



## Products overview

Product name	Parameter	Value	Aggregation	Starting year
<b>TmaxrecabsM1961</b>	Max. Temperature	Absolute	Monthly	1961
<b>TmaxrecabsM1901</b>	Max. Temperature	Absolute	Monthly	1901
<b>TmaxrecabsY1961</b>	Max. Temperature	Absolute	Yearly	1961
<b>TmaxrecabsY1901</b>	Max. Temperature	Absolute	Yearly	1901
<b>Tmaxrecanom8110M1961</b>	Max. Temperature	Anomaly to period 81-10	Monthly	1961
<b>Tmaxrecanom8110M1901</b>	Max. Temperature	Anomaly to period 81-10	Monthly	1901
<b>Tmaxrecanom8110Y1961</b>	Max. Temperature	Anomaly to period 81-10	Yearly	1961
<b>Tmaxrecanom8110Y1901</b>	Max. Temperature	Anomaly to period 81-10	Yearly	1901
<b>TminrecabsM1961</b>	Min. Temperature	Absolute	Monthly	1961
<b>TminrecabsM1901</b>	Min. Temperature	Absolute	Monthly	1901
<b>TminrecabsY1961</b>	Min. Temperature	Absolute	Yearly	1961
<b>TminrecabsY1901</b>	Min. Temperature	Absolute	Yearly	1901
<b>Tminrecanom8110M1961</b>	Min. Temperature	Anomaly to period 81-10	Monthly	1961
<b>Tminrecanom8110M1901</b>	Min. Temperature	Anomaly to period 81-10	Monthly	1901
<b>Tminrecanom8110Y1961</b>	Min. Temperature	Anomaly to period 81-10	Yearly	1961
<b>Tminrecanom8110Y1901</b>	Min. Temperature	Anomaly to period 81-10	Yearly	1901

Table 1: Overview of reconstruction products.

## Temperature and precipitation reconstructions

<b>Variables</b>	Monthly and yearly mean maximum temperature (“Tmax” in the product nomenclature) or monthly and yearly mean minimum temperature (“Tmin”). Both temperature parameters are in degrees Celsius. Available as absolute values (“abs”) and anomalies (“anom”). Anomalies are the difference of surface mean temperature in 1981-2010 (norm period).
<b>Application</b>	Climate monitoring, trend calculation, analyses over a long time period, applications requiring high standards in temporal consistency. These products are the only gridded datasets, for maximum and minimum, that extend beyond 1961.
<b>Overview</b>	The reconstruction products are spatial analyses of monthly and yearly maximum and minimum temperature covering the entire territory of Switzerland and extending over a multi-decadal period (1961-present) or over more than a century (1901-present). These reconstructions are an extension to the already completed reconstruction of the mean temperature (TrecabsM) and the precipitation (RrecabsM). Compared to other products, such as TmaxM or TminM, where the focus is placed on spatial detail and high local accuracy when exploiting all available measurements, the reconstruction products are characterized by high temporal consistency. To this end, only homogeneous stations are used, without gaps over the whole period to guarantee a fully constant network of input data. The small number of stations satisfying these requirements precludes classical interpolation commonly used in spatial climatology. Here, a reconstruction method, called RSOI, is adopted (see section “method”). The method described here is presented in detail in Isotta et al. (2019).
<b>Data base</b>	The reconstruction products are based on monthly mean maximum and minimum temperature measured at the high-resolution station network of MeteoSwiss. The station locations and numbers are shown in Figure 2 and Table 2. For a few time series, gaps in the time series have been carefully filled using representative stations in the surroundings. The reconstructions make use of gridded datasets previously generated using all quality checked station measurements available for a particular month (TmaxM and TminM). In addition, homogenized time series (Begert et al. 2005) are considered, which are fully continuous over the whole period targeted with the respective product (see details in the “method” section).

## Temperature and precipitation reconstructions

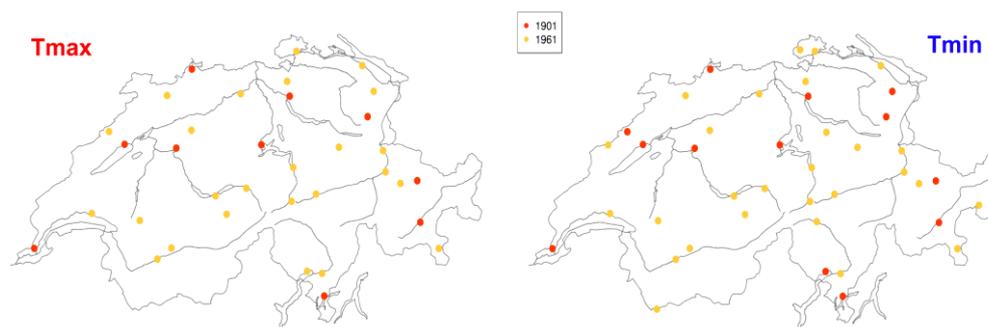


Figure 2. Location of stations with continuous and homogeneity-tested data series since 1901 (red) and 1961 (yellow and red). Left panel is for maximum temperature, right panel for minimum temperature.

