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Weak precipitation, warm winters and springs impact glaciers of south slopes of Mt. Everest (central Himalaya) in the last two decades (1994–2013)

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Supplementary Material 1

Reconstruction methods of the daily temperature and precipitation time series at Pyramid station (5035 m a.s.l.)

In the following, we describe the missing daily data reconstruction performed on daily T (minimum, maximum, and mean) and Prec time series collected at Pyramid (5035 m a.s.l.) for the 1994-2013 period. As already mentioned in the main text, we consider AWS1 as the reference station (REF) for the reconstruction, which has been operating continuously from 2000 to the present. This station replaced AWS0 (1994-2005). These two stations have a recorded percentage of missing daily values of approximately 20% over the last twenty years (Table 1). The other five stations (ABC, AWSKP, AWS2, AWSN and AWS3) taken into account for the reconstruction process will be referred to as secondary stations.

The time series reconstruction process considers four steps:

1) Pre-processing of data
2) Infilling method
3) Multiple imputation technique
4) Monthly aggregation of data

Step 1 – Pre-processing of data

Table 1 shows the sampling frequency of stations (ranging from 10 minutes to 2 hours). After an accurate data quality control according to Ikoma et al., 2007, a daily aggregation of the time series (temporal homogenization) is performed. Daily data have been computed only if the 100% of sub-daily data are available; otherwise, it is considered missing. These rules ensure a maximum quality of daily values with a loss of information limited to the first and last day of the failure events.

Step 2 – Infilling method

The selected daily infilling method is based on a quantile mapping regression (e.g. Déqué 2007). This method estimates a rescaling function *F* between two time series. This function ensures that the daily cumulated density function (cdf) of a secondary station reproduces the daily cdf of the REF over their over their common observation period. Applying the inverse function (F^{-1}) to each secondary station, a new time series is computed for each of them. In the following, these new time series with the systematic bias corrected are indicated as '*' (e.g., AWS0*, ABC*). In our case the bias is mainly due to the altitude gradient, all stations being located along the same valley (Fig. 1b).

A new time series (REF_filled) has been created merging REF and the * time series according to a priority criterion based on the degree of correlation among data (Fig. S1). The specific rules of computing are described below:

- all available data of REF are maintained in the final reconstruction without any further processing;

- the priority criterion for infilling is based on the magnitude of correlation coefficient (*r*) between REF and each secondary station, for each variable (Table S1); In case the daily data of the secondary station with higher *r* is missing the station with the slight lower r is selected.

We can observe from Table S1 that AWS0, located few tens of meters far from REF, presenting *r* = 0.99 and r = 0.97 for temperature and precipitation, respectively, has been the first choice. The 82% of missing daily values of temperature and 72% of precipitation are filled using the AWS0*. The second choice is ABC. Together these two stations cover more than the 90% of missing values; the whole infilling procedure allows for filling the 86% and the 91% of the overall missing values of temperature and precipitation, respectively.

Table S1. Correlation coefficients (r) between the reference station (REF) and the other secondary stations for temperature and precipitation. Furthermore the table reports the number of daily data (n) that each station has provided to the reconstruction of the time series.

Stations	Temperature		Precipitation	
	r	*n*	*r*	*n*
AWS0	0.99	2,144 (82.2%)	0.97	2,298 (72.2%)
ABC	0.98	254 (9.7%)	0.84	646 (20.3%)
AWSKP	0.96	48 (1.8%)	0.62	13 (0.4%)
AWS2	0.94	95 (3.6%)	0.81	145 (4.6%)
AWSN	0.92	66 (2.5%)	0.56	78 (2.5%)
AWS3	0.87	0 (0.0%)	0.53	3 (0.1%)
Total infilled missing values		2,607		3,183

