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Estimating trends and the current climate mean in a changing climate

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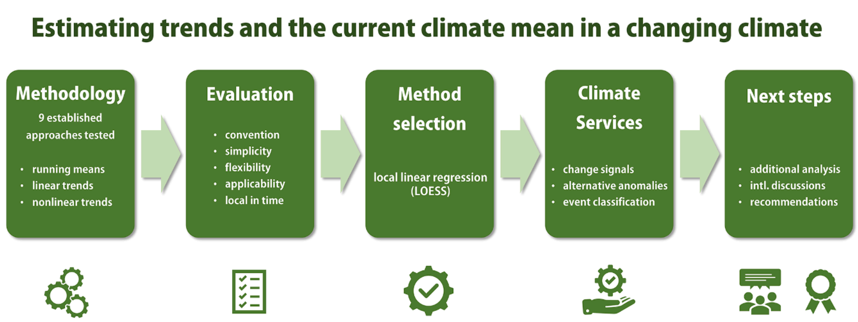
HIGHLIGHTS

- Climate trend and mean estimators are assessed with a criteria-based approach.
- Local linear regression is especially promising in describing climate trends and means.
- Ideas for novel climate services in an operational setting are presented.
- There is a need for international recommendations to improve climate services.

GRAPHICAL ABSTRACT



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ABSTRACT

Describing the climate evolution using trend lines and estimating the current climate mean (CCM) on the local scale is an important climate service. For an increasing number of variables, accelerating climate change disqualifies the use of traditional climatological normals and long-term linear trends as CCM estimators. Although several alternatives are available and already in use, there are few comprehensive assessments of the different approaches let alone a consensus for recommending a particular method. Here we evaluate frequently used approaches that use past climate data to estimate the CCM applying several transparent criteria. The performance is assessed in a perfect model framework for the strongly changing Swiss mean temperature 1864–2099 with the centered 30-year mean as CCM benchmark. Short-term linear trends, cubic splines and local linear regression with optimized parameters all provide unbiased CCM estimates for a broad range of climate evolutions and independent of trend magnitudes. To enable broad usability, additional criteria are considered such as a wide applicability to a large number of climate variables and simplicity in terms of use, settings and communication. In the overall assessment, local linear regression emerges as a particularly promising method to describe nonlinear climate trends and to determine the CCM. The criteria-based assessment approach has proven very useful in choosing a method as objectively as possible. We present ideas for modern climate services to complement the toolbox of climate monitoring and encourage the community to develop recommendations at the international level to increase the coherence, objectivity and robustness of climate monitoring products.

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Practical implications

Estimating the current climate mean (CCM) is a core task of climate monitoring and an important climate service. It is used to classify climate anomalies and to determine change signals. A prominent application is the definition of the time at which the global 1.5 or 2 °C target is reached (United Nations, 2015; Trewin, 2022; Betts et al., 2023). It is traditionally determined using averages computed over 30 consecutive years, so called climate normals. Another important metric are temporal temperature trends, often expressed linearly in °C per century. However, intensifying and thus nonlinear climate change more and more disqualifies the use of long-term linear trends and climatological normals for this task. Both, the 30-year standard reference period recommended by the World Meteorological Organization (WMO), commonly used to estimate the CCM through averaging, and long-term linear temporal trends, used to describe climate evolution, reach their methodological limits in the present day climate that is characterized by a strong non-stationarity and nonlinear evolution. For instance, using the WMO 30-year standard reference period to estimate the CCM (defined as the mean climate of the present year) is, by definition, at least 15 years out of date and may differ substantially from the "true" CCM. This example illustrates the need for additional methods suitable to deal with non-stationarity when estimating the CCM. A similar argument can be made regarding the estimation of linear climate trends in time. As climate evolution has shown to be highly nonlinear for many climate variables influenced by temperature (e.g. IPCC, 2021), the mathematical assumptions required when using a linear regression model (independent and identically distributed residuals) are not met.

In this study, we evaluate a range of commonly used methods to estimate nonlinear climate evolution and, based thereon, the CCM. This evaluation is contingent on a set of transparently defined criteria. The most obvious is performance, i.e. how accurate a certain method can describe the current mean using past data. Another important criterion is the compatibility with the climatological convention (e.g. 30-year averages). A method compatible with the convention is preferred over others if the methods perform otherwise similarly well. Further criteria relate to the questions whether the method can be applied to a wide range of climate variables and whether it is simple to calculate and to communicate. The use of multiple criteria beyond performance alone to select a method has proven to be powerful. It can be applied to select methods in general, but the criteria are not universal. They need to be defined depending on the purpose and context of the analysis (cf. Keizer et al., 2023).

Here, we present the method that proved most suitable for the intended purpose: a smooth nonlinear climate trend based on local linear regression (1st order LOESS with a 42-year window). It proved suitable to estimate both nonlinear climate trends and the CCM in a changing climate on the global, regional and local scale and is thus an excellent candidate to provide robust and coherent long-term climate monitoring products. Very similar approaches to model nonlinear trends have been recently promoted in the literature (e.g. Hawkins et al., 2020; Clarke and Richardson, 2021; Cheng et al., 2022). The climate trend based on local linear regression describes the nonlinear long-term climate evolution of temperature very well and is a good option to replace long-term linear trends, in which the temperature evolution is usually modeled only as a function of time. The representation of smooth nonlinear climate evolutions is attractive for visualization purposes and dashboards (e.g. the KNMI climate dashboard at https://www.knmi.nl/klimaat). Also the multi-annual climate variability can be attractively represented using shorter smoothing windows for example with a 14-year window to trace the 10-year moving average.

There are many potential applications of the CCM to complement the traditional climate monitoring toolbox. It is potentially useful to classify weather and climate extremes more accurately with respect to the current conditions. Gubler et al. (2023) apply a similar concept to daily temperature extremes. It can also be used to compute up-to-date change signals using differences between the values of the climate trend for an end and a start time point. Interesting, but more challenging, is the communication of anomalies with respect to the CCM instead of deviations from 30-year normals as widely done in climate bulletins and reports today. Since the CCM, i.e. the reference, changes every year, the same value (in absolute terms) would result in a different anomaly every year, and thus change the way anomalies are used and communicated substantially. Therefore, a careful consideration of the benefits and risks of the application of the methods is necessary to decide whether it might be worth taking this step. We also want to stress that classical climate normals still have their justification in several areas and no complete replacement is suggested here.

