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Long-term changes in annual maximum snow depth and snowfall in Switzerland based on extreme value statistics

Christoph Marty · Juliette Blanchet

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Abstract Mountain snow cover is an important source of water and essential for winter tourism in Alpine countries. However, large amounts of snow can lead to destructive avalanches, floods, traffic interruptions or even the collapse of buildings. We use annual maximum snow depth and snowfall data from 25 stations (between 200 and 2,500 m) collected during the last 80 winters (1930/31 to 2009/2010) to highlight temporal trends of annual maximum snow depth and 3-day snowfall sum. The generalized extreme value (GEV) distribution with time as a covariate is used to assess such trends. It allows us in particular to infer how return levels and return periods have been modified during the last 80 years. All the stations, even the highest one, show a decrease in extreme snow depth, which is mainly significant at low altitudes (below 800 m). A negative trend is also observed for extreme snowfalls at low and high altitudes but the pattern at mid-altitudes (between 800 and 1,500 m) is less clear. The decreasing trend of extreme snow depth and snowfall at low altitudes seems to be mainly caused by a reduction in the magnitude of the extremes rather than the scale (variability) of the extremes. This may be caused by the observed decrease in the snow/rain ratio due to increasing air temperatures. In contrast, the decreasing trend in extreme snow depth above 1,500 m is caused by a reduction in the scale (variability) of the extremes and not by a reduction in the magnitude of the extremes. However, the decreasing trends are significant for only about half of the stations and can only be seen as an indication that climate change may be already impacting extreme snow depth and extreme snowfall.

1 Introduction

Heavy snowfall and extreme snow depth cause serious loss of human life and property in many middle and high latitude countries almost every winter. Although changes in mean

C. Marty (✉) · J. Blanchet
WSL Institute for Snow and Avalanche Research SLF Davos, Flüelastr. 11, 7260 Davos, Switzerland
e-mail: marty@slf.ch

J. Blanchet
Institute of Mathematics, Ecole Polytechnique Fédérale de Lausanne, 1015 Lausanne, Switzerland

snow fall and snow depth are an important indicator of climate change, it can be argued that the most damaging and memorable winters are those with extremely large amounts of snow. Heavy snowfalls are often accompanied by extreme snow storms and avalanches which cause hazardous conditions on roads, railways and airports–sometimes even leading to the interruption of major transport routes. Winter resorts may have to close tourist infrastructure due to high winds, low visibility and avalanche hazards. Heavy snowfall events can be a high economic burden for society due to snow load damages to buildings, increased snow removal costs or spring flooding. Snow-prone countries such as Switzerland have successfully reacted to such threats by defining snow load codes for buildings, by establishing standards for avalanche defence structures or by planning residential areas based on avalanche hazard maps of runout zones. These measures are effective in reducing the damage in densely populated regions such as the Alps.

Nevertheless, due to the rare frequency of catastrophic events per affected person and due to the high cost of such measures, current standards or codes are sometimes questioned. Codes and run-out zones are based on return periods of extreme events, which are calculated with the help of the extreme value theory. An important assumption of the classical extreme value theory refers to the (temporal) stationarity of the process under study, which implies that the model parameters do not change over time. However, as recently emphasized (Hegerl et al. 2011; Katz 2010; Cooley 2009), climatic series are known to be non-stationary. The well-founded approach for the modelling of a trend in extremes is to use time as a covariate in classical extreme value theory, leading to the non-stationary extreme value theory (Coles 2001, chapter 6). This approach allows estimating within the extreme value theory how extreme events have evolved with time. It has been quite widely used for climate data such as wind speed (Hundecha et al. 2008), precipitation (Beguería et al. 2010), temperature (Brown et al. 2008), etc. However, to our knowledge, it has never been applied to snow events, for which so far only the temporal evolution of events of fixed magnitude and of fixed quantiles have been studied (Kunkel et al. 2009; Falarz 2008). The main difference to the non-stationary extreme value method is that only fixed statistics (e.g. the 90% quantile) can be studied, which does not allow deriving the general dependence of quantiles through time. Furthermore, the 90% quantile corresponds to a 10-year return level, which is thus not that extreme a case (referred to as 'soft' extremes by Klein Tank and Können 2003). One could also argue that this approach is, from a theoretical point of view, improper since it does not apply the well-founded theory of extremes values. Note that few studies exist on extreme snow events based on extreme value theory but all these studies focus on the spatial characteristics, without any temporal dependence: Bocchiola et al (2006) studied the 3-day snowfall sum in the Italian Alps and Bocchiola et al (2008), Blanchet et al. (2009), Blanchet and Lehning (2010a) and Blanchet and Davison (2010) studied extreme snowfall and snow depth in Switzerland.

A temporal pattern for extreme snow events is a priori not obvious. Several studies showed that mean snow depth and snow days have been decreasing in the Alps in the last 20 years (Marty 2008; Durand et al. 2009; Valt and Cianfarra 2010), especially at altitudes below 1,300 m (Laternser and Schneebeli 2003; Scherrer et al. 2004). However, climate models predict a likely increase in the frequency of extreme precipitation events in a future warmer world (IPCC 2007). Such an increase has been observed for extreme winter precipitation north of the Alps (Schmidli and Frei 2005) and is predicted by regional climate models (Beniston et al. 2007; Frei et al. 2006). An increase in heavy snow fall events would however be in contradiction with the decrease in average snow events. Whether and to what extent extreme snow events have already been affected by climate change is thus still an open question. We give a first answer in this paper by making use of the non-stationary extreme value theory to assess how heavy snow fall and extreme snow depth in Switzerland have evolved over the last 80 years.

2 Data

The analysis is based on manually measured daily snow depth and new snow during the last 80 years (1931–2010) from the observational networks of the Swiss Federal Office for Meteorology and Climatology (MeteoSwiss) and of the WSL Institute for Snow and Avalanche Research (SLF). As input for the extreme value analysis we computed the annual maximum snow depth (HSmax) and annual maximum new snow sum over three successive days (HN3max) for each available station. We used HN3max because new snow amounts causing damages are rather due to heavy snowfall over several days than due to a huge 1 day snowfall (Bocchiola et al. 2008).

