the seasonal maximum values: The trends for HSmax, absolute maximum snow depths and extreme values. The performed homogenization increases the confidence in the derived extreme values, which is particularly useful for engineering applications. As far as snow days are concerned, the quantile based adjustments had the strongest impact on the larger snow depth thresholds.

Separating the breakpoint detection from the adjustment procedure, i.e. using the robust combined detection approach described in Buchmann et al. (2022) in combination with the adjustment procedure from Resch et al. (2022) has proven to be

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promising. The ability to easily manually adjust the automatic selection process of the (reference) stations used for comparison with the candidate station is crucial to achieve the best-possible results. A combination of several selection criteria such as correlation, horizontal and vertical distances as well as manual interventions seems to be more advantageous for snow in combination with the complex topography prevalent in mountainous regions such as the Alps than using only a single selection criterion.

Since the break detection is preferably done separately, there is no incentive or obvious benefit to rely only on automatic homogenization methods, such as HOMER and Climatol. To achieve reasonable results, even these methods require some degree of user intervention, e.g. use a pre-defined selection of reference stations, using thresholds for correlation, horizontal and vertical distances. Therefore it would be best to use the results of the described 2-out-of-3 method for break point detection and interpQM for the adjustments, albeit being laborious.

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Code and data availability. Input data for the various homogenization methods are available on EnviDat https://doi.org/10.16904/envidat.336

Author contributions. The study was devised by MBU and CM with input from GR, WS and MBT. Snow day analysis was performed by GR, HSavg and HSmax by MBU. Figures were produced by GR and MBU. GR and MBU discussed the results with input from CM, SB and WS. MBU wrote the initial and GR the final draft with input from all co-authors.

Competing interests. We do not have any competing interests.

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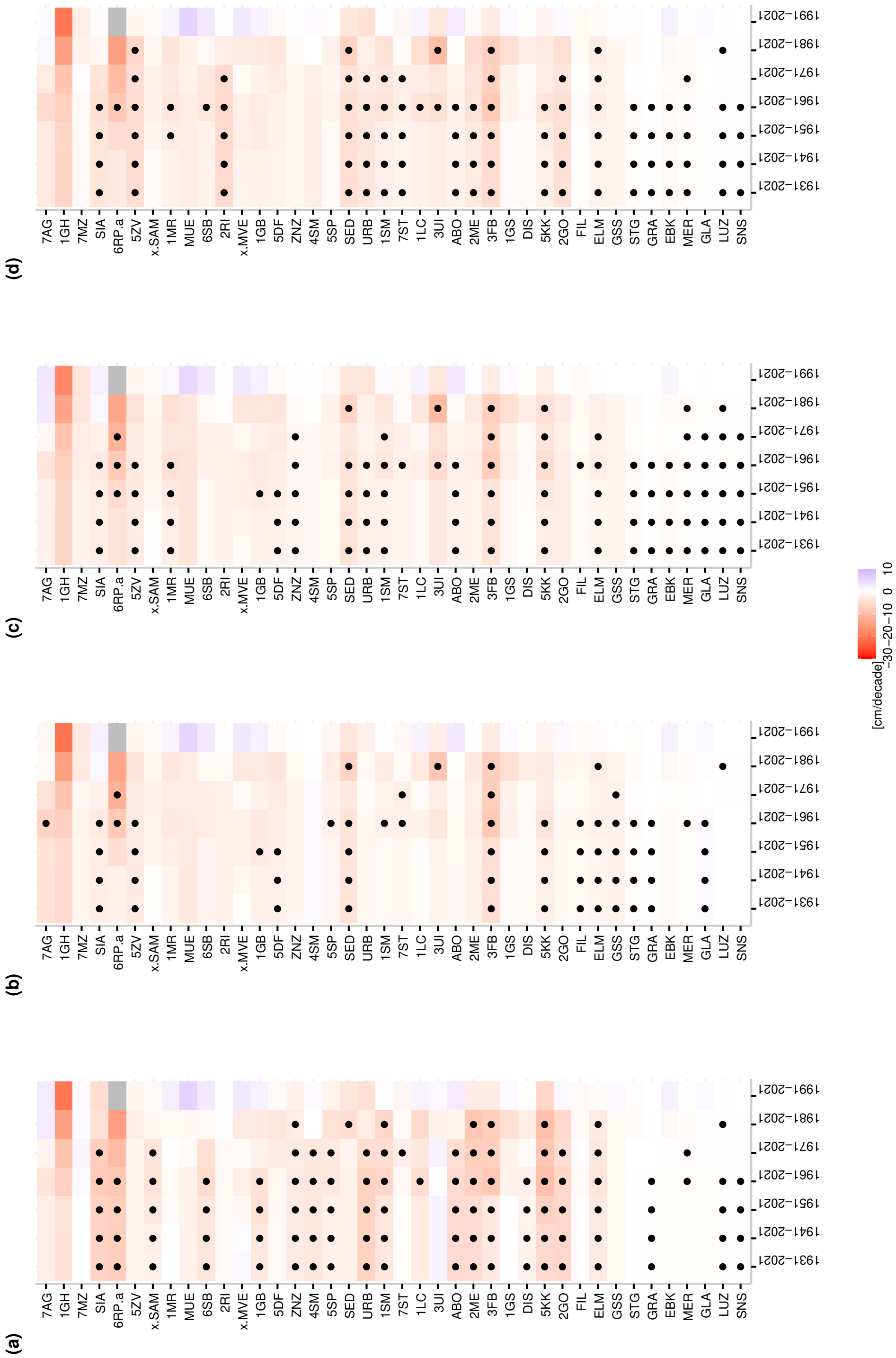