We encourage the climate service community to initiate discussions and develop recommendations at the international level on how to estimate trends and the CCM in a strongly changing climate (i.e., through working bodies of the World Meteorological Organization). A harmonization of methods and communication procedures would significantly increase the comparability and objectivity of climate monitoring results and strengthen the coherence and robustness of climate service products.

1. Introduction

Estimating the current climate mean (CCM) is a core task of climate monitoring and an important climate service. It can for example be used to classify climate anomalies and to determine change signals. A prominent application is the question when the global 1.5 or 2 °C target are reached (United Nations, 2015; Trewin, 2022; Betts et al., 2023). Traditionally, averages computed over at least 30 consecutive years, so called climate normals, are used to define climate means (WMO, 2017). However, the concept of climate normals is based on the strong assumption of a stationary (i.e. "trendless") climate within the averaging period. Due to anthropogenic climate change, this stationarity assumption is violated for an increasing number of variables such as temperature, absolute humidity, heavy precipitation or evapotranspiration in the last few decades (IPCC, 2021). As a result, the CCM based on past climate normals is increasingly biased. The problem has been widely discussed in the literature (e.g. Scherrer et al., 2006; Livezey et al., 2007; Milly et al., 2008) and by the World Meteorological Organization (WMO; WMO, 2007) already more than fifteen years ago. For some years now, WMO has been recommending updating climate normals frequently, at least every ten years (WMO, 2017). The literature, however, shows that further alternative approaches are desirable and can potentially help users make better informed decisions (cf. Livezey et al., 2007; Arguez and Vose, 2011; Wilks, 2013; Wilks and Livezey, 2013; Krakauer and Devineni, 2015). A wide variety of approaches were proposed under the terms "optimal", "non-stationary", "supplemental" or "new" normals. Livezey et al. (2007) evaluated several approaches, including an adjustment of the averaging period (so-called "optimal climate normals") and an estimation using "piece-wise" linear trends (so-called "hinge fits"). At that time, these worked reasonably for the past range of trends on a regional and local level. Arguez and Vose (2011) summarized possible alternatives and Arguez et al. (2013) presented a set of approaches, from which seven were implemented operationally at the US National Oceanic and Atmospheric Administration (NOAA) as "supplemental normals" in addition to the WMO normals.

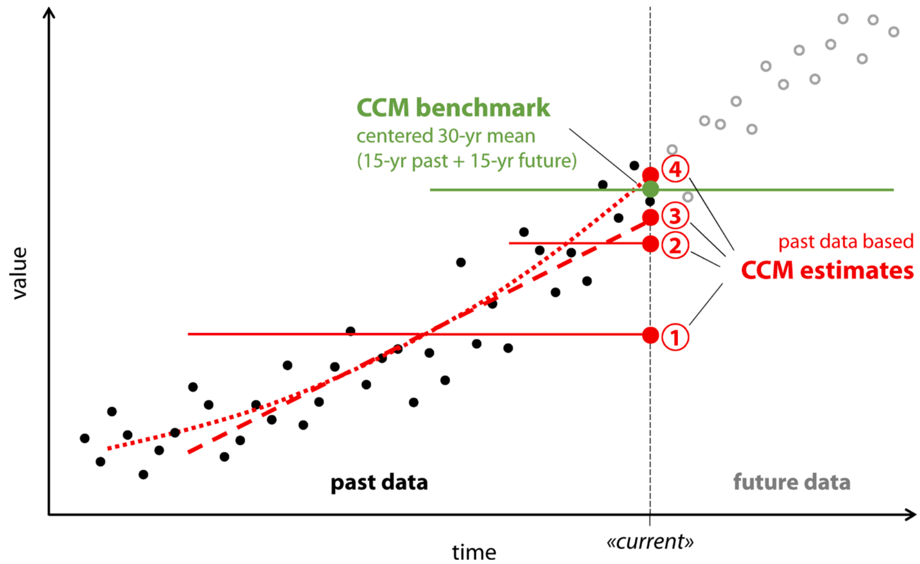

Fig. 1. Schematic illustration of some options to estimate the CCM using past data for a strongly changing climate variable (e.g. temperature). ① long-term (e.g. 30-year) mean, ② short-term (e.g. 10-year) mean, ③ linear fit over a recent time period and ④ smooth nonlinear estimate. The filled circles show observed values, the open circles show predictions for the future. The benchmark used in this study is the centered 30-year mean (filled green circle) using a combination of 15 years of past and 15 years of future data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Approaches to estimate the CCM assessed in the present work with some methodological details and examples of their usage (not an exhaustive list). The approaches in italic are only applied for the observational period 1864–2020. Further technical details are given in the Appendix A (Table A1).

Approach	Description	e.g. used by/in
MA30.upd.10	30-year means updated every 10 years	WMO (2017), Kaspar et al. (2023)
MA30	30-year means updated annually	MeteoSwiss reports
MA10	10-year means updated annually	NOAA, IPCC (2021), Kaspar et al. (2023) MeteoSwiss website
KS15	Gaussian kernel smoother (bandwidth = 15 years, optimized)	MeteoSwiss reports
LT30	Linear trend fit (last 30-year data, updated annually)	Copernicus Climate Service (C3S, 2021)
SP6	Cubic spline smoother (degree of freedom, df = 6)	Rigal et al. (2019)
LO42	Local linear regression smoother (1st order LOESS), 42-year window, tricube weighting scheme	KNMI (de Valk, 2020), Clarke and Richardson (2021)
LM.GMT	Linear model, predictor: LOESS smoothed global temperature	Hawkins et al. (2020)
LM.NHLT	Linear model, predictor: LOESS smoothed northern hemisphere land temperature	Gubler et al. (2023)

Wilks (2013) and Wilks and Livezey (2013) showed that the choice of the best method strongly depends on the magnitude of the trend.

An alternative option to estimate the CCM is fitting a smooth trend line to the data and use the last time step of the smoothed series as CCM estimate. Some time ago, Mann (2004, 2008) proposed an elaborate method that adaptively weights boundary constraints to optimize the fit yielding an accurate representation of long-term warming trends also at the time series boundaries. More recently, Rigal et al. (2019) presented a statistical model based on cubic splines which showed negligible biases even for strong future warming. Steinacker (2021) suggested a mean value smoothing spline to estimate the climatic trend. De Valk (2020) proposed a trend line based on weighted local linear regression, the first order implementation of LOESS (cf. Cleveland, 1979; Cleveland and Devlin, 1988). Climate trend lines with a very similar configuration have recently been promoted by Hawkins et al. (2020) and Clarke and Richardson (2021) to monitor global mean temperature and by Cheng et al. (2022) to describe the evolution of the ocean heat content. Also, the National Aeronautics and Space Administration (NASA) uses the approach to visualize the evolution of their global temperature data set GISTEMP but with a narrower 5-year bandwidth (e.g. Lenssen et al., 2019). The European Copernicus Climate Change Service (C3S) applies a moving 30-year linear trend to estimate the CCM in its global temperature trend monitor (C3S, 2021). In the Sixth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) started to communicate the CCM of temperature via the average of the last available 10 years (IPCC, 2021).