The daily data were quality checked and missing data were interpolated. An advantage of using historical snow data is the fact that the method of snow measurement has not changed since the introduction of the national meteorological network. Snow depth and snowfall are still measured using a permanent measurement stake and a nearby new-snow board. Nevertheless, inhomogeneities can still occur due to the displacement of a station or change in the station's surroundings. Dates of displacements are known from the metadata of each station, but small changes in altitude (typically less than 50 m) might not have a measurable impact on the data series. For example, a displacement from a location 30 m above the valley bottom to the valley bottom itself may imply slightly less snow fall but also slightly less melting or settling of the snow cover due to the cold reservoir during clear-sky conditions. However, the only two stations with an elevation change of more than 50 m (i.e. 70 m for both stations) were adjusted for the snowfall data with an altitude gradient of 3 cm/100 m (Blanchet et al. 2009). We homogenized the data series from two other stations, which was only possible thanks to overlapping time periods of two parallel measurement series from MeteoSwiss and SLF at the same site. Two other stations were disregarded due to known discontinuities or inconsistent measurement procedures. We finally ended up with 18 HSmax series and 25 HN3max series. Among the 18 stations measuring HSmax, 14 have HN3max data as well, which means that 4 stations measure HSmax exclusively and 11 have only HN3max data. In order to investigate changes about the development at high altitudes we also included the only available station above 2,000 m which fulfilled our requirements, despite the fact that it missed the first 5 years of the investigated 80 years (1931–1935). The stations chosen are spatially and altitudinally more or less uniformly distributed over Switzerland with the exception of a concentration in the eastern corner, especially concerning HSmax (Fig. 1). The stations are located between 275 and 2,540 m asl. For the analysis we often refer to low (0–800 m), mid (801–1,500 m) and high altitude (1,501–2,600 m) stations. About 47% of the stations are located at low altitudes, 30% at mid altitudes and 23% at high altitudes.

3 Evidence of trends

A first picture of the general trend in HSmax and HN3max in Switzerland can be obtained by computing anomalies of the annual time series, named henceforth "normalized" HSmax and HN3max. More precisely, for each series of annual maxima, we computed the mean and standard deviation of the 80 annual values and derived the

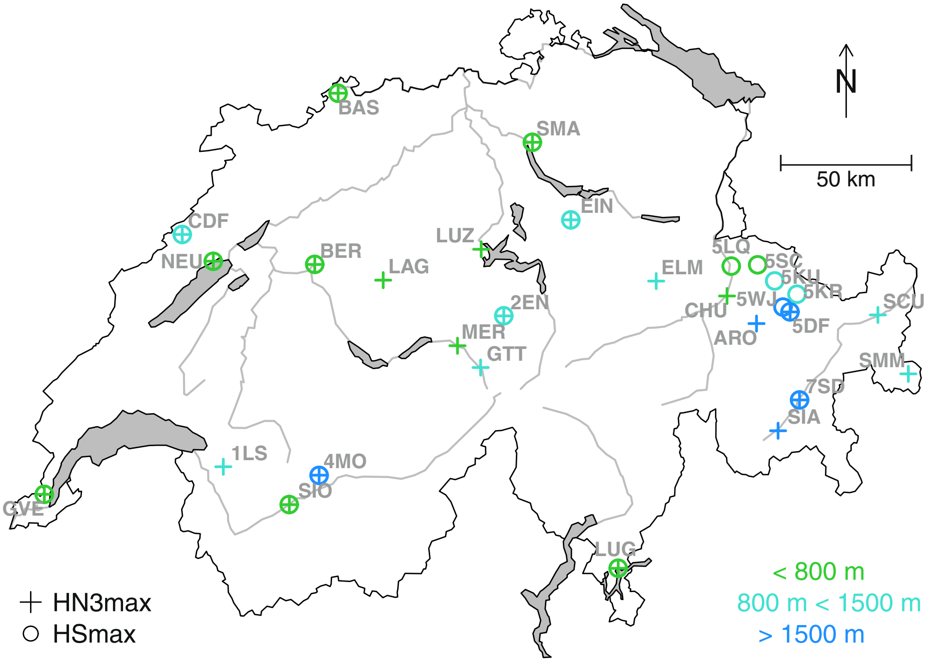

Fig. 1 Spatial and altitudinal distribution of the investigated stations in Switzerland

normalized series by subtracting the mean and dividing by the standard deviation. This allows us to basically remove (or at least strongly reduce) the altitudinal influence and all stations can thus be more easily compared. Figure 2 depicts a summary of these normalized time series for HSmax (left) and HN3max (right). For each winter, the inter-station variability is rather high (see shaded bands) because snow abundance is often limited to one side of the Alps or limited to low or high altitudes only (Scherrer and Appenzeller 2006). Nevertheless, most of the known snowy and avalanche prone winters such as 1944/45, 1967/68 and 1998/99 are clearly visible. The avalanche winter of 1950/1951 is not prominent since it did not affect the low altitude stations and the southwestern part of the Alps. On the other hand, the snow scarce winters of 1932/33, 1963/64 and 1989/90 and 2006/07 stick out well with very low HSmax and HN3max values. First evidence towards a general trend in extremes can be obtained, for example, by fitting a linear trend to the mean of the 18 normalized HSmax and of the 25 normalized HN3max (bold lines in Fig. 2). Negative trends of magnitude −0.007 and −0.01 are found for the normalized HSmax and HN3max respectively. This corresponds to an average decrease of 1.5 cm/decade for HSmax and 1 cm/decade for HN3max. The average relative decrease between the beginning and the end of the 80-year period amounts 25% for HSmax and 19% for HS3max. Furthermore both trends found on the normalized series are significant (p=0.02 for both variables), which is mainly caused by a relatively large number of years with high negative anomalies in the last 20 years (Marty 2008). However, this gives only a first evidence of a negative trend in extremes and does not make use of the extreme value theory which is the well-founded theory for studying trends in extremes (Katz 2010). The rest of this paper will be devoted to this issue.

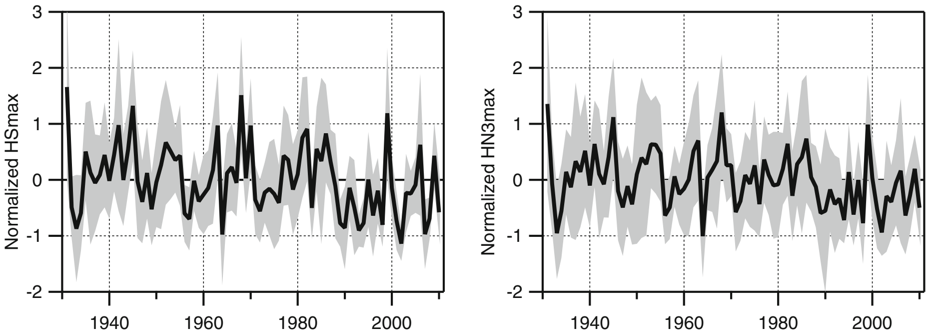

Fig. 2 Mean and standard deviation of the normalized annual maximum (*left*) snow depth (HSmax) and (*right*) the 3 day snowfall (HN3max) of all involved stations. A linear trend analysis reveals a significant negative trend of HSmax and HN3max, which is mainly caused by a relatively large number of years with high negative anomalies in the last 20 years