Period	Tmax	Tmin
1901-2017	10	13
1961-2017	35	42

Table 2. Number of homogeneous and fully continuous maximum temperature (second column) and minimum temperature (third column) time series available during the two reconstruction periods (first column).

### Method

The temperature analyses are obtained by applying a statistical reconstruction technique, the “Reduced Space Optimal Interpolation (RSOI)”. In short, RSOI represents fields in a transformed state space, spanned by a truncated set of principal component loadings (the reduced space), and estimates a linear model between that representation and the long-term data, such that the expected reconstruction error is minimized (optimal interpolation). Technically, the procedure involves a Principal Component Analysis (PCA) of the high-resolution grid dataset, and an Optimal Interpolation (OI) of PCA scores from long-term station data. These steps are further explained in the following. More technical descriptions of RSOI are given in Kaplan et al. (1997), Schmidli et al. (2001) and Schiemann et al. (2010).

*PCA step.* The gridded datasets TmaxM for maximum temperature and TminM for minimum temperature are subjected to a PCA using the variance-covariance matrix (e.g. Wilks 2005) over the calibration period defined as 1981–2010. The resulting ordered set of PC loadings represents spatial patterns of variability. Only the leading vectors of the principal-components basis are retained (truncation), which reduces the dimensionality of the data space describing the temperature fields. For the longer period of Tmax (1901, the truncation was set after 6 leading principal components, while for the shorter period (1961) 26 out of 35 principal-components were retained. For the longer period of Tmin (1901) the truncation was set after 8 principal components and for the shorter period (1961) 26 out of 42 principal components were chosen. For both variables, more than 95% of the variability is explained by the subset of principal components retained.

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The PCA is calculated from anomalies (deviations from the calendar-month means of the period 1981-2010), in order to separate the annual cycle from the actual reconstruction.

*OI step:* The reconstruction is modelled as a linear relationship between the observations at the long-term stations and the coordinates of the reconstructed field in the reduced space (PC scores). The model (matrix) is estimated by reference to a reconstruction error, that involves errors in local representativity of the long-term measurements (attribution of stations to grid cells) and errors for the truncated representation of the reconstruction (e.g. Schiemann et al. 2010). The error covariance matrix is estimated from data over a calibration period (1981-2010) when both, high-resolution grids and long-term station data, are jointly available. The OI cost function also involves a penalty for variance in the higher order PCA scores in order to improve robustness and to balance the information flow between areas of different station density (Kaplan et al. 1997). Once estimated, the linear relationship is applied to the long-term station data, to yield reconstruction fields that can be considered best estimates given the empirical error covariance in the calibration period.

**Target users** The reconstruction products meet needs for long-term spatial climate data desired for climate and environmental monitoring such as in glaciology, hydrology, and climate change studies. The long period covered by the datasets, more than 100 years, is attractive for analyses in periods when no other spatial datasets can be provided by MeteoSwiss.

**Accuracy and interpretation** RSOI permits to recover spatial patterns that are not explicitly resolved by the coarse density of long-term climate stations. It combines long-term measurements with statistical information (i.e. the spatial covariance structure) from a high-resolution analysis. The RSOI method is targeted for regions with a complex orography, such as the Alps, where temperature and precipitation fields show anomaly patterns that are geographically locked.

The following issues should be considered when interpreting the reconstruction fields:

- **Grid spacing vs. effective resolution:** Despite the ability to recover spatial patterns not explicitly resolved, the effective resolution of the reconstruction datasets is coarser than in datasets constructed with high-resolution station data (TmaxM and TminM). Our assessment reveals that the loss in detail may be relatively small in comparison to the gridded data set (Tmax and TminM). Clearly, the km-scale grid spacing does not imply that these scales are resolved. As with all grid datasets, the user should be careful in relying on estimates at single or very few grid points. In particular, the reconstructions are not suitable to obtain statistics on local extremes.

There is a pronounced underrepresentation of stations at higher altitudes and in complex topographic conditions, especially for reconstructions starting in 1901 (see Table 2, a big reduction happens in the products starting from 1901 compared to the one from 1961). The strong reduction and the very small number of observations is particularly limited within and to the South of the Alps (Valais, Grisons and Ticino). As a result, the reconstructions do not portray finer-scale detail at high accuracy there.

Small-scale effects such as urban heat islands and local cold pools are not completely reproduced in the present datasets. In-situ measurements for these expositions are mostly missing.

- **Interpolation errors:** a leave-one-out cross-validation was calculated to estimate interpolation errors. This reveals the magnitude of errors for the case when values at a grid point are interpreted as local point estimates. In fact, such interpretation should rather

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be avoided. But these numbers serve as conservative error measures when the analyses are interpreted as local averages.

The Mean Absolute Error (MAE) is very similar for both, the maximum temperature and the minimum temperature. For the shorter period (1961-2018) the MAE amounts to 0.30 for the maximum temperature and to 0.32 for the minimum temperature. For the longer period (1901-2018) the MAE is 0.42 and 0.41, respectively.