In this paper, we assess nine frequently used approaches that use past climate data to estimate the CCM on the regional to local scale. To ensure a broad applicability, a multiple criteria-based selection approach is adopted. Several transparent criteria are defined and assessed to come up with a recommended method. A central criterion is performance with respect to a centered 30-year benchmark using combined observational and climate scenario data. This is determined to a large degree by the methods ability to correctly represent fast climate changes and should ensure the applicability of the method in the decades to come. Further criteria include whether the method can be applied to a wide range of climate variables, and are simple to calculate and communicate. We present performance results and discuss the options based on the assessment including all additional criteria. We then give some examples for the preferred approach that has been operationally implemented by the Royal Netherlands Meteorological Institute KNMI and will be implemented by the Federal Office of Meteorology and Climatology MeteoSwiss in 2024 to complement the current climate monitoring soon. Ideas of potential climate services based on the CCM are shortly discussed. We close with a conclusion and a short outlook of possible next steps.

Table 2

Criteria used to assess measures to compute the current climate mean (CCM) and climate trend lines. Adapted and extended from de Valk (2020).

#	Criterion		Description
C1	compatibility with convention	C6 PERFORMANCE	1) Estimate is a good predictor for the centered 30-year average. 2) The variance matches the one of the centered 30-year average.
C2	local in time		Estimates depend only on the data reasonably close to the year concerned
C3	flexibility		Can represent fast climate changes (i.e. any trend line shape)
C4	wide applicability		Can be easily applied to most climate variables and indices (e.g. bounded and count variables)
C5	simplicity		Is simple to explain to a wide audience and simple to compute (no settings need to be made by user)

2. Methodology and data

2.1. CCM approaches

There are many ways to estimate the CCM using past climate data. Fig. 1 visualizes some possibilities for an arbitrary climate variable with a positive nonlinear trend. A good example is near surface air temperature that currently behaves like this in most regions of the world. It illustrates the considerable differences between the approaches. Nine commonly used approaches are discussed in this paper. They are listed in Table 1 and include the periodically updated 30-year mean (M30.upd.10) recommended by WMO, two moving averages (MA30 and MA10), a moving linear trend (LT30), a Gaussian kernel smoother (KS15), a cubic spline (SP6), a locally weighted linear regression (LO42) and two linear models using large-scale temperature as predictor (LM.GMT and LM.NHLT).

The configurations of these methods were determined by already established configurations and guidance based on the CCM error behavior (with respect to a centered 30-year mean benchmark) for regional temperature in the past and future (cf. Appendix A for details). For most approaches the optimized parameters turned out to be reasonably close to the established ones. We thus use the latter in this paper (cf. Table 1). For the kernel smoother, no well-known configuration exists and the error-optimized configuration is used. In contrast to the other seven approaches, LM.GMT and LM.NHLT are calculated by linearly scaling large-scale temperature. This potentially allows modeling some nonlinearities in the time series (e.g., Gubler et al., 2023). Note that the performance analysis for LM.GMT and LM.NHLT is restricted to the observational period 1864–2020 because future information on global temperature is not available in the regional scenario data used in this study (cf. data section).

2.2. Evaluation criteria

From the perspective of a climate service provider, there are several criteria that determine a "good" method for estimating the CCM. An important overall criterion analyzed in detail in this study is "performance". It measures how good a method can estimate the CCM with respect to a benchmark (see performance metrics section for details). Hence, the benchmark or more general, the compatibility of a method with convention is a crucial criterion which strongly determines if a method performs well. Other criteria that contribute to a good performance are whether the estimates are local in time, i.e. only depend on the values reasonably close to the year in question and whether the method is flexible enough to represent trends at the end of the sequence reasonably well. Further important criteria are whether the method can be applied to a large range of climate variables and indices and whether it is easy to explain and compute.

Table 2 gives an overview of the above criteria. The criteria are essentially the same to assess to suitability of climate trend lines to describe the evolution of climate series (cf. de Valk, 2020). We use the six criteria including performance as basis to rate the different CCM approaches. Note, that the criteria to apply depend on the problem and they might differ from those applied in this study. The availability of information on the uncertainty of the CCM estimates is a plus but can in principle be computed numerically using bootstrap methods (cf. Efron and Tibshirani, 1994) for all methods. We therefore decided not to use it as formal criterion in this study.

2.3. Data

The main climate variable analyzed in this study is the strongly changing near surface air temperature. We mainly focus on regional temperature on the annual time scale. The testbed is Switzerland, a central European country with complex topography covering an area of about 41,300 km^2. For the past (1864–2020) we use the Swiss mean temperature data set introduced by Begert and Frei (2018). It is freely available in monthly and annual resolution and operationally updated to the present. The series is characterized by a strong nonlinear trend and large interannual variability. To test how the CCM approaches perform in a future climate, the observations are combined with climate scenario data from the current Swiss climate scenarios CH2018 (CH2018, 2018; Fischer et al., 2022) which are based on EURO-CORDEX regional climate model simulations (cf. Jacob et al., 2014, 2020). A total of 45 simulations from three different emission scenarios are considered (8 "low-emission" simulations (RCP2.6), 16 "intermediate-emission" simulations (RCP4.5) and 21 "high-emission" simulations (RCP8.5), see Appendix B for details). The raw EURO-CORDEX regional climate model data, available for the period 1981–2099, were downscaled and corrected for systematic distributional biases of daily data using quantile mapping (Feigenwinter et al., 2018). The observational time series covering the past (1864–2020) is simply concatenated with the 45 bias corrected climate model realizations (2021–2099) to create 45 continuous 236 year time series for the period 1864–2099. The combined time series mostly show a reasonable gradual evolution around the year 2021 where the observational and scenario data sets have been concatenated. HadCRUT5.0.1.0 global mean temperature (Morice et al., 2021) is used for the LM.GMT and CRUTEM.5.0.1.0 northern hemispheric land temperature (Osborn et al., 2021) for the LM.NHLT approach. Additional data sets from different data sources are used for the application examples (see Fig. 4 legend for details).