4 Methods

The approach followed in this study is based on extreme value theory, which dates back to the theorem of Fisher and Tippett (1928). It insures that the asymptotic distribution of block maxima (e.g. annual maxima), if it exists, either belongs to the Fréchet, Weibull or Gumbel distribution. This means that the tail behaviour of the original daily time series can be estimated from one of these three extreme value types. The Generalized Extreme Value (GEV) distribution merges all three distributions in one single parameterization. This flexibility makes the GEV the universal tool for modelling the block maxima *X*: for blocks long enough, the distribution of *X,* $P(X \leq x)$, is expected to be given by:

$$F(x)\exp\left\{-\left[1+\xi\frac{x-\mu}{\sigma}\right]^{\frac{-1}{\xi}}\right\}, \quad (\mathit{provided\ that}\ (1+\xi(x-\mu)/\sigma)>0) \tag{1}$$

where μ, $\sigma > 0$, ξ are the location, scale and shape parameters, respectively. The location specifies where the distribution is centred and the scale its spread. The shape describes the tail behavior, leading to the three aforementioned extremal distributions: a heavy-tailed distribution (Fréchet) when $\xi > 0$, a light-tailed distribution (Gumbel) when $\xi = 0$, a bounded distribution (Weibull) when $\xi < 0$. These parameters can be estimated by maximum likelihood (Coles 2001, chapter 3.3) and standard errors can be derived by the delta method for $\xi < 1$. Note that all these results still hold for block maxima of shortly dependent daily data (Leadbetter et al. 1983), which seems to be a reasonable assumption for daily snow depth (Blanchet and Lehning 2010b; Blanchet and Davison 2010). Three-day snowfall sums can be expected to be 3-day dependent, which is also short enough for extreme value theory to hold. Note also that these results are asymptotic, which means that they theoretically hold for blocks of infinite length, which obviously never arises in practice. Here blocks correspond to 181 or 182 days (6 winter months). Goodness-of-fit plots (QQ-plots, not shown) reveal a fairly good agreement to the GEV distributions, which suggests that extreme value theory can be applied to our HSmax and HN3max.

To account for a non-stationarity due to long-term climate change for example, the location and scale parameters in the present work are assumed to change with time. The shape parameter is difficult to estimate with precision in practice, so it is usually unrealistic to try modelling ξ as a function of time. It will therefore be left constant in this study (as for example also in Maraun et al. 2010). This leads to a non-stationary GEV (NSGEV) model, in which, unlike in the stationary case (SGEV) of Eq. (1), the location μ and shape σ are a function of time t, denoted $\mu(t)$ and $\sigma(t)$ henceforth.

The most sophisticated approach would be to assume a smooth non-parametric dependence of μ and σ with time as in Chavez-Demoulin and Davison (2005). Nevertheless, such models are quite complex and, given the relatively short data at hand (80 years, i.e. 80 values), we prefer using a more simplistic model which is already a further step compared to the usual linear trend (of e.g. quantiles) used so far for analysing trends in extreme snow events (Kunkel et al. 2009; Falarz 2008).

The location parameter $\mu(t)$ and the shape parameter $\sigma(t)$ were originally allowed to change linearly or quadratically with time. The quadratic model has the nice property of being able to model more complex trends than the linear model (e.g. situations when the beginning and end of the observation period are relatively snow-scarce). However it may not be robust for prediction into the future: huge changes may be predicted in the future when only slight changes have been found on the observation period. This is exactly what we found on our HSmax and HN3max data: for some stations with an observed decrease of 10% between 1930 and 2010, an unrealistic decrease of 140% was predicted between 2010 and 2050 with the quadratic model! We thus decided to put aside the quadratic models and to use linear models only for $\mu(t)$ and $\sigma(t)$. Note however that using the quadratic models would barely change the results of this paper, which focuses mainly on the observation period during which quadratic and linear models give similar results. Assuming a linear trend for the location and scale parameters is quite a strong assumption but it has the advantage of being a simple enough model for being estimated from few data and to be robust enough for being extrapolated to future change.

Thus, we consider in this analysis three different NSGEV models with a linear trend in the location and/or scale (see Table 1). Model 1 represents a trend in the location, i.e. in the magnitude of the extremes (increasing trend if $B > 0$, decreasing trend if $B < 0$). Model 2 corresponds to a trend in the scale, i.e. in the spread of the extremes (increasing trend if $D > 0$, decreasing trend if $D < 0$). Model 3 represents a trend in both the magnitude and the spread of the extremes. An illustration of these 3 models is given in Fig. 3. For the three models, the distribution of X, $P(X \leq x)$, is then given by (1) where parameters μ and/or σ depend linearly on time. Thus the distribution of X itself also depends on time, as well as its statistics (mean, quantiles, etc.).

In total, four GEV distributions (one SGEV and three NSGEV) are considered. These four distributions are estimated at each station separately, for both HSmax and HN3max, by maximum likelihood using the 80 annual maximum values. The Akaike information criterion AIC (Akaike 1974) is used to decide which of the three non-stationary models performs better with a minimum number of free parameters. It is given by

Table 1 The 3 different non-stationary GEV models, which are applied to the annual extreme values of extreme snow depth and snowfall. Here "time" t has to be understood as "year number"; it thus ranges between 0 and 79 for the 80 years of study

	Location μ	Scale σ	Shape ξ
Model 1:	$A + B \cdot t$	const.	const.
Model 2:	const.	$C + D \cdot t$	const.
Model 3:	$E + F \cdot t$	$G + H \cdot t$	const.

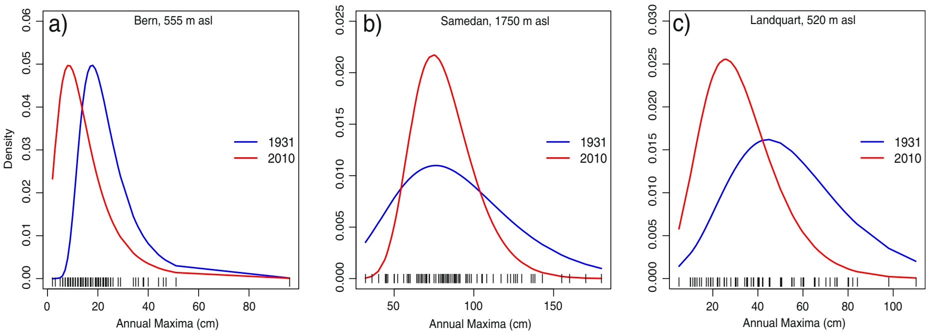

Fig. 3 Probability density function of the NSGEV model for HSmax at three stations. **a** A negative trend of the location parameter implies a shift of the centre of the extreme values. **b** On the other hand, a negative trend in the scale parameter implies a decrease in the variance of the extremes. **c** A negative trend in the location & scale parameter implies a decrease in the centre and variance of the extremes. The bars along the x-axis represent the 80 annual HSmax values