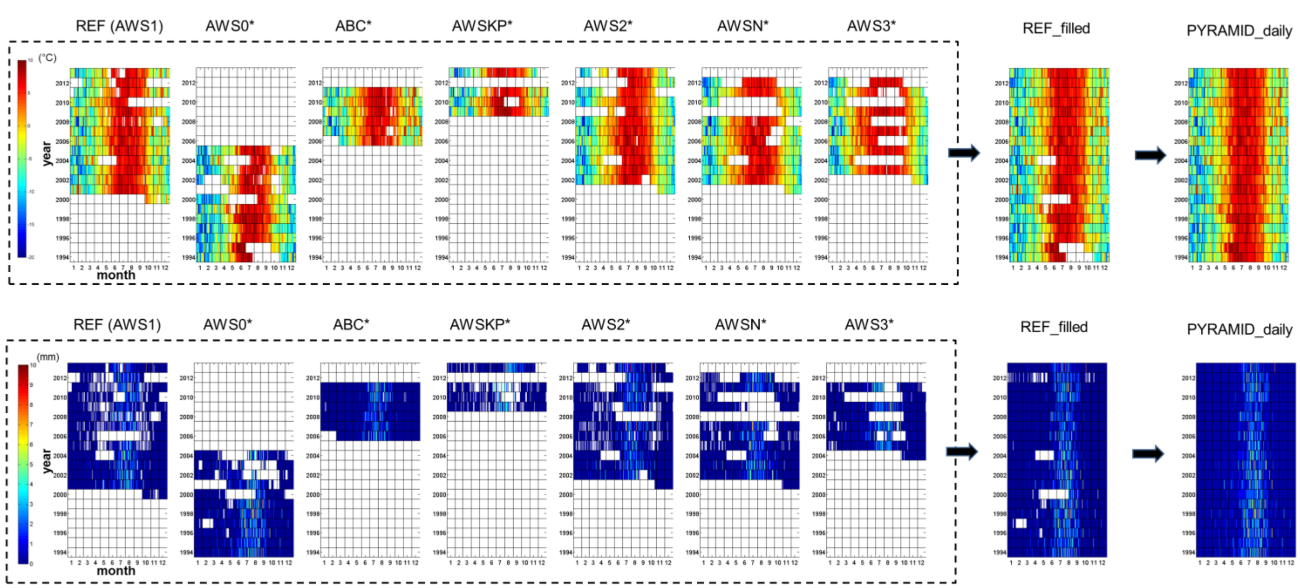

Figure S1. Scheme followed for the infilling process. Upper panel: daily mean temperature. Lower panel: precipitation. On the left, for each station, the daily data availability and the re-computed *values, according to the quantile mapping procedure, are shown. On the right, a new time series (REF_filled) is created by merging REF (reference station) and the * time series, according to a priority criterion described in the text. In case all stations recorded some simultaneous gaps, a multiple imputation technique is applied to obtain the PYRAMID_daily time series.*

The uncertainty associated with REF_filled (σ_{REF_filled}) time series derives from the quantile mapping procedure and in particular from the miss-correlation and possible non stationarity in the quantile relationship.

In order to estimate the σ_{REF_filled}, the probability distribution of the residues between REF and *time series is considered. In order to take into account the possible seasonal variability of the uncertainty, residues have been analyzed on monthly basis.

The Kolmogorov-Smirnov test (Massey, 1951), applied to distribution of the residues, verifies their normality. As a consequence, the daily uncertainty σ_{REF_filled} is estimated as the standard deviation of the residues. The estimated daily uncertainties are reported in Table S2.

Table S2. Daily uncertainty (expressed as °C and mm for temperature and precipitation, respectively) for each station associated with the daily data infilled through the quantile mapping regression.

Minimum Temperature (minT)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
AWS0	0.95	0.98	0.72	0.65	0.49	0.48	0.29	0.35	0.49	0.77	1.09	0.86
ABC	0.82	0.79	1.6	1.29	0.9	0.58	0.66	0.45	0.56	1	0.87	0.89
AWSKP	1.41	1.3	2.25	1.62	1.54	0.84	0.84	0.71	0.65	1.29	1.18	1.61
AWS2	2.06	2.09	2.11	1.85	1.49	1.11	0.88	0.78	0.99	1.99	2.15	1.87
AWSN	2.8	2.44	1.98	1.3	1.14	0.81	0.62	0.72	0.79	1.89	2.95	2.96
AWS3	3.18	2.48	2.35	1.33	1.31	1.25	0.82	0.8	0.88	2.02	3.39	3.23

Maximum Temperature (maxT)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
AWS0	0.81	0.9	0.71	1.05	0.65	0.75	0.63	0.61	0.71	1.02	0.74	1.43
ABC	0.61	0.92	1.68	1.2	1.53	1	1.07	0.65	0.75	0.77	0.65	0.62
AWSKP	1.4	1.91	2	1.58	2.12	1.31	1.02	1.07	0.8	1.21	1.49	1.35
AWS2	2.2	2.05	2.07	1.71	1.62	1.13	1.06	0.99	1.12	1.47	1.91	1.9
AWSN	3.41	3.04	2.89	2.25	2.06	1.84	1.42	1.3	1.39	2.14	3.31	3.26
AWS3	4.08	4.11	3.99	2.68	2.6	2.55	2.2	2.23	2.62	3.11	4.15	3.91