2.4. Performance metrics

The 45 combined observational and scenario temperature time series for the period 1864–2099 are used to test the performance of the different CCM approaches. As CCM benchmark (BM), a centered 30-year mean is used. The 30-year window ensures compatibility with climatological convention and is not challenged in this paper. The CCM error is defined as $T_{i,m}(t)$-$T_{i,BM}(t)$, where $T_{i,m}(t)$ is the CCM estimate of approach m (1…9) for simulation i (1…45) in year t (1900…2084) using only information from the past (i.e. up to year t) and $T_{i,BM}(t)$ is the centered 30-year mean benchmark for simulation i in year t using 15 years of data from the past and 15 years of data from the future. Until the year 2020, the input data is observations, after 2020 it's data from climate projections. We analyze the CCM and CCM error time series, biases (mean errors over a certain time period) and the error variance (standard deviation of the CCM error) for the different approaches. The CCM error variance is also compared with the BM 95 % confidence interval which is roughly approximated applying a simple one-sample *t*-test confidence interval (Student, 1908).

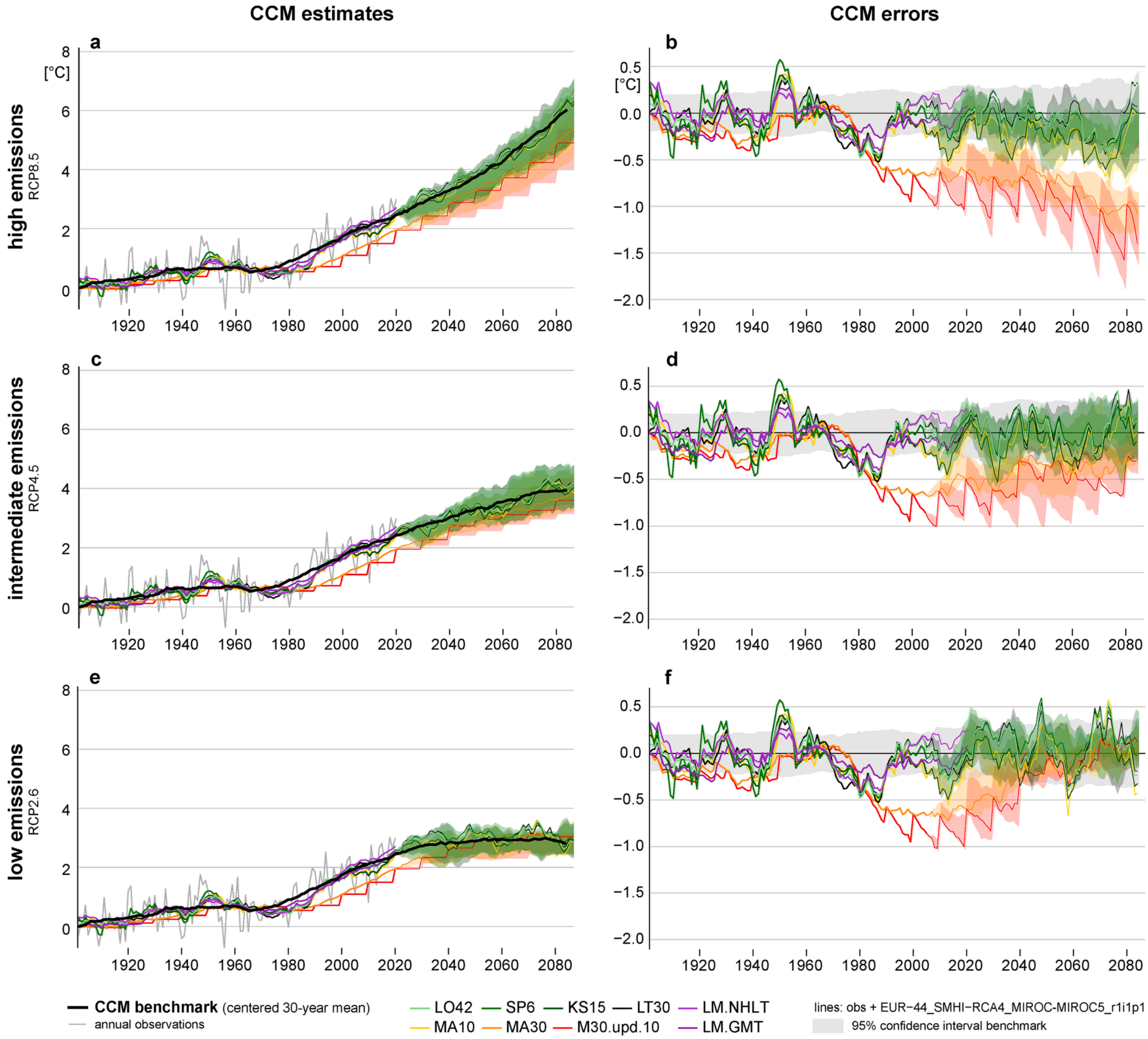

Fig. 2. CCM series (left panels a,c,e) and CCM error series (right panels b,d,f) for the nine approaches (colored lines) listed in Table 1 from the early 1900s to the 2080s. See legend inset for color key. Left panels: The centered 30-year mean benchmark is shown as a bold black line, the annual observations 1864–2020 as a thin gray line. The colored bands show the 90 % uncertainty range of the 21 high-emission scenario runs (panels a,b), 16 intermediate- scenario runs (panels c,d) and 8 low-emission scenario runs (panels e,f) for the period after the year 2005. The gray band (panels b,d,f) shows the approximate 95 % confidence interval of the centered 30-year mean benchmark. Until 2005, the error is based on observations only. Between 2006 and 2020, it is a combination of observations and scenario data. After 2020, the estimate is solely based on scenario data. The thin lines show an example realization of the MIROC5-RCA4 model chain.