$$AIC_M = 2k_M - 2logL_M, \tag{2}$$

where M is one of the three non-stationary models of Table 1, k_M is the number of free parameters in Model M ($k=3$ in Models 1 and 2, $k=4$ in Model 3) and L_M is the maximum likelihood value. Basically, AIC is a compromise between a good fit (high likelihood) and low complexity (low number a free parameters). Three values of AIC (corresponding to Model 1, 2 and 3) are computed for each station and each variable (HSmax and HN3max); in each case, the selected model is the one having the lowest value of AIC. Once a non-stationary model has been selected, a likelihood ratio test at level 95% (Coles 2001, chapter 6.2) is then used to decide whether it performs significantly better than the classical SGEV model. More precisely, the likelihood ratio test computes, for each station, the statistics

$$-2log(L_{M_0}/L_{M_{sel}}), \tag{3}$$

where $L_{M_0}$is the maximum likelihood value of the SGEV model, and $L_{M_{sel}}$is the maximum likelihood value of the selected NSGEV model. Under the null hypothesis of a SGEV model, this ratio follows a chi-square distribution with $k_{M_{sel}} - 3$ degrees of freedom, where $K_{M_{sel}}$ is the number of free parameters in the selected NSGEV model. The NSGEV model will then be preferred at level 95% if the statistics (3) is higher than the 0.95-quantile of the corresponding chi-square distribution; in this case, by a slight stretch of language, we will say that the trend is significant, otherwise we will say that it is not significant. However, we claim that the estimated trends, even when not significant, are still a first indication of trend in extremes. The selected NSGEV model will therefore be further investigated through this paper, for all HSmax and HN3max time series.

A first variable of interest that can be derived from the selected non-stationary models is the mean annual values of HSmax and HN3max. The mean of the NSGEV, *m(t)*, depends on the considered year *t*; it is given by (for $\xi \leq 1$)

$$m(t) = \mu(t) + \sigma(t)\frac{\Gamma(1-\xi) - 1}{\xi}, \tag{4}$$

where Γ is the Gamma function and where, depending on the selected NSGEV model, either the location $\mu(t)$ and/or the scale $\sigma(t)$ depend on time (i.e. on the considered years).

It follows from Eq. (4) and Table 1 that in Model 1, the mean annual maximum is linearly increasing (resp. decreasing) with years if $B > 0$ (resp. $B < 0$). In Model 2, it is linearly increasing (resp. decreasing) with years if $D > 0$ (resp. $D < 0$). In Model 3, it is linearly increasing if $F + H(\Gamma(1-\xi)-1)/\xi$ is positive, and decreasing otherwise.

Return levels and return periods are in practice of more interest for construction norms, land-use planning, etc than the mean of extremes. The T-year return level x_T is the level exceeded on average every T years. Its computation is obtained by inverting $F(x_T) = 1-1/T$ in (1), leading to the following expression:

$$x_T(t) = \mu(t) + \frac{\sigma(t)}{\xi}\left[\left\{-\log\left(1-\frac{1}{T}\right)\right\}^{-\xi} - 1\right] \tag{5}$$

As the mean (4), return levels x_T are linearly dependent on time. More precisely, in Model 1 (see Table 1), return levels x_T linearly increase (resp. decrease) in time if $B > 0$ (resp. $B < 0$). In Model 2, x_T linearly increase (resp. decrease) in time if $D > 0$ (resp. $D < 0$). In Model 3, x_T linearly increase (resp. decrease) if $F + H\left(\{-\log(1-1/T)\}^{-\xi} - 1\right)/\xi$ is positive (resp. negative).

The return period T_x of a given extreme event of magnitude x is obtained by solving $F(x) = 1-1/T_x$, which gives: $T_x = 1/(1-F(x))$, i.e.

$$T_x(t) = 1/\left[1 - \exp\left\{-\left(1+\xi\frac{x-\mu(t)}{\sigma(t)}\right)^{\frac{-1}{\xi}}\right\}\right] \tag{6}$$

Return periods T_x also depend on time, but non linearly. For large return levels x, a Taylor expansion of (5) gives the approximation

$$T_x(t) \approx \left\{1+\xi\frac{x-\mu(t)}{\sigma(t)}\right\}^{\frac{1}{\xi}} \tag{7}$$

Return levels T_x are then polynomials of time. The uncertainty of the x_T and T_x estimation is obtained using the delta method (Coles 2001, chapter 2.6). For both variables, it gives symmetric confidence intervals whose lengths are non-linear in time. The profile likelihood method (Coles 2001, chapter 2.6) is an alternative method for deriving x_T, T_x and their uncertainties. It usually gives more accurate estimators at the price of a much more intensive computation, particularly in our NSGEV case where x_T and T_x are time varying. We compared the confidence intervals obtained with the delta method and the profile likelihood method in the SGEV case. It turned out that very similar values for x_T and T_x were found but with typically only slightly narrower confidence intervals with the profile likelihood method. As the profile likelihood method is very computationally intensive and seem to give similar accuracy than the delta method, we decided to use in this paper the delta method exclusively for the computation of confidence intervals.

5 Results

5.1 Trends in extreme snow depth

The three cases of change considered in this study are illustrated in Fig. 3, which depicts examples of NSGEV density under Model 1, 2 and 3 of Table 1. The GEV density is obtained by deriving Eq. (1) with respect to x; it is obviously year-dependent in the non-stationary case. Figure 3a shows the case of a significant change in the location parameter (Model 1 in Table 1), i.e. a change in the centre of the extremes. The theoretical centre of HSmax for the depicted station (Bern) changes between the beginning and end of the investigated period from 20 cm to about 10 cm (relative change about −50%). Figure 3b depicts the case of a significant change in the scale parameter, i.e. in the spread of HSmax. The third possibility covers the combination of both former changes, when both the centre and the spread of HSmax decrease (Fig. 3c).

Figure 3 gives only an illustration of the trends found for three of the stations. A first way of giving a more general picture of all trends is to compute how much the means of the annual values have evolved during the 80-year period, according to the selected NSGEV models. In order to be able to make a comparison of all stations, we computed the relative changes over the 80-year period, i.e. the percentages of increase/decrease between 1931 and 2010. This is computed as *(m(1931)-m(2010))/m(1931)* where *m(t)*, the mean at year t, is given by (4). Figure 4 depicts the relative changes in the mean of the annual values against altitude. A negative relative change implies a decreasing trend; a positive relative change implies an increasing trend. For example a relative change of −15% means that at the end of the period, the average annual maximum was 15% lower than at the beginning of the period. It is striking that all stations reveal negative trends (negative relative changes). The average relative decrease of the mean amounts 17%. This is of the same order as the relative decrease found in chapter 3 by applying linear trends to the normalized annual values. However, according to the likelihood ratio test at level 95%, these trends are significant for only 44% of the stations (filled symbols). Low altitude stations tend nevertheless to have a clearer decreasing trend since it is significant for the majority of them (60%). Note that this overall decrease was also found by the quadratic models initially considered (see chapter 4) which revealed a decreasing trend for 50% of all stations. Another finding is that none of the trends at low altitude are due to a trend in the scale alone (triangle symbols). Furthermore, for the two stations with a trend in both location and scale,