Mean Temperature (meanT)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
AWS0	0.56	0.7	0.57	0.24	0.28	0.29	0.24	0.24	0.27	0.46	0.45	0.5
ABC	0.34	0.32	1.46	1.02	0.96	0.54	0.72	0.41	0.36	0.59	0.46	0.4
AWSKP	0.91	0.74	2.08	1.3	1.29	0.82	0.58	0.52	0.47	0.94	1.07	1.4
AWS2	1.8	1.88	1.71	1.38	1.1	0.66	0.5	0.43	0.57	1.56	1.88	1.53
AWSN	2.78	2.43	1.85	1.17	1.03	0.69	0.56	0.54	0.64	1.78	2.79	2.83
AWS3	3.09	2.44	2.43	1.41	1.25	1.15	0.75	0.79	1.03	1.91	3.16	3.06

Precipitation (P)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
AWS0	0.68	0.22	0.43	0.99	0.61	0.72	1.34	0.93	0.61	0.29	0.38	0.04
ABC	0.02	0.03	0.07	0.28	0.52	1.17	1.91	3.42	1.49	0.1	0.19	0.04
AWSKP	0.27	0.42	0.46	1.04	0.79	1.62	2.79	2.8	1.97	2.09	0.09	0.19
AWS2	0.31	0.15	0.22	0.42	0.7	2.36	4.71	3.68	2.04	1.93	0.6	0
AWSN	0.42	0.66	0.69	1.1	1.19	2.2	5.41	5.13	3.07	1.41	0.27	0.8
AWS3	0.14	0.29	0.43	0.68	0.44	2.06	5.35	5.11	4.57	0.88	0.43	0.11

Step 3 – Multiple imputation technique

Unfortunately, all stations recorded some simultaneous gaps for a given variable: 5.7% and 4.3% for temperature and precipitation, respectively. For these cases, we applied a multiple imputation technique (the Regularized Expectation Maximization algorithm, RegEM; Schneider, 2001) to obtain the final PYRAMID_daily time series (Fig. S1).

This algorithm considers more available meteorological variables. In our case, we feed the procedure with the minimum, maximum and mean temperatures, precipitation, atmospheric pressure and relative humidity. The additional two variables (atmospheric pressure and relative humidity) allowed for a reduction of the estimated uncertainty associated with the computing of these missing data (σ_{RegEM}).

RegEM has been applied to the daily missing data on a monthly basis, considering the possible seasonal effect on the uncertainty. Table S3 reports the number of days imputed to the complete PYRAMID_daily time series for each month and for each variable. The daily standard error σ_{RegEM} estimated by the RegEM algorithm (Table S4) has been associated with each imputed data filled into the complete and final time series reconstructions for daily minimum, maximum, and mean temperatures and precipitation.

Table S3. Number of days imputed through RegEM

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
minT	0	1	1	35	87	48	68	71	60	33	10	0
maxT	0	1	1	35	87	48	68	71	60	33	10	0
meanT	0	1	1	35	87	48	68	71	60	33	10	0
Prec	13	31	14	52	99	48	31	9	1	9	4	0

Table S4. Uncertainty (°C and mm for temperature and precipitation, respectively) associated to the daily imputed thought RegEM

Variable	Jan	Feb	Mar	Apr	May	Jun	Jul	Ago	Sep	Oct	Nov	Dic
minT	-	3.25	2.89	2.34	2.21	1.95	0.83	0.96	1.37	2.54	2.46	-
maxT	-	3.64	3.22	2.82	2.47	1.87	1.34	1.31	1.44	2.30	2.55	-
meanT	-	3.20	2.82	2.34	2.07	1.58	0.72	0.84	1.16	2.17	2.29	-
p	0.18	0.35	0.65	0.86	0.93	2.73	4.54	4.51	2.73	1.59	0.69	-

Step 4- Monthly aggregation

Finally, the PYRAMID_daily time series, for each variable, have been aggregated on the monthly scale (hereinafter referred to as PYRAMID). The uncertainty associated with each value of the PYRAMID (named σ_{m}) is estimated considering the propagation of the daily uncertainty to the monthly one through the computation of the mean (for temperature) or of the sum (for precipitation).