3. Performance analysis

3.1. CCM estimates and error series

Fig. 2 shows the CCM series (left panels) and the CCM error series (right panels) from the early 1900s to the late 21st century for all approaches. The WMO normal approach (M30.upd.10) works reasonably well until the 1970s but shows very strong negative biases up to 1 °C in the last decades (cf. also Scherrer et al., 2006). The main reason for this is the large temperature increase in this period. M30.upd.10 is lagging the CCM benchmark by 15 years and is representative for the mean 15 years before present but not for the end of the series (“current” climate). Since the values are updated only every 10 years, the error curve is zigzagged with the smallest errors following an update and the largest errors just before an update. The errors further increase in the future for the high-emission scenario due to its increasing rate of warming. For the intermediate-emission scenario, the errors stay roughly constant in the coming decades. For the low-emission scenario with a clearly decreasing rate of warming, the errors are currently at a maximum and decrease towards zero in the second half of the 21st century. Apart from not zigzagging, the moving 30-year normal MA30, which has been used by MeteoSwiss until recently to communicate change signals, performs only slightly better than M30.upd.10 with negative errors up to 0.7 °C in the last decades.

Shortening the moving average window helps to reduce the mean bias considerably without increasing the error variance a lot. However, also for MA10, as used in the recent sixth IPCC assessment report (IPCC, 2021), and also for the Gaussian kernel smoother KS15, there is a

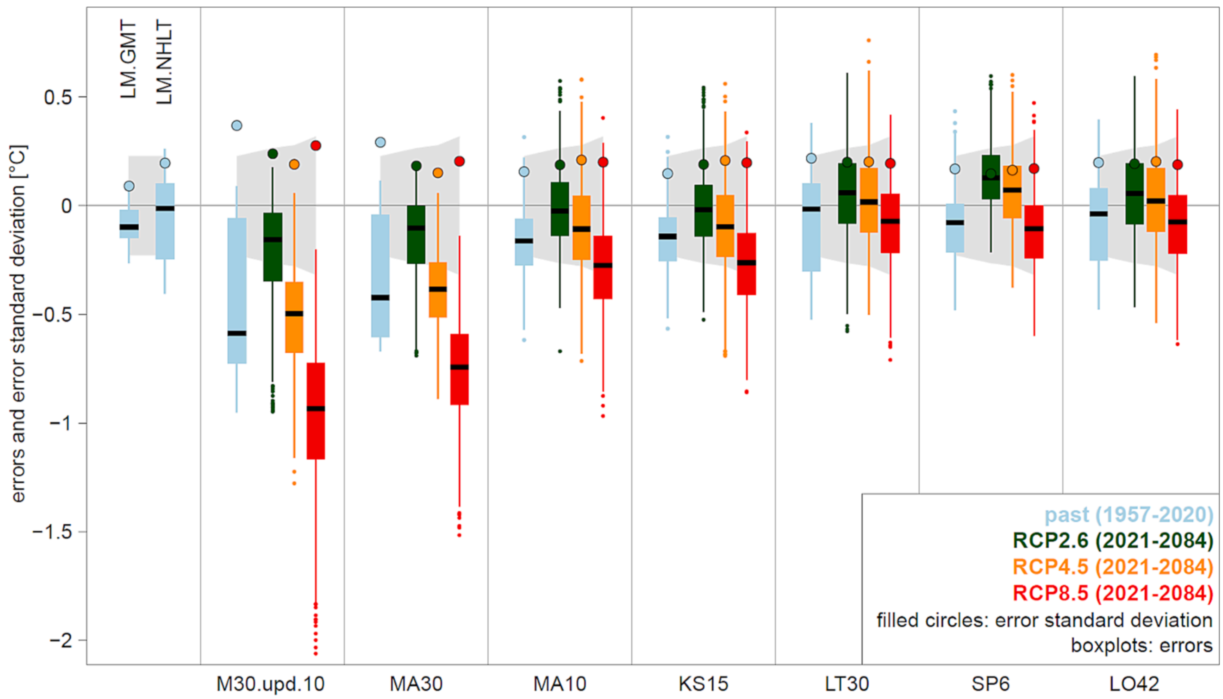

Fig. 3. CCM error statistics for different time periods and the approaches presented in Table 1. Shown are results for the past (1957–2020) in light blue and for the future (2021–2084) in green (low-emissions RCP2.6), in orange (intermediate emissions RCP4.5) and red (high-emissions RCP8.5). The errors are given as boxplots (median in black, box: 25th to 75th percentile, whiskers: max(min error; 25th percentile minus 1.5 times the interquartile range) to min(max error; 75th percentile plus 1.5 times the interquartile range) as lines and outliers as dots). The standard deviation of the errors are depicted as filled circles. The gray band shows the approximate 95 % confidence interval of the centered 30-year mean benchmark. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

systematic negative bias in the order of 0.2–0.3 °C in times with strong trends. The moving 30-year linear trend fit LT30, the cubic spline SP6 and the LOESS smoother LO42 show even smaller biases in the near past and future. Note however, that all these approaches show substantial biases in the early 1950s, a few years after the 1940s local temperature peak and in the 1980s, after the local temperature minimum in the 1970s. LM.GMT and LM.NHLT perform very well. This is not surprising, as the predictor and predictand series are subject to similar non-linearities which cannot be modeled well with (linear) time as only predictor. The errors have the same sign as those of the other methods though. This shows that also these approaches cannot predict the reversal of trends reasonably. To achieve this, skillful predictions of the near future, so called decadal predictions (e.g. Boer et al., 2016) would be necessary. For the future, LT30, SP6 and LO42 all show relatively small biases for all climate scenarios considered. Although there are short periods with larger errors, they mostly stay within the approximated 95 % confidence interval of the BM (Fig. 2, gray band) which amounts to about ±0.2 °C in the observation period and up to ±0.3 °C in the scenario period.

3.2. CCM error statistics

Fig. 3 summarizes the error statistics for the nine candidate approaches aggregated for the recent past (1957–2020) and the three different climate scenarios analyzed for the next several decades (2021–2084). As Fig. 2 already suggested, M30.upd.10 and MA30 are strongly negatively biased in the past. Small past negative biases are also found for MA10 and KS15, while LT30, SP6 and LO42 are almost unbiased. In the future, M30.upd.10 and MA30 are still heavily biased, but the bias strongly depends on the scenario with much larger bias for RCP8.5 than RCP4.5 and RCP2.6. MA10 and KS15 perform well for RCP2.6 (cf. also Fig. A1 and Table A2), but tend to have a considerably negative bias for RCP4.5 and RCP8.5 up to −0.3 °C. Kernel smoothing biases near the time series end are a well-documented feature in the statistical literature (e.g. Gasser and Müller, 1979; Hart and Wehrly, 1992). LT30, SP6 and LO42 show small median biases for all scenarios with errors mostly smaller than ±0.1 °C. For the past, LM.NHLT shows the smallest bias (-0.01 °C) and also the LM.GMT bias is quite small (-0.11 °C).