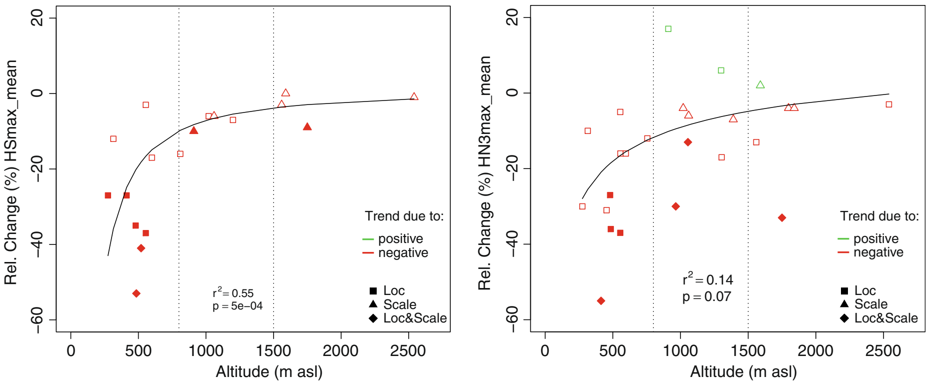

Fig. 4 Relative change of the mean of (*left*) HSmax and (*right*) HN3max between 1931 and 2010 based on the selected NSGEV model, versus the altitude of each station. Stations with a significant trend (compared to the SGEV model) have a filled symbol. For HSmax all stations show a negative trend, which is significant (filled symbols) for most of the low altitude stations. Low- and mid altitude stations mostly show a negative trend due to a decrease of the location parameter and high altitude stations solely disclose a decrease in the scale parameter. For HN3max the majority of the stations also disclose a decrease, which is caused by negative trend in the location parameter for the low altitude stations and by a negative trend in the scale parameter at the high altitude stations

the second best model corresponds to a trend in the location, which is still significant. As the location parameter represents the centre of the extremes, we can thus conclude that the decreasing trend in HSmax at low altitude is mainly caused by a decrease in the magnitude of the extremes (cf. Fig. 3a). On the other hand, most of mid and high latitude stations (75%) show a trend in the scale parameter, although only two of these trends are significant (see Fig. 4 left). This implies that the decrease at mid and high altitude can mainly be explained by a decrease in the spread of HSmax (cf. Fig. 3b). Note also that all points nicely align along a power function. The steep increase at low altitudes means that the relative decrease is much more drastic at low altitudes than at higher altitudes.

In practice, high return levels are of more interest than the mean of the extremes since the most catastrophic events occur for events of very high magnitude. Figure 5, left panel, shows an example of the linear change in the 100-year return level obtained from the selected NSGEV model. It corresponds to the high altitude station Davos (1,560 m asl), with a negative trend in the scale parameter, producing thus a linear decrease of the 100-year return level. The 100-year return level of HSmax changes linearly within the investigated 80 years from about 237 cm to 212 cm (relative change −11%). The 95% uncertainty of the 100-year return level remains quite constant and reasonable (about 20%). More generally, all T-year return levels decrease linearly with time for this station with higher return levels and larger confidence bands for larger return periods. For example, the 30-year return level (not shown) for the same station is linearly decreasing from 207 cm to 188 cm (relative change 9%) with a narrower uncertainty band of about 15%. Although this is the example of just one station, it is quite illustrative of the general trend experienced by the other stations. In particular, all the stations show a decrease for all return levels. However, the magnitude of this decrease is quite variable among the stations. On average, the 100-year return level has decreased between 1931 and 2010 by 14%, but 4 of the 18 stations show a decrease larger than 20% (maximum decrease 49%). A surprising finding is that the relative decrease of the 100-year return level seems to be almost independent of elevation unlike that of the mean (see Fig. 4, left, for the mean of HSmax). A reason is that the low altitude stations have heavier tails than the high altitude stations (in other words, the shape ξ is higher; see also Blanchet et al. (2009) and Blanchet and Lehning (2010b)). Thus, the largest HSmax are much more extreme (compared to the "usual HSmax") at low altitudes than at high altitudes and as a consequence the relative change of the 100-year return level is less drastic than that of the mean.

Figure 5, right panel, depicts the change in return period of a 160 cm snow depth at the same station. It is obtained by Eq. (6) for x=160 cm. The return period for such a snow depth changes non-linearly from about 6 years to 8 years between 1931 and 2010.

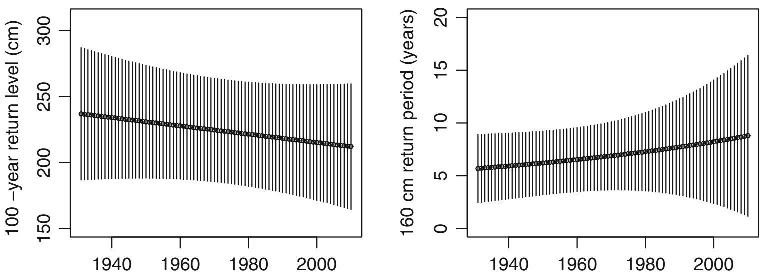

Fig. 5 Impact of decreasing spread of HSmax on (*left*) the 100-year return level and (*right*) the 160 cm return period for the station Davos (1,560 m asl). The error bars reflect the 95% uncertainty

However, the uncertainty in return period increases strongly with time due to the fact that years with 160 cm HSmax become more and more rare, which therefore increases the uncertainty in its computation. This pattern occurs for all stations but is more striking for the stations with a significant decreasing trend.

5.2 Trends in extreme snow fall

The non-stationary extreme value analysis of HN3max reveals a more diverse picture than for HSmax (Fig. 4 right). Three of the 25 stations (12%) show an increasing trend, although no significant. These three stations are located at mid altitudes between 910 and 1,590 m asl. All the other stations show negative trends, but the trend is significant for only seven of all these stations (32%). In agreement with HSmax, none of the stations below 800 m show a trend in the scale alone (triangles). Furthermore, for the only station with a trend in both location and scale, the second best model has a trend in the location. The low altitude stations thus all show a trend in the centre of HN3max, which is a decreasing trend for all the stations. On the other hand, the trend pattern at mid and high altitude is much less clear. The three kinds of trends are equally found; about a third show a trend in the location (squares), a third in the scale (triangles) and a third in both location and scale (diamonds). Above 1,600 m only negative trends are found, but unlike for HSmax, the highest station (about 2,500 m of altitude) shows a trend in the location contrary to the three other stations. Furthermore, the relationship between altitude and the relative change in the mean of HN3max is much less clear than for HSmax (see Fig. 4). This larger spatial variability of HN3max is probably due to the fact that HN3max is mainly controlled by one single precipitation event (during 3 days), often also accompanied by high winds. HSmax, on the other hand, is controlled by both temperature (causing melting and compacting of the snow cover) and precipitation sum since the start of the snow cover (i.e. an integration over several days, weeks or even months). The accumulating effect on snow depth of one single heavy snow fall may be reduced by the next warm period or by the eroding effect of a next snow fall with high wind speeds. As a result, HN3max (or more generally snow fall) is usually spatially more variable than HSmax (or more generally snow depth). This explains the less clear altitudinal pattern of HN3max in Fig. 4.