The propagation of the uncertainty from the daily data d_i to the monthly one is different if we consider the monthly average M_m (as for temperature) or the monthly accumulation M_c (as for precipitation):

$$\sigma_m = \sqrt{\sum_{j=1}^{N}\left(\frac{\partial M_m}{\partial d_j}\cdot\sigma_{d_j}\right)^2} = \sqrt{\sum_{j=1}^{N}\left(\frac{\partial\left(\frac{1}{N}\sum_{i=1}^{N}d_i\right)}{\partial d_j}\cdot\sigma_{d_j}\right)^2} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\sigma_{d_j}{}^2} \quad (1)$$

where $M_m = \frac{1}{N}\sum_{i=1}^{N}d_i$

and

$$\sigma_m = \sqrt{\sum_{j=1}^{N}\left(\frac{\partial Mc}{\partial d_j}\cdot\sigma_{d_j}\right)^2} = \sqrt{\sum_{j=1}^{N}\left(\frac{\partial\sum_{i=1}^{N}d_i}{\partial d_j}\cdot\sigma_{d_j}\right)^2} = \sqrt{\sum_{j=1}^{N}\sigma_{d_j}{}^2} \quad (2)$$

where $M_c = \sum_{i=1}^{N}d_i$

N is the number of days of a given month and $\sigma_{d_j}$the daily uncertainty as :

$$\begin{Bmatrix} \sigma_{d_j} = 0 & if\ the\ data\ belongs\ to\ the\ REF \\ \sigma_{d_j} = \sigma_{REF\_filled} & if\ the\ data\ is\ imputed\ through\ infilling\ step \\ \sigma_{d_j} = \sigma_{RegEM} & if\ the\ data\ is\ imputed\ through\ RegEM \end{Bmatrix}$$

Finally, we estimated the uncertainty associated with the annual Sen's slopes (1994-2013) of each time series through a Monte Carlo uncertainty analysis (e.g., James and Oldenburg 1997):

- For each month value, a random realization of the normal distribution with zero-mean and σ_m standard deviation is computed.
- This uncertainty is added to each monthly estimate coming from eq. (1) or (2), obtaining a time series perturbed by the uncertainty.
- The Sen's slope and associated p-value is computed.
- The process is repeated until the convergence of the mean value of the Sen's slope and the associated standard deviation. In these regards, we observed that approximately 5000 runs are enough to ensure the convergence with a threshold of 10^{-5} °C a^{-1} and 10^{-3} mm a^{-1} for temperature and precipitation, respectively.

Table S5 reports the Sen's slopes for the 1994-2013 period calculated for each reconstructed monthly time series (PYRAMID), associated intervals of confidence (95%), median p-value and the associated [5% and 95%] quantiles.

Table S5. Sen's slopes for the 1994-2013 period calculated for each reconstructed monthly time series (PYRAMID), associated intervals of confidence (95%), median p-value and the associated [5% and 95%] quantiles.

Time series	Sen's slope	Interval of confidence (95%)	p-value	quantiles [5% and 95%]
PYRAMID minT	0.072 °C a^{-1}	+/- 0.011	0.0021	[0.0001-0.0212]
PYRAMID maxT	0.009 °C a^{-1}	+/- 0.012	0.7212	[0.2843-0.9741]
PYRAMID meanT	0.044 °C a^{-1}	+/- 0.008	0.035	[0.0053-0.1443]
PYRAMID Prec	-13.66 mm a^{-1}	+/- 2.36	0.0021	[0.0002-0.0252]

REFERENCES

Ikoma, E., K. Tamagawa, T. Ohta, T. Koike, and M. Kitsuregawa (2007), QUASUR: Web-based quality assurance system for CEOP reference data, *J. Meteorol. Soc. JPN.*, *85A*, 461-473.

Massey, F. J. (1951), The Kolmogorov-Smirnov Test for Goodness of Fit, *J. Am. Stat. Assoc.*, *46*(253), 68–78.

Supplementary Material 2

Further analysis on the non-stationarity of the reconstructed daily precipitation time series at Pyramid station

The analysis described in the following aims at assessing whether the decreasing trend of precipitation observed for the daily time series reconstructed at Pyramid (1994-2013) is due to a reduction of duration or to a reduction of intensity.

To this goal we considered two different periods *p*, say *p1* = 1994-1998 and *p2* = 2009-2013, which correspond to the first and last five years of the whole analysis period *p0* = 1994-2013. For a given week *w*, the mean weekly-cumulated precipitation RR_w^p is defined as $RR_w^p = \left(\sum_{y=1}^{N} RR_{w,y}\right)/N$, where *N* is the number of years during the period *p*.

