Supplementary material on assumptions, data bases and updates on data bases. The references are listed in the main paper: Probabilistic estimates of extreme snow avalanche runout distance by DM McClung and Peter Höller.

Assumptions for the method used

The RR method employed here for comparing data sets contains three implicit assumptions which are mostly justified by the results. The first assumption is, that a mountain range is a suitable unit to define a population. It is shown below that the results are quite different from range to range. For example, there is a stark difference between results collected in COLORADO versus CANADA and the differences are primarily related to terrain scales. Second, it is assumed the extreme position reached by avalanches on a path can be located in an unbiased manner for typical time scales of about 100 year return period which are appropriate for most of the data here. For this paper, the return period is defined as the average time between which events reach or exceed a given location. The location condition is largely satisfied by the group of experienced people who collected the data. By human experience with avalanches, paths which could not confidently be seen to fulfill the condition were rejected from use. Published records are available for the European data bases and estimated forest cover damage seeking trees of ages several hundred years old were used for most of the data from North America. A third assumption is that the choice of the β is a good reference from which to scale runout distances. This was originally shown in [3] as they tested other reference positions and it has been shown by other people (e.g.[8, 13]) . Most importantly, it has been shown for many data sets worldwide, including the data sets in this paper, by strong correlation of α with β. The reason α correlates well, on average, with β is that extreme flowing avalanches tend to stop around a 10^0 slope

angle. Very few extreme avalanches stop on slopes above 10^0, thus, the data show that the β point is a good reference to gauge runout distance from.

In addition to the implicit assumptions above, it is reasonable to demand attention to the normal conditions demanded for data for application of a statistical model as for example in stream flow analysis. However, the problem addressed here is quite different than most problems in flood hydrology. The data analyzed here are already extreme values for a set of avalanche paths not like stream flow data to predict the maximum (extreme) at a given location. The usual conditions for flood frequency analysis are [40], randomness, independence, homogeneity and stationarity. The criteria are described in Table S1 for the problem here.

Table S1: Basic assumptions and explanation.

Criterion	Explanation
Randomness	The fluctuations of the variable arise from natural causes. This would be satisfied since human intervention such as explosive control was not a factor for the events registered.
Independence	The events here are from different paths so independence is expected. Even the historical long running events on a single path should be independent.

Homogeneity	All data from a given data set (range) originate from a population in a single snow climate regime and all will be from release of natural snow slab avalanches.
Stationarity	Stationarity means that, excluding random fluctuations, the data series is invariant with respect to time. Given that climate change is expected, information on possible effects of climate change are discussed below.

Effects of stationarity of distributions in relation to possible climate change

Climate is the average weather at a place. Individual snow avalanche events, including extreme ones, respond to weather (including snow conditions) not climate. However, the average conditions, including runout distances, can change as the climate changes.

In [6], analysis was provided for snow avalanche runout from the perspective of altitude reached not runout distance. They analyzed 19,660 avalanches from 2725 paths in France over 61 (1946 – 2006) winters of data. Of these events, 17%, on average, reached the valley floor (termed high magnitude avalanches). If averaged over the two data intervals considered (1946 – 1975; 1976 – 2006), the median fraction of avalanches reaching the valley floor is about the same as 0.17 [6]. From 1946 – 1975 there was basically no trend. However, from 1976 -2006 there was a steady decline in the median % reaching the valley floor. A linear regression (time trend) line

($R^2 = 0.72;\ S.E. = 0.31$) using the median yearly values for 1976-2006 in [6] gave a strong downward trend. The Spearman rank correlation coefficient between the median yearly fraction reaching the valley floor over the period versus time in (31) years since 1975 was $r_s = -0.86$ with significance $p = 5x10^{-10}$. In this paper, the t-statistic was calculated by: $t = r_s\sqrt{(N-2)/\left(1-r_s^2\right)}$ where $N-2$ is the number of degrees of freedom. The values of p were then calculated from the t-statistic and $N-2$ [29]. The linearized trend regression line implies a median of about 1:4 avalanches reached the valley floor in 1976 versus about 1:15 by 2006. On the other hand, during the period from 1976 – 2006, 13 of 31 (42%) years had a yearly median value which exceeded the long term average trend (0.17) and in 17 years (55%) the percentage reaching the valley floor equaled or exceeded the long term trend. Since extreme avalanche runout distance was not reported it is not possible to say whether these data imply anything in relation to the current study which applies mostly to extreme events of time scale about 100 years. The study was extended [39] by adding 3 more winters with from 2007- 2009 with 50,199 avalanches. The results were basically unchanged assuming a linear trend line through the data. The linear trend of the 2013 analysis predicted about 1:4 avalanches reached the valley floor around 1976 with about 1:15 predicted in 2009- 2010.