Figure 4 gives a general picture of the altitudinal dependence, which seems to be roughly similar for HN3max and HSmax (despite the higher variability of HN3max). One could think that this similar pattern is due to the similar temporal trends of HSmax and HN3max at a given location. This is however not the case. Pointwise comparisons at the 14 stations measuring both snowfall and snow depth reveal that there are quite large local differences in the relative changes of HN3max and HSmax. For example the station Davos (1,560 m asl) experienced a relative decrease of 13% for HN3max, and only 3% for HSmax. This is also a consequence of the intrinsic higher variability of snowfall than snow depth.

Last but not least, investigation on the 100 year level for HN3max reveals that it decreased within the investigated 80 years by about 15%, which is similar to the decrease of HSmax (section 5.2). However, as for HSmax, the inter-station variability of this relative change is very high. Seven of the 25 stations show a relative decrease higher than 20% (maximum decrease about 55%) and four stations show an increase (maximum increase 9%). As for HSmax and for the same main reason (heavier tails at low altitude; see section 5.1), this relative change seems to be almost independent of elevation.

5.3 Impact of NSGEV vs SGEV on return levels

For practitioners it is important to know what would be the impact of using NSGEV instead of SGEV for computing return levels, which is an important basis for many practical applications. A question of practical interest is whether the current codes of return level computation, based so far on SGEV, should be changed in favour of NSGEV. We thus compare in this section the return levels obtained by both methods. Return levels computed with NSGEV depend on the year in which they are computed (Eq. 5), unlike SGEV. For illustration we focus here on winter 2010 and on the 100-year return level. Furthermore, as results for HSmax and HN3max are fairly similar, we only present the case of HSmax. The goal is thus to decide whether the 100-year return levels estimated in 2010 by SGEV and NSGEV differ significantly. More precisely, we compare in Fig. 6 the values obtained by SGEV, i.e. when assuming no trend in extremes, with those obtained in winter 2010 by the selected NSGEV models. Both are obtained by Eq. (5) but the three GEV parameters are constant in the SGEV case. Only one station shows a positive difference between NSGEV and SGEV return levels but this southern station is quite badly fitted by the GEV distributions anyway (see the large 85% error bars) which produces unrealistic return levels with both methods. This station has indeed by far the highest shape parameter for HSmax and HN3max, which indicates a very heavy tail distribution. In agreement with Blanchet et al. (2009), the majority of the other stations disclose light-tailed or bounded distributions (low or negative shape parameters). In total, for 67% of the stations (HN3max: 54%), the 100-year return levels of NSGEV in 2010 and SGEV differ by less than 10% (red bars). Thus, for the majority of the stations, using one or the other method has little influence. Uncertainty of both methods is also comparable: the 85% confidence intervals of SGEV are on average only 3% narrower than those of NSGEV. On the other hand, inter-station variability is high: 22% of the stations (HN3max: 21%) show differences between 20 and

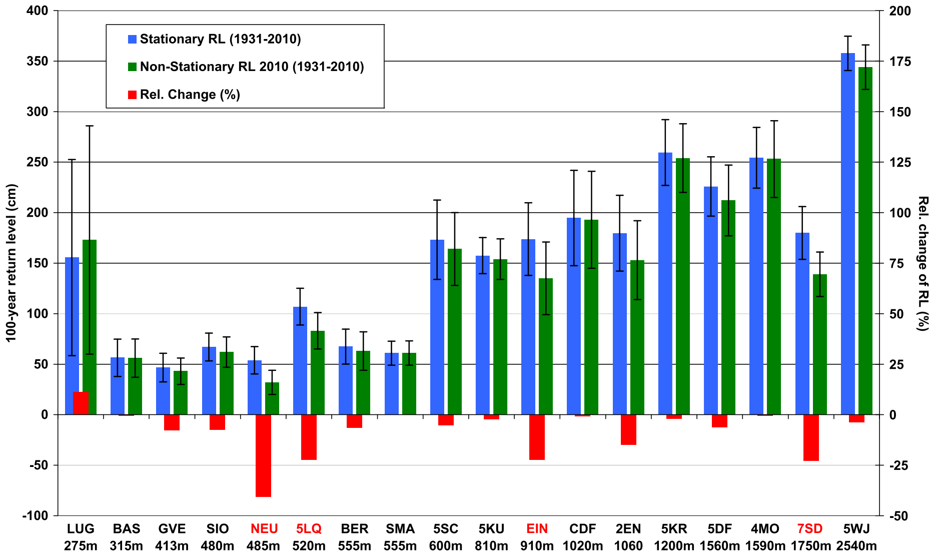

Fig. 6 Left axis: comparison of the 100-year return level (with 85% confidence interval) of HSmax for every station based on the stationary GEV (*blue bars*) and the non-stationary GEV (*green bars*). Right axis: relative difference of these values (*red bars*). The four stations in red show significant difference in the 100-year return level between the two methods

40%, which can be considered as being large enough to question the use of SGEV in practice. An automatic criterion to decide whether NSGEV should be used in practice, rather than the simpler SGEV, is still needed. Theoretically, to answer this question, we would need to construct confidence intervals for the difference of the 100-year return level of NSGEV and SGEV. We would thus conclude at a given level that the two return levels differ significantly if the corresponding confidence interval does not include 0. However, it is to our knowledge not possible to construct such confidence intervals and another practical procedure is thus needed. The procedure we decided to follow is to consider that the two estimated values differ significantly if the 100-year return level of NSGEV is outside the 85% confidence interval of that of SGEV, or reciprocally. The 85% confidence interval is simply given by the estimated return level +/− its standard error. This is one easy way of assessing whether the two return levels (including their uncertainty) are significantly different from each other. However, this only indicates whether the values seem to vary significantly among the methods and should not be taken as a true test of significant difference. Furthermore, the 85% confidence interval is quite subjective and has here been taken as a compromise between high and low credibility. The results of this procedure are summarized in Fig. 6 which shows that 4 of the 18 stations (22%, in red in Fig. 6) have a significant difference in the 100-year return level (HN3max: 20%). For the large majority of the stations, results obtained by SGEV, which is currently applied in practice, are similar to those of the more sophisticated NSGEV.

6 Discussion

The results reported in the previous section revealed a general decreasing trend in both HSmax and HN3max. One could think that the decrease in HSmax is mainly due to increased melting and compacting resulting from increasing winter temperatures during the last decades in Switzerland (Begert et al. 2005). However, a separate analysis revealed that HSmax and winter mean temperatures are only weakly (negatively) correlated, unlike the number of snow days for example (Scherrer et al. 2004; Marty 2008). Furthermore, the decrease of HN3max can also not be attributed to an increased melting since HN3max is only dependent on the snow fall sum of 3 consecutive days.