To get a feeling for the range of the errors for individual parts of the time series, the error variance can be used. It is expressed here simply as standard deviation of the errors (large dots in Fig. 3). MA30.upd.10 and MA30 perform poorly, especially in the past with values of 0.37 and 0.29 °C respectively. The smallest value is found for LM.GMT (0.09 °C). For the other approaches, values between 0.15 and 0.22 °C are found. Note that the LM.NHLT value is relatively high (0.20 °C). The very small LM.NHLT bias thus comes with the price of higher error variance. For all approaches, the values for the future are similar to those for the past.

An additional quality measure is the comparison of the errors with the uncertainty of the benchmark. For LT30, SP6 and LO42, 82–89 % of the errors for the future period stay within the 95 % confidence interval of the benchmark. Note that the LT30 and LO42 error evolution and statistics are very similar. The reason is the way LO42 is constructed. The linear term in the local regression leads to an approximately linear behavior near the end of time series and to a similar CCM estimate as the one of LT30 (cf. de Valk, 2020).

4. Evaluation and choice of method

To help identify the most suitable approaches to estimate the CCM, we evaluate the six criteria C1-C6 listed in Table 2. A categorical rating (positive "+", neutral "·" or negative "–") is issued for each combination of criterion and approach and presented in Table 3. It should be mentioned, that the rating is not a fully objective for every criterion/ approach combination, but the evaluation of all six criteria together allows to make a relatively objective method selection.

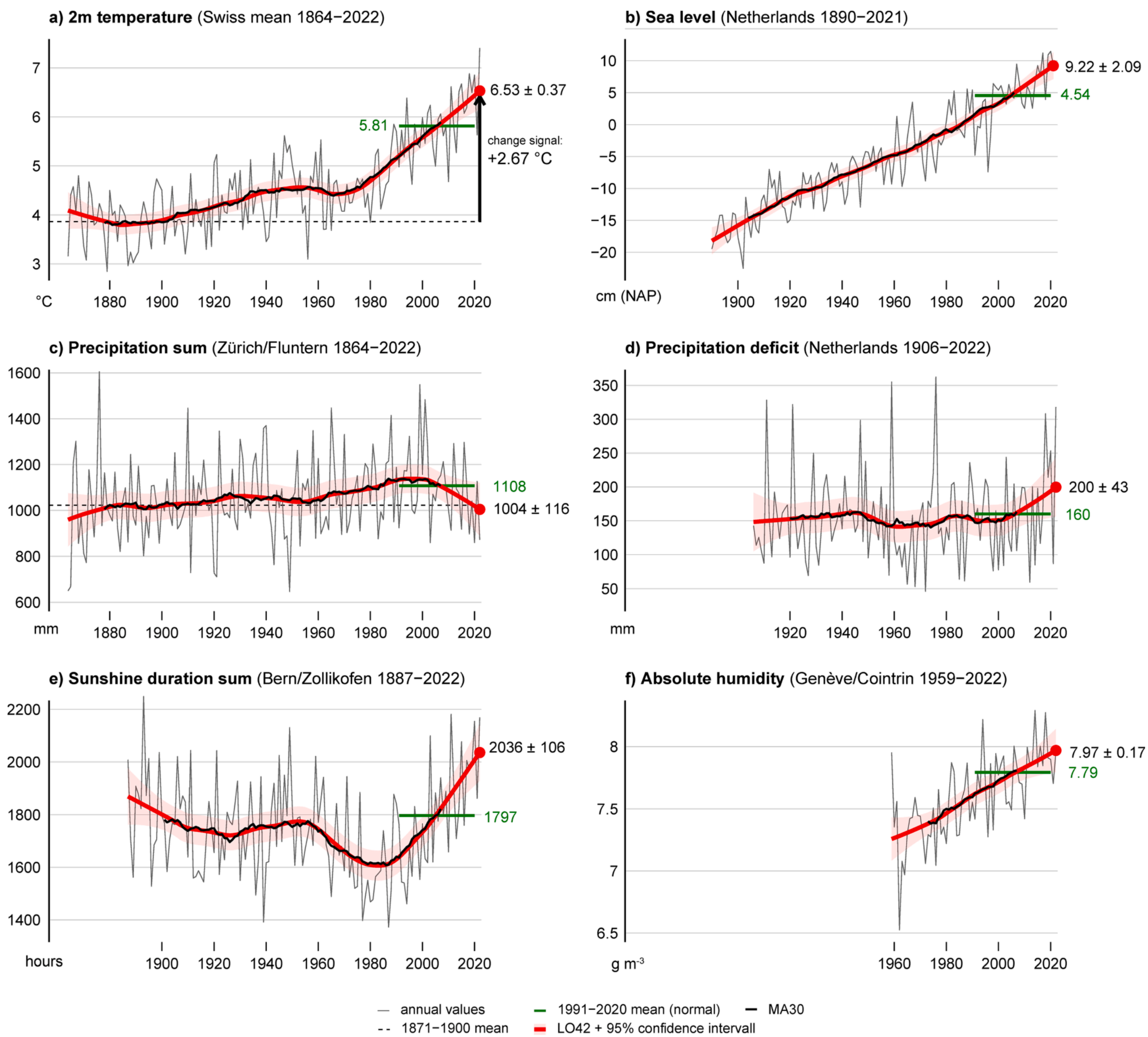

Fig. 4. Example evolution and CCM estimates of six regional and local climate variables in Switzerland and the Netherlands. a) annual Swiss mean 2 m temperature since 1864, b) annual mean sea level in the Netherlands (mean of six Rijkswaterstaat gauges) 1890–2021, c) annual precipitation sum in Zürich since 1864, d) precipitation deficit (maximum of cumulative potential evaporation minus precipitation from April to September, cf. Beersma and Buishand, 2004) in the Netherlands since 1906, e) annual sunshine duration in Bern since 1887, f) annual absolute humidity in Genève since 1959. The annual values are shown as thin black lines. The red line and the pink area show the LO42 climate trend line and its 95 % confidence interval. The red dot and the numbers show the climate mean estimate at the end of the series with the 95 % confidence interval given as numbers. The 30-year moving average (MA30) is shown as a semi-bold black line. The green lines and numbers are the normals 1991–2020 (MA30.upd.10), the dashed horizontal line shows the 1871–1900 (pre-industrial) mean where available. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Evaluation of the criteria C1–C6 (Table 2) for the approaches listed in Table 1. A positive behavior is rated with a plus (+), a negative behavior is rated with a minus (−). If the behavior is neutral or average, the rating is a dot (·). The performance row is in bold because it is the main criterion analyzed in detail in this study. The performance ratings of LM.GMT and LM.NHLT are put in parentheses because they were only assessed for the past.