Figure A1. Trends for HSavg: Shown are all methods and all decades. Original (a), HOMER (b), Climatol (c), and interpQM (d).

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Figure A2. Comparison of differences of trends calculated with Climatol, HOMER, and interpQM for the period 1961-2021. Differences are expressed as original minus homogenized. Stations are ordered according to elevation (low-high, bottom-top) with an corresponding altitudinal scale in panel (b). Black dots indicate statistical significance with p-values below 0.05.

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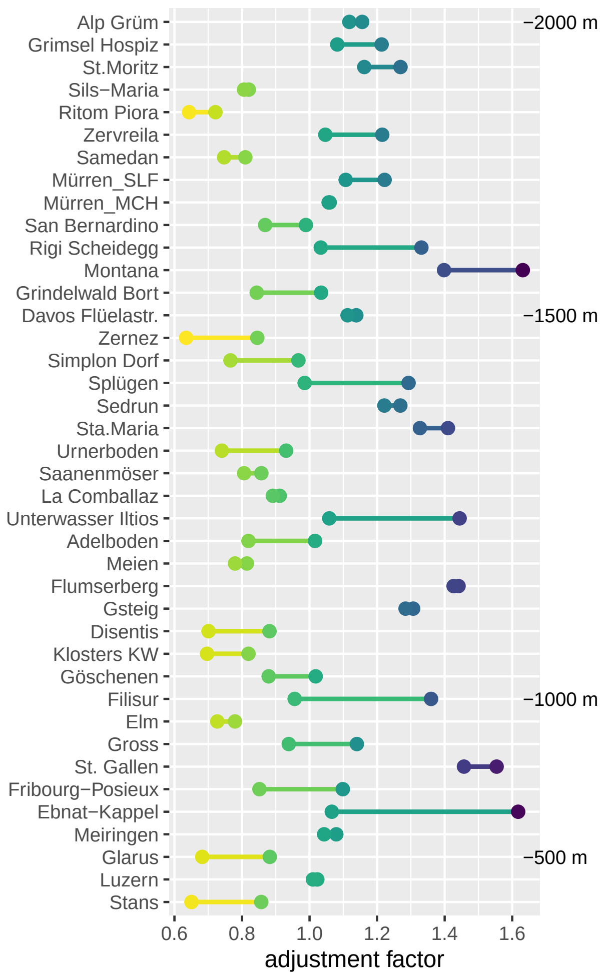

Figure A3. Range of the applied adjustment factors of interpQM for the different quantiles

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