A study based on about 25,000 avalanche events from (1980 -2010) in British Columbia [41] comparing El Niño and La Niña may have some relevance to climate change. In British Columbia, El Niño implies less snow and warmer conditions compared to La Niña. Thus, El Niño may be closer to conditions under climate change. The study showed that there was a decrease in number of avalanches during El Niño compared to La Niña as expected for lower snow supply. However, the increase in avalanches during La Niña was mostly caused by smaller

avalanches (D2) on the Destructive Scale [25] but no change was estimated for larger events $\geq D3$.

Since avalanches, including extreme avalanches, respond to weather (including snow conditions) not climate, the use of the data here as approximately stationary would depend on how often the extreme conditions would be repeated over a time scale of 100 years or more which is unknown. If observations are carried out over 100 years would the extreme conditions appear again? Balanced against that, would be the chance of observing a 100 year event in 100 years of observations. Assuming the extreme avalanches are rare, discrete, independent events, it would seem permissible to assume that they follow a Poisson distribution. For a Poisson distribution, the encounter probability [37] of at least on event at a place with a return period 100 years over 100 years of observation is 0.63. For the study in [39] by with 64 years of record, the chance of at least one event at a place with a return period 100 years would be 0.47 and for the 34 years from 1976- 2009, over which the change was postulated, it would be 0.29.

A study in 1997 [42] contained a review of avalanche data and information in Switzerland from 1500 – 1990. They showed that until 1870 only descriptive information is available. It is only since about 1940 that data with significant quality are available. From 1890 -1990, they identified 15 winters as large damage avalanche years. In conclusion, in spite of climate change, there are no high quality data sets on extreme runout regarding a changed frequency of extreme events. The disastrous winters of 1950-51 and 1998-99 in the Alps suggest that the extreme conditions still appear. For 1998-99, the study in [6] showed that the median percentage of avalanches reaching the valley floor was about 0.17 which was the long term average. Even though numerous extreme avalanches were reported during that year in the Alps [26] [12 deaths

in France; 12 in Switzerland; 39 in Austria], the median percentage reaching the valley floor in France during that year (Eckert et al., 2010) is not remarkable. In [43] a similar conclusion was reached based on runout altitude data that there is no clear evidence yet that long term or extreme events are affected by climate change. In {44], data were analyzed from 50 years (1951-2001) of records in Switzerland and were unable to detect a change in avalanche activity. In [45], it was concluded concluded that there were no changes in the number of catastrophic avalanches around Davos, Switzerland during the 20th century. In [46],) 9 major avalanche cycles were found in the Alps with fatalities associated with facilities between 1950-51 and 1998-99.

In [47], information was reviewed for effects of climate change on snow avalanche activity. They provided information on average conditions related to avalanche runout as cited above but they did not provide information on the effect of runout for extreme events which is the focus of this paper. Instead, they suggested that future research should focus extreme weather, snow and avalanche conditions and how they are affected by climate change. Our field experience has shown that extreme avalanche runout depends not only on a large amount of snow but also on the condition of the surface over which avalanches run. Since prediction of extreme avalanche runout will require a model [11], any changes to account for climate change would probably require adjustment of the exceedance probability or return period used rather than invalidation of the data bases of extreme avalanche runout which, at present, there is no information on.

The data in the present paper represent information on extreme avalanche runout distance for typical time scales of 100 years. The use of altitude data such as the valley floor [6, 39] instead of distance to make inferences about extreme avalanche runout is not very useful. The median

runout distances of extreme avalanches past the β point are typically 200 m (Table 1 of the paper) but the values range as high as 1430 m for the data here.