Criterion	M30.upd.10	MA30	MA10	KS15	LT30	SP6	LO42	LM.GMT	LM.NHLT
C1 compatibility with convention	+	+	−	+	·	·	+	·	·
C2 local in time	·	·	+	+	·	·	+	+	+
C3 flexibility	−	−	·	·	+	+	+	+	+
C4 wide applicability	+	+	+	+	+	+	+	−	−
C5 simplicity	+	+	+	·	·	·	·	−	−
C6 PERFORMANCE	**−**	**−**	**·**	**·**	**+**	**+**	**+**	**(+)**	**(+)**

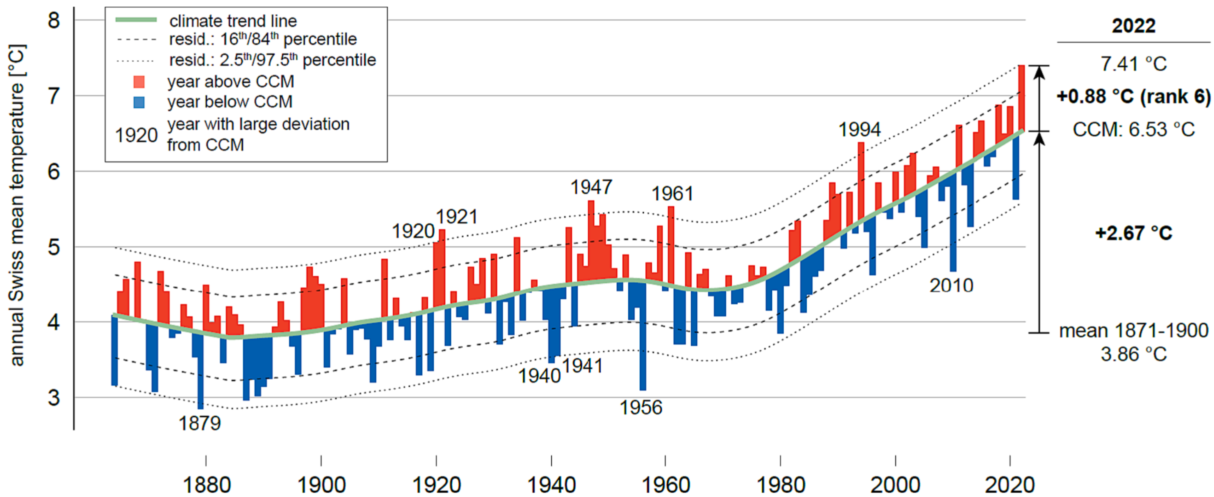

Fig. 5. Evolution of the annual Swiss mean temperature 1864–2022 showing the climate trend line (green) and deviations from it (positive deviations in red, negative deviations in blue). Also shown are lines for the 16th and 84th (dashed lines) and the 2.5th and 97.5th (dotted lines) percentile of the deviations. The years with the five most positive and the five most negative deviations are labeled. For the year 2022, the observed mean, the CCM estimate, the deviation from the CCM including rank and the change signal with respect to the pre-industrial mean 1871–1900 are given. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table A1
Technical details on LOESS (LO), spline (SP) and kernel smoother (KS) approaches used. The table lists the R-function used and some configuration details (cf. Chambers and Hastie, 1992).

Approach	R-function	Configuration
LOESS (LO)	loess()	degree of the polynomial used: 1 (linear), span: window length/length of time series, weighting: tricubic, details: https://www.itl.nist.gov/div898/handbook/pmd/section1/pmd144.htm
cubic spline (SP)	smooth.spline()	fixed equivalent number of degrees of freedom df (trace of the smoother matrix)
kernel smoother (KS)	ksmooth()	kernel: normalbandwidth: kernels (viewed as probability densities) are scaled so that their quartiles are at +/− '0.25*bandwidth'

M30.upd.10, MA30 are compatible with the convention (C1) except at the boundaries of the time series. LO42 and KS15 were constructed to meet the convention as closely as possible. MA10 can deviate quite substantially from a 30-year mean and is rated negative. The other approaches are rated neutral. MA30, M30.upd.10, LT30 and SP6, for which the coefficients are estimated using the whole time series (globally), are not very local (criterion C2). They are all rated neutral. The other approaches are reasonably local and get a positive rating. Concerning criterion C3 (flexibility), MA30 and M30.upd.10 are not responsive to rapid changes and are given a negative rating for flexibility. MA10 and KS15 somewhat lag the evolution in certain cases. They are rated neutral, while all other approaches are flexible and get a positive rating. Concerning criterion C4 (wide applicability), LM.GMT and LM.NHLT are rated negative, since large scale temperature is not necessarily a good predictor for an arbitrary variable on the local and regional scale. The other approaches are easily applicable to most variables and are rated positive. In terms of simplicity (C5), LM.GMT and LM.NHLT are rated negative since global scale data is needed and the procedure is not trivial to explain to the general public. M30.upd.10, MA30 and MA10 are easy to compute and communicate and thus rated positive. KS15, LT30, SP6 and LO42 are categorized as neutral, as the calculation is somewhat more demanding than the calculation of simple arithmetic means, but it can be explained relatively easily as a "smooth curve". The performance criterion C6 is based on the performance analysis with respect to temperature presented above. LT30, SP6 and LO42 are high performers in the past and during the 21st century and get a positive rating. LM.GMT and LM.NHLT also performed very well. Since they have been assessed here only for the past, they get a positive rating in parentheses. MA10 and KS15 are rated neutral for their mediocre performance, while MA30 and M30.upd.10 get a negative rating for their minor overall performance.

Overall, LO42 scores best according to our criteria, closely followed by SP6 and LT30. Note that in Table 3, we evaluated merely the use-case of estimating the CCM. The approaches based on fitting a smooth nonlinear trend line have the additional advantage of being able to visualize the evolution of the time series in an attractive way. There is one more additional benefit of LO42 in this group of approaches. It matches the variance of the centered 30-year average and has been constructed to be a smoothed version of this well-established climatological measure (cf. de Valk, 2020). Note that in principle also the spline approach could probably be configured to meet this criterion. Regarding all these aspects, it is attractive to choose local linear regression (LO42) as the preferred method to estimate the CCM. It is also an excellent climate trend line, e.g. for visualization purposes and can be used to produce several modern climate services, some of which we discuss in the next section.