Another possibility to depict the accuracy of the reconstructions is to compare the temporal variance to the “true” variance of a reference dataset. The reference datasets are in this case the gridded datasets (TmaxM and TminM). When looking at the shorter period, the temporal variance of Tmax is in average 5% lower and the temporal variance of Tmin 8% lower on the Swiss plateau. On the southern Alpine side however, the variance is between 15 and 40% lower for Tmax (especially in Valais) and in average even lower for Tmin (especially in Ticino, but also in Valais and Grisons and even in Jura). Considering the longer period, the temporal variance is even lower: the variance in the southern regions of both datasets is up to more than 40% lower than the variance of the reference. These regional differences are mainly due to more complex topography, very few available long-term measurements and a different climate. The overall lower variance arises mainly because of the smaller number of stations in the reduced dimensional datasets compared to the reference. This is also the reason why the variance is even lower in the longer period than in the shorter period.

A slightly more complex measure is the spatial Mean Squared Error Skill Score (MSESS), which in cross-validation experiments is typically around 0.9 for maximum temperature and around 0.85 for minimum temperature. The error is larger in winter, when gridding is more complex due to inversions and higher spatial variability. Furthermore, the spatial Mean Squared Error Skill Score (MSESS) was calculated for every grid cell, where the explained variance at each grid cell of the reconstruction is compared to the explained variance of the reference datasets (TmaxM and TminM). Considering the temporal MSESS, slightly stronger variations emerge between the regions: while most of the Swiss plateau exhibits values around 0.9, the Alps and the Southern Alpine region show skill scores slightly above 0.8. Consequently, for both reconstructions, errors increase for stations isolated (horizontally or in elevation) from other measurement devices or in special climatological regions, as for example the before mentioned southern regions.

- In general, higher uncertainties are to be expected in regions of complex topography, very low station density or areas with a special climatology (e.g. cold pools). Larger errors are to be expected especially along the northern rim of the Alps, in the Valais, Grisons and northern Ticino. The reconstruction performance varies from month to month, depending on the nature and scale of the weather patterns during the month and similarity to frequently recurring patterns.
- Temporal homogeneity: The method used for the reconstructions focuses on high temporal consistency. The products are suitable for studies on long-term variations (e.g. trends).
- The availability of reconstruction products with two different starting dates permits to benefit from the improvement of network density over time. Thus, the reconstructions covering a shorter period are generally more accurate than the longer ones. The differences are found to be relatively small over the Swiss plateau, but more substantial in regions of complex topography and regions with low station density (Valais and Ticino). We recommend users to use the shortest dataset covering the entire period of interest. A mixing of the different products should be avoided as this violated temporal consistency (e.g. trend calculation with a dataset where TmaxrecabsM1901 from 1901 to 1960 is mixed with TmaxrecabsM1961 from 1961 onward).

For more information please refer to Isotta et al. (2019).

## Temperature and precipitation reconstructions

<b>Related products</b>	If time consistency is not of major relevance, or if the period of interest starts after 1961, or if daily fields are required, the original maximum temperature (TmaxD, TmaxM, TmaxY) and original minimum temperature (TminD, TminM, TminY), or the respective norm datasets (e.g. TmaxnormM8110, TminnormM8110), are likely more appropriated, because of a better spatial representativity owing to the higher station density.
<b>Grid structures</b>	The monthly and yearly temperature and precipitation reconstructions are available in the following grid structure: ch02.lonlat
<b>Versions</b>	Current version: v1.0 Previous versions: none
<b>Production cycle</b>	The monthly fields are produced typically on the 25 <sup>th</sup> of the following month to include all available manual measurements and to await all the regular processing for data quality. The yearly fields are available typically on the 25 <sup>th</sup> of January of the following year. All products are fully updated if major changes are made in the homogenized long time series.
<b>References</b>	<p>Begert M, Schlegel T, Kirchhofer W. 2005. Homogeneous temperature and precipitation series of Switzerland from 1864 to 2000. <i>International Journal of Climatology</i> 25: 65-80.</p> <p>Isotta FA, Begert M, Frei C. 2019. Long-term consistent monthly temperature and precipitation grid datasets for Switzerland over the past 150 years. <i>Journal of Geophysical Research</i> 124: 3783-3799. DOI: 10.1029/2018JD029910</p> <p>Kaplan A, Kushnir Y, Cane MA, Blumenthal MB. 1997. Reduced space optimal analysis for historical data sets: 136 years of Atlantic sea surface temperatures. <i>Journal of Geophysical Research</i> 102: 835–860.</p> <p>Schiemann R, Liniger MA, Frei C. 2007. Reduced space optimal interpolation of daily rain gauge precipitation in Switzerland. <i>Journal of Geophysical Research</i> 115. DOI: 10.1029/2009JD013047</p> <p>Schmidli J, Frei C, Schär C. 2001. Reconstruction of mesoscale precipitation fields from sparse observations in complex terrain. <i>Journal of Climate</i> 14: 3289–3306.</p> <p>Schmidli J, Schmutz C, Frei C, Wanner H, Schar C. 2002. Mesoscale precipitation variability in the region of the European Alps during the 20th century. <i>International Journal of Climatology</i>, 22: 1049-1074.</p>

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