The study by Schmidli and Frei (2005) revealed increasing extreme winter precipitation in Switzerland. An increase in extreme winter precipitation is also found for our data set and time period (1931–2010). More precisely, winter (Nov-Apr) maximum precipitation sum over three successive days (RR3max) increased for the majority (72%) of our 25 stations with long term daily snow fall measurements, whereas only a minority (16%) of the stations show an increasing trend in HN3max (see section 5.2). More precisely, 78% of all the stations with an increasing RR3max show a decreasing HN3max. This result increases to 88% if we only consider the 10 stations with homogenized daily precipitation data. Namely, there is a known inhomogeneity in the precipitation data, since the measurement procedure changed from manual to automatic at most of the stations in the 1980's. This caused an artificial decrease of the measured winter precipitation of about 5–6% (Begert et al. 2005), which can mask the trend of increasing winter precipitation. The decrease in HN3max and the concurrent increase in RR3max are in agreement with a decrease in snow days (Scherrer et al. 2004; Marty 2008) and with a decrease in the snow/rain ratio (Serquet et al. 2011). Therefore, a possible explanation for the increasing winter RR3max and the concurrent decrease in HN3max at the majority of the stations is an increase in the snow/rain ratio due to increasing temperatures. As snowfall is known to be under-caught by precipitation gauges (Yang et al. 1999; Fuchs et al. 2001; Goodison et al. 1998) at least part of the increase in RR3max is caused by an increase in fluid precipitation at the cost of solid precipitation.

Another finding of this study is the decreasing spread of HSmax (and to a lesser extent of HN3max) at mid and high altitudes. Decreased variance in Switzerland was also found by Beniston and Goyette (2007), but for annual maximum and minimum temperatures. To our knowledge, this is the first time that a decreasing trend in the variance of extreme precipitation has been found.

Last but not least, the trends revealed in this paper for HSmax and HN3max are only significant for about half of the stations and one could argue that it may be dangerous to conclude that climate change has already affected extreme snow depth and extreme snow fall in Switzerland. However, trends in extreme snow fall and snow depth have also been found in other parts of the world, although not on the basis of extreme value theory. Decreasing trends have been found for example in the snow abundant regions of Japan (Ishizaka 2004), in the US (Kunkel et al. 2009) and in the southern regions of Scandinavia (Hyvärinen 2003). Other studies, on the contrary, observed increasing trends of long-term snow depth on the high plateau of Tibet (Yang et al. 2007) and in northern Scandinavia (Hyvärinen 2003; Kohler et al. 2006), due to increasing snowfall. We claim that the non significance of the trends obtained in this study for half the stations is mainly due to the large decadal variability of extreme snow depth and snow fall in the Swiss Alpine region. However, this is already an indication that extreme snow depth and snow fall may be decreasing, even if the decreasing pattern seems so far to be clearer for “average” snow events. The coming decade will show whether this observed decrease in HSmax and HN3max will become significant or not.

Similarly, a comparison of return levels obtained by NSGEV and the practical SGEV revealed significant differences for only 4 of 18 (22%) stations. One could thus conclude that it is so far unnecessary to modify the standard code of return level computation. However, 22% is not a negligible proportion. Our analysis could not clearly decide against or in favour of a systematic use of NSGEV in practice. This analysis shows for the first time evidence that climate change may be already impacting extreme snow depth and snow fall in Switzerland. We claim that this may only be the first signs of the effects of climate change and the coming decades may give a clearer answer.

7 Conclusions

Snow is a uniquely sensitive climate variable, which depends on temperature and precipitation at a variety of temporal and spatial scales. Our analysis of extreme snow depth and extreme snowfall based on the NSGEV with linear trends reveals that none of the stations, not even the highest one at 2,500 m asl, has experienced significant ($p<0.05$) increasing extreme amounts during the last 80 years.

Quite the contrary, almost half (44%) of the stations reveal a significantly decreasing trend of extreme snow depth. The other half showed no significant trends but this may be due to the high inter-annual variability and the relatively low number of data used in this study (80 values for each station). As the linear slopes of the NSGEV models were negative for all stations for HSmax, it can be concluded that all stations show decreasing tendencies for HSmax.

For extreme snow fall, the pattern is slightly less clear with 12% of the stations showing an increase, but not significant, and 88% showing a decrease (significant for 28% of all stations). For both, extreme snow depth and extreme snowfall, the stations with a significant decrease are mainly located below 1,000 m asl. Extreme snow events seems thus to disclose a similar temporal evolution as the mean number of snow days or the mean snow depth. Their reduction is mainly caused by a reduction in the magnitude of the extreme events. The decrease in extreme snowfall and the already observed concurrent increase in extreme winter precipitation can be explained by a decreasing snow/rain ratio due to warmer winter temperatures. In contrast to the low-altitude stations, the decreasing extreme snow depths above about 1,500 m are surprisingly rather caused by a reduction of the spread than a reduction in the magnitude of the extremes. For extreme snowfall, the pattern at mid- and high-altitude is less clear and the decrease can also be due to a reduction in the magnitude.

The NSGEV proved to be a good tool to investigate the impact of changing extremes on the return period or return level. The NSGEV models we considered are simple but can already bring to light a decreasing tendency of extreme snow depth and snow fall. Our results demonstrate that the 100-year return level of HSmax and HN3max decreased on average by about 15% during the last 80 years, although inter-station variability is high (largest decrease is 55%). Investigations on other return levels revealed very similar decreases. However, the 100-year return levels estimated by the NSGEV seem to differ significantly from the stationary ones for only 4 of 18 (22%) stations. For the majority of the stations, using one or the other method has thus little influence. Nevertheless, the proportion of 22% is not negligible and, with the expected warming, NSGEV might in the future be the most appropriate method to be used for the estimation of realistic return levels.