Update on data bases

All data used were analyzed using the reference β point where the slope angle first reaches 10^0 proceeding downslope from the start position as defined in [3]. The data from western Norway (NORWAY) were described in [3, 19, 15, 23]. The data from the Sierra Nevada, California (SIERRA), Coastal Alaska (ALASKA), the Colorado Rockies (COLORADO) and the Canadian Rockies and Purcell Ranges (CANADA) were presented in [15]. The data from AUSTRIA were reported in [48] which is an internal report from the Torrent and Avalanche Control Service in Innsbruck, Austria and a paper in 1995 [49]. We have also included a SHORT SLOPE data set [8,9] from several ranges in western Canada specifically collected for short avalanche paths with $H \leq 350$ m .FOREST is a data set for penetration of avalanches from harvested terrain (clear cuts) into forest cover described in [24, 50]. The data from ICELAND were described in [22]. The data from Austria were obtained from Mr. Neuner of the Torrent and Avalanche Control Service in Innsbruck, Austria in `1999 and presented in [48 – 49]. The Austrian data contained 80 values each of α, β and map coordinates of the β point and estimated end position of the tip of the dense part of the flowing avalanches. The reported data had distance values to the nearest meter with α , β represented by calculated values. The information included description of the avalanche events, maps of scale 1:5000 and 1:25000 as well as photos. The data included map coordinates of the β point and the position of the tip of the avalanche debris as well as, in many cases, the coordinates of the reach of the powder component of the flow. In the calculations here, the data were used for the tip of the dense avalanche debris with considerations of the avalanche

powder cloud excluded. For the calculations here, 79 values of the data set were retained. One event was eliminated because it implied negative runout distance and it was not in the received (modified) version of the 1994 report of [48]. The reported data for the vertical fall height, H and X_β,for all 79 events were taken from [48].

The data from Norway were supplied by S. Bakkehøi from the Norwegian Geotechnical Institute. They included only the angles: α, β, δ to the nearest degree. The RR were calculated from equation 1. In the calculations reported in this paper, there were missing data from Norway including $\Delta x, H, X_\beta$ which are described as N/A: not available.

For land-use planning, it is common practice to use the expected return period to delineate zones. The return period is the average time between which events reach or exceed a location. For many of the data here, there are no recorded avalanche events so it is not possible to accurately specify return periods for the paths. Such is a common case in consulting applications. In [3], it was suggested that the data from NORWAY represent approximately 100 year return period on average. It was suggested [15] that for data from CANADA, SIERRA, COLORADO, ALASKA, return periods may have roughly varied between 50 – 300 years with a mean of about 100 years. For the data from ICELAND it was suggested [22] they had average return period of about 100 years. The data from ICELAND contained 20 of 45 avalanche paths which terminated in the sea so that some of the extreme positions recorded are slightly shorter than the real ones. It has been suggested [48] that the data from AUSTRIA vary with return periods 50 – 350 years. The SHORT SLOPE data most likely had an average return period of about 50 years [8] varying between 30 -100 years. In [9], the authors reported on 46 values of the RR. The data set received

from A.Jones contained 47 values which were used in this paper. The SHORT SLOPE data base included values of $\Delta x, X_\beta$ which were used to calculate the RR in this paper.

The forest penetration data set: FOREST has no approximate return period specified but it consists of single very large events penetrating and damaging forest cover from harvested terrain. Of the 45 forest penetration events, 43 were of size 3 or greater on the Destructive Size Scale and 11 were of size 4 or greater on the Destructive Size Scale [25, 51]. The data set used in this paper represents one which was slightly corrected by D. McClung and G. Anderson using field notes. Thus, the data base used here is slightly different than in the paper [50] published in 2012.

For most cases, the terrain field data were collected during a snow free time so the data were not associated with specific individually recorded events during a winter period. The extreme runout positions for data from NORWAY, ICELAND and AUSTRIA were determined by published records or vegetative damage. The remainder of the extreme runout position data (USA and Canada) were collected by examining vegetative damage.