The difference between the mean weekly-cumulated precipitation RR_w^{p1} and RR_w^{p2} may be attributed to a change in the corresponding duration and/or intensity. To separate the relative contributions, we defined two descriptors:

1-The duration of precipitation for a given week *w* of the year *y* is described by the number of wet days $W_{w,y}$, where a "wet day" is defined by the threshold RR>1 mm. Then, the mean W_w^p over a given period *p* of *N* years is computed as:

$$W_w^p = \frac{1}{N}\sum_{y=1}^{N} W_{w,y} \qquad (1)$$

2- The daily intensity of precipitation for a given week *w* of the year *y* is computed as the cumulative precipitation $RR_{w,y}$ divided by the number of wet days $W_{w,y}$. Then, a mean intensity index $SDII_w^p$ over a given period *p* of *N* years is computed as:

$$SDII_w^p = \frac{1}{N}\sum_{y=1}^{N} \frac{RR_{w,y}}{W_{w,y}} \qquad (2)$$

An attempt to quantify the contribution to the variation in precipitation arising from variation in duration and/or intensity is to consider one of the two terms stationary over the whole period. This is a rough approximation as the non-stationarity may not be linear. However, an estimation of the relative contribution arising from the change in duration can be expressed considering the intensity of precipitation as stationary over the whole period p0 ($SDII_w^{p0}$) and computing the variation of precipitation due only to a variation in duration, i.e. $(W_w^{p2} - W_w^{p1}) * SDII_w^{p0}$. The relative contribution RLD to the total change $(RR_w^{p2} - RR_w^{p1})$ can be estimated as:

$$RLD = \frac{(W_w^{p2} - W_w^{p1}) * SDII_w^{p0}}{(RR_w^{p2} - RR_w^{p1})} * 100 \qquad (3)$$

The indexes proposed above are shown in figure S6 in dark blue area for the 1994-1998 period and light blue area for the 2009-2013 period for the W_w^p, $SDII_w^p$ and RR_w^p (panel a, b and c respectively). For each index, we defined as residues the difference between the two periods (red bar plot).

The *RLD* (shown in red on the right axis of the panel c) indicates that the early and late monsoon are more affected by the reduction in duration than intensity, while it is the opposite during the monsoon.

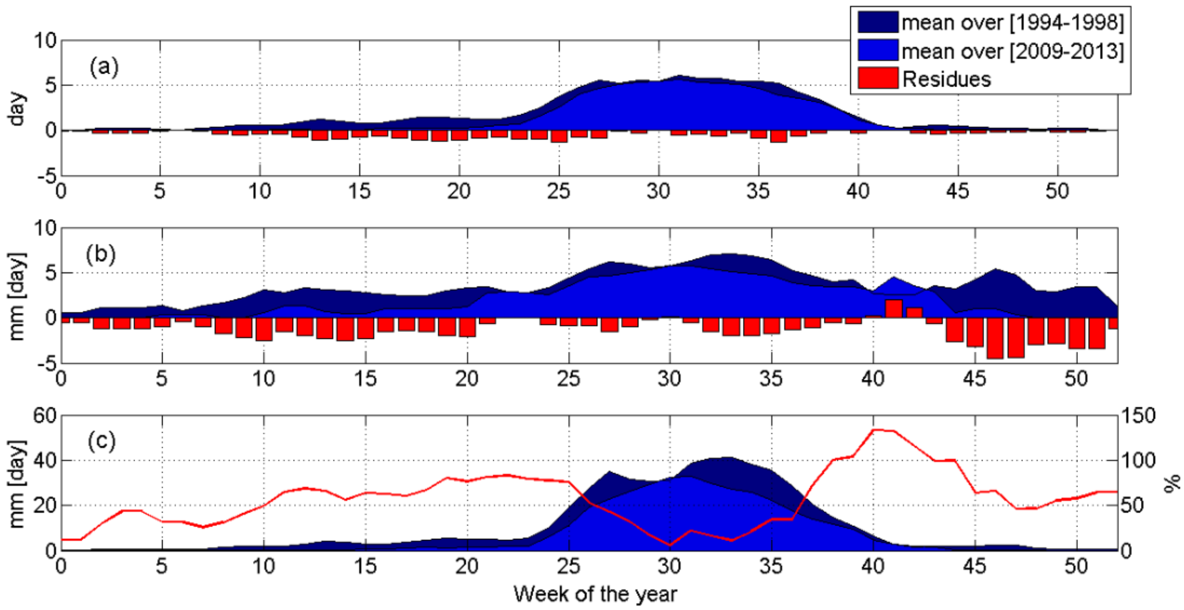

Figure S6. Panel a: Mean number of wet day per week W_w^p. Panel b: Mean daily precipitation intensity $SDII_w^p$ (mm). Panel c: Mean weekly-cumulated precipitation RR_w^p and relative contribution of the change in duration RLD in % (red line)