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References

Akaike H (1974) A new look at the statistical model identification. Automat Contr IEEE Trans 19(6):716–723

Begert M, Schlegel T, Kirchhofer W (2005) Homogeneous temperature and precipitation series of Switzerland from 1864 to 2000. Int J Climatol 25(1):65–80

Beguería S, Angulo-Martínez M, Vicente-Serrano SM, López-Moreno JI, El-Kenawy A (2010) Assessing trends in extreme precipitation events intensity and magnitude using non-stationary peaks-over-threshold analysis: a case study in northeast Spain from 1930 to 2006. Int J Climatol:n/a-n/a. doi:10.1002/joc.2218

Beniston M, Goyette S (2007) Changes in variability and persistence of climate in Switzerland: exploring 20th century observations and 21st century simulations. Glob Planet Change 57(1–2):1–15

Beniston M, Stephenson D, Christensen O, Ferro C, Frei C, Goyette S, Halsnaes K, Holt T, Jylhä K, Koffi B, Palutikof J, Schöll R, Semmler T, Woth K (2007) Future extreme events in European climate: an exploration of regional climate model projections. Clim Chang 81:71–95. doi:10.1007/s10584-006-9226-z

Blanchet J, Davison AC (2010) Spatial modelling of extreme snow depth. Annals of Applied Statistics, Under revision

Blanchet J, Lehning M (2010a) Mapping snow depth return levels: smooth spatial modeling versus station interpolation. Hydrol Earth Syst Sci 14(12):2527–2544. doi:10.5194/hess-14-2527-2010

Blanchet J, Lehning M (2010b) Mapping snow depth return levels: smooth spatial modeling versus station interpolation. Hydrol Earth Syst Sci Discuss 7(4):6129–6177. doi:10.5194/hessd-7-6129-2010

Blanchet J, Marty C, Lehning M (2009) Extreme value statistics of snowfall in the Swiss Alpine region. Water Resour Res 45:12. doi:10.1029/2009wr007916

Bocchiola D, Medagliani M, Rosso R (2006) Regional snow depth frequency curves for avalanche hazard mapping in central Italian Alps. Cold Reg Sci Tech 46(3):204–221

Bocchiola D, Janetti EB, Gorni E, Marty C, Sovilla B (2008) Regional evaluation of 3 day snow depth for avalanche hazard mapping in Switzerland. Nat Hazards Earth Syst Sci 8(4):685–705

Brown SJ, Caesar J, Ferro CAT (2008) Global changes in extreme daily temperature since 1950. J Geophys Res 113(D5):D05115. doi:10.1029/2006jd008091

Chavez-Demoulin V, Davison AC (2005) Generalized additive modelling of sample extremes. J Roy Stat Soc C Appl Stat 54(1):207–222. doi:10.1111/j.1467-9876.2005.00479.x

Coles S (2001) An introduction to statistical modeling of extreme values. Springer

Cooley D (2009) Extreme value analysis and the study of climate change. Clim Chang 97(1):77–83. doi:10.1007/s10584-009-9627-x

Durand Y, Giraud G, Laternser M, Etchevers P, Merindol L, Lesaffre B (2009) Reanalysis of 47 years of climate in the French Alps (1958–2005): climatology and trends for snow cover. J Appl Meteorol Clim 48(12):2487–2512

Falarz M (2008) Changes in extreme nival conditions in Poland during the second half of the 20th century. Meteorol Z 17:339–344

Fisher RA, Tippett LHC (1928) Limiting forms of the frequency distribution of the largest and smallest member of a sample. Proc Cambridge Phil Soc 24:180–190

Frei C, Schöll R, Fukutome S, Schmidli J, Vidale PL (2006) Future changes of precipitation extremes in Europe. J Geophys Res 111. doi:10.1029/2005JD005965

Fuchs T, Rapp J, Rubel F, Rudolf B (2001) Correction of synoptic precipitation observations due to systematic measuring errors with special regard to precipitation phases. Phys Chem Earth Part A Hydrol Ocean Atmos 26(9):689–693

Goodison BE, Louie PYT, Yang D (1998) WMO solid precipitation measurement intercomparison. Instruments and observing methods, vol 76. WMO, Geneva

Hegerl GC, Hanlon H, Beierkuhnlein C (2011) Climate science: elusive extremes. Nat Geosci 4(3):142–143

Hundecha Y, St-Hilaire A, Ouarda TBMJ, El Adlouni S, Gachon P (2008) A nonstationary extreme value analysis for the assessment of changes in extreme annual wind speed over the Gulf of St. Lawrence, Canada. J Appl Meteorol Clim 47(11):2745–2759. doi:10.1175/2008JAMC1665.1

Hyvärinen V (2003) Trends and characteristics of hydrological time series in Finland. Nord Hydrol 34(1–2):71–90

IPCC (2007) Climate change 2007: synthesis report. Contribution of working groups i, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC, Geneva

Ishizaka M (2004) Climatic response of snow depth to recent warmer winter seasons in heavy-snowfall areas in Japan. Ann Glaciol 38:299–304

Katz RW (2010) Statistics of extremes in climate change. Clim Chang 100(1):71–76. doi:10.1007/s10584-010-9834-5

Klein Tank AMG, Können GP (2003) Trends in indices of daily temperature and precipitation extremes in Europe, 1946–1999. J Clim 16(22):3665–3680. doi:10.1175/1520-0442(2003)016<3665:TIIODT>2.0.CO;2

Kohler J, Brandt O, Johansson M, Callaghan T (2006) A long-term Arctic snow depth record from Abisko, northern Sweden, 1913–2004. Polar Res 25(2):91–113

Kunkel KE, Palecki MA, Ensor L, Easterling D, Hubbard KG, Robinson D, Redmond K (2009) Trends in twentieth-century U.S. extreme snowfall seasons. J Clim 22(23):6204–6216. doi:10.1175/2009JCLI2631.1

Laternser M, Schneebeli M (2003) Long-term snow climate trends of the Swiss Alps (1931–99). Int J Climatol 23(7):733–750. doi:10.1002/joc.912

Leadbetter MR, Lindgren G, Rootzen H (1983) Extremes and related properties of random sequences and processes. Springer, New York

Maraun D, Rust H, Osborn T (2010) Synoptic airflow and UK daily precipitation extremes. Extremes 13(2):133–153. doi:10.1007/s10687-010-0102-x

Marty C (2008) Regime shift of snow days in Switzerland. Geophys Res Lett 35. doi:10.1029/2008GL033998

Scherrer SC, Appenzeller C (2006) Swiss Alpine snow pack variability: major patterns and links to local climate and large-scale flow. Clim Res 32(3):187–199

Scherrer SC, Appenzeller C, Laternser M (2004) Trends in Swiss Alpine snow days: the role of local- and large-scale climate variability. Geophys Res Lett 31. doi:10.1029/2004GL020255

Schmidli J, Frei C (2005) Trends of heavy precipitation and wet and dry spells in Switzerland during the 20th century. Int J Climatol 25:753–771

Serquet G, Marty C, Dulex J-P, Rebetez M (2011) Seasonal trends and temperature dependence of the snowfall/precipitation-day ratio in Switzerland. Geophys Res Lett 38(7):L07703. doi:10.1029/2011gl046976

Valt M, Cianfarra P (2010) Recent snow cover variability in the Italian Alps. Cold Reg Sci Tech In Press, Accepted Manuscript

Yang D, Elomaa E, Tuominen A, Aaltonen A, Goodison B, Gunther T, Golubev V, Sevruk B, Madsen H, Milkovic J (1999) Wind-induced precipitation undercatch of the Hellmann gauges. Nord Hydrol 30 (1):57–80

Yang J, Ding Y, Liu S, Liu J-F (2007) Variations of snow cover in the source regions of the Yangtze and Yellow Rivers in China between 1960 and 1999. J Glaciol 53:420–426