The positions of the β points for the data from USA and Canada were measured using an inclinometer with an accuracy to the nearest 1^0. For NORWAY, ICELAND and AUSTRIA, the β points were determined either from maps (scale 1:5000) or measured with an inclinometer to the nearest degree. For ICELAND, fits to points surrounding the β point using high quality maps to determine where the slope was 10^o for β point definition. For ICELAND, paths with an abrupt transition above and below slope angles of 10^o, the β point was taken at the transition point [22]. In [52] a discussion of the errors in determining β points comparing field measured values to the spatial resolution of Digital Elevation Models (DEM) in computer mapping was

presented. The comparison showed that for DEMs with spatial resolution or contour intervals between 1m (laser terrain model: 7 paths) and 15 m - 30 m DEM (23 paths), the median difference was 0.8% of X_β which would imply 8 m on a 1000 m horizontal reach path but with ranges up to about 2% of X_β. GIS models [12, 13] as well as machine learning techniques [14] represent the future in collection of data for statistical analysis of runout. In [52], it was pointed out that use of DEM requires judgement as does field determination and that field checking is still very important.

The δ angles for the data from USA and Canada were measured in the field with an inclinometer or determined from high quality maps. The δ angles for data from NORWAY and ICELAND were determined from high quality maps. The δ values from AUSTRIA were determined from the map coordinates of the β points and end position of the dense debris in [48].

All data in this paper may be considered of high quality. Runout positions found in the field by experienced people are as accurate as possible (COLORADO, SIERRA, ALASKA, CANADA, SHORT SLOPE, FOREST) and similarly from known positions registered historically (NORWAY, ICELAND, AUSTRIA). For the data from ICELAND, some had runout which ended in the ocean [22] which limits accuracy for determining the position of α. No result or conclusion of this study would be affected by eliminating the data set from ICELAND. As with any data set there will be errors but the large number of events in our data sets should reduce them.

Table of the 65 distributions used in the calculations: Probabilistic estimates of extreme snow avalanche runout distance by David McClung and Peter Hoeller. The Table includes the distribution name and number of parameters in parentheses.

Distribution number	Distribution and number of parameters
1	Beta (4)
2	Burr (3)
3	Burr (4)
4	Cauchy (2)
5	Chi-squared (1)
6	Chi-squared (2)
7	Dagum (3)
8	Dagum (4)
9	Erlang (2)
10	Erlang (3)
11	Error (3)
12	Error Function (1)
13	Exponential (1)
14	Exponential (2)
15	Fatigue Life (2)
16	Fatigue Life (3)
17	Frechet (2)
18	Frechet (3)
19	Gamma (2)
20	Gamma (3)
21	Gen. Extreme Value (3)

22	Gen. Gamma (3)
23	Gen. Gamma (4)
24	Gen. Logistic (3)
25	Gen. Pareto (3)
26	Gumbel Max. (2)
27	Gumbel Min. (2)
28	Hypersecant (2)
29	Inv. Gaussian (2)
30	Inv. Gaussian (3)
31	Johnson SB (4)
32	Kumaraswamy (4)
33	Laplace (2)
34	Levy (1)
35	Levy (2)
36	Log-Gamma (2)
37	Log-Logistic (2)
38	Log-Logistic (3)
39	Log-Pearson 3 (3)
40	Logistic (2)
41	Lognormal (2)
42	Lognormal (3)
43	Nakagami (2)
44	Normal (2)

45	Pareto (2)
46	Pareto 2 (2)
47	Pearson 5 (2)
48	Pearson 5 (3)
49	Pearson 6 (3)
50	Pearson 6 (4)
51	Pert (3)
52	Phased Bi-Exponential (4)
53	Phased Bi-Weibull (6)
54	Power Function (3)
55	Rayleigh (1)
56	Rayleigh (2)
57	Reciprocal (2)
58	Rice (2)
59	Student’s t (1)
60	Triangular (3)
61	Uniform (2)
62	Wakeby (5)
63	Weibull (2)
64	Weibull (3)
65	Johnson SU (4)