5. Climate services examples

5.1. Trend lines, current climate mean and change signals

Fig. 4 illustrates some examples using the LO42 climate trend lines and CCM estimates for regional and local scale climate variables in Switzerland and the Netherlands. In 2022, the Swiss mean temperature (Fig. 4a) reached a climate mean (CM) of 6.53 ± 0.37 °C (95 % confidence interval, assuming that the errors are normally distributed and independent). This is 0.72 °C higher than the current climate normal 1991–2020, which also lies clearly outside the 95 % confidence interval. The 2022 CM estimate corresponds to a change signal of +2.67 °C with respect to the 1871–1900 mean, a proxy for the pre-industrial level (cf.

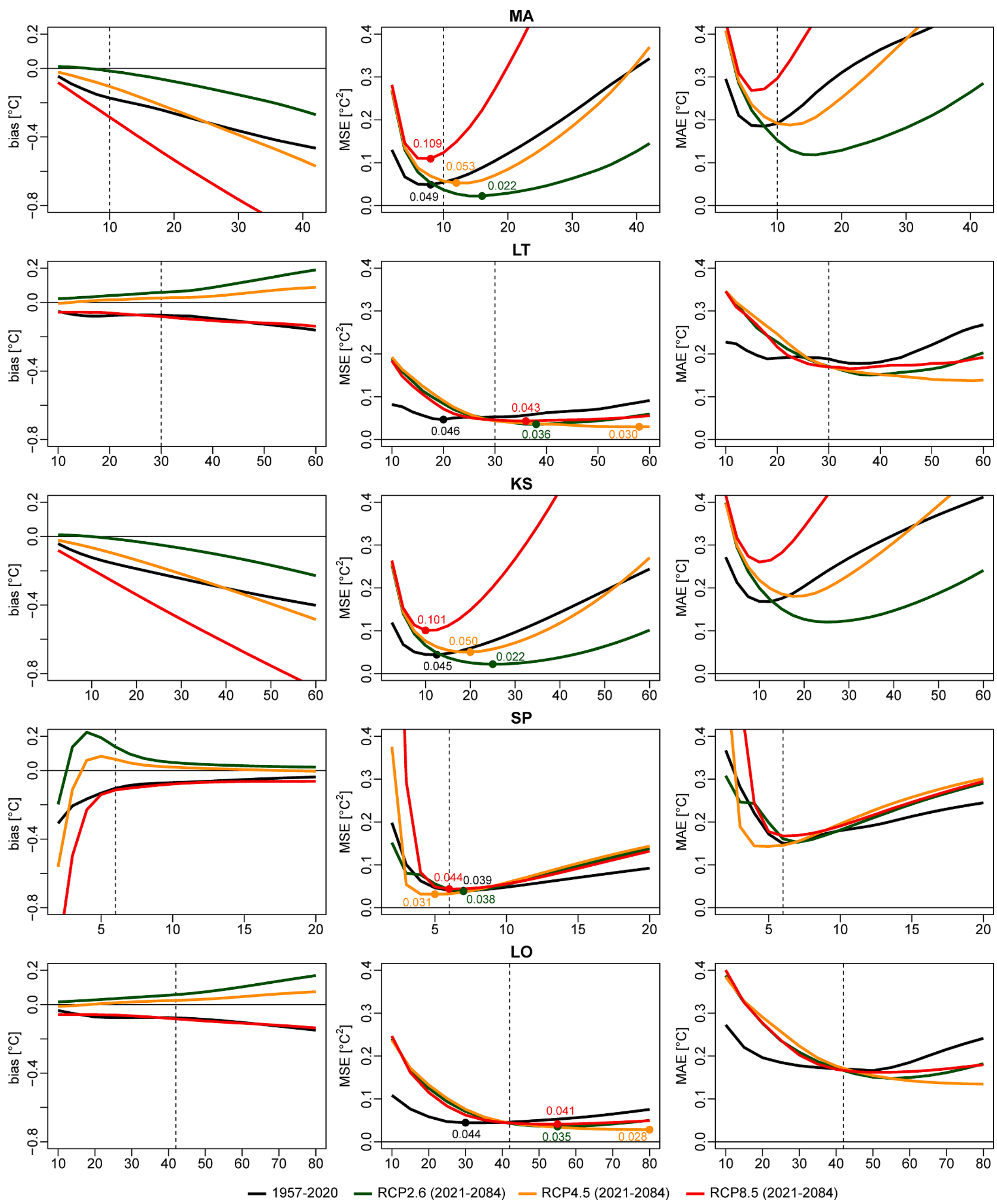

Fig. A1. Annual Swiss mean temperature CCM bias (left panels, in °C), mean square error MSE (center panels, in °C^2) and mean absolute error MAE (right panels, in °C) of moving average (MA, first row), linear trend (LT, second row), kernel smoother (KS, third row), cubic spline (SP, fourth row) and 1st order LOESS (LO, fifth row) for different parameter choices (x-axis). Shown are the aggregated error measures using 64 end years of the past (1957–2020, black) and the future (2021–2084, RCP2.6: green, RCP4.5: orange, RCP8.5: red). The dots and the numbers in the center panels show the position and respective minima of the MSE. The vertical lines indicate the parameter implementation by other weather services ($w_{MA} = 10$ years, $w_{LT} = 30$ years, $df_{SP} = 6$, $w_{LO} = 42$ years). For KS, SP and LO all years since 1864 up to the year in question are used for the estimate.

Table A2
Lowest MSE values (in °C^2) for the five CCM approaches MA, LT, KS, SP and LO for the past and future. The lowest MSE values per time frame are shown in bold, the highest MSE values are shown in italic. The optimized parameter for the lowest MSE values is shown in parenthesis.

time frame \ method		MA	LT	KS	SP	LO
past (1957–2020)		*0.049*	0.046	0.045	**0.039 (7)**	0.044
future (2021–2084)	RCP2.6	**0.022 (16)**	0.036	**0.022 (24)**	*0.038*	0.035
	RCP4.5	*0.053*	0.030	0.050	0.031	**0.028 (80)**
	RCP8.5	*0.109*	0.043	0.101	0.044	**0.041 (55)**

Table B1
List of the 45 EURO-CORDEX simulations (RCM-GCM combinations) used. The ensemble includes 8 RCP2.6, 16 RCP4.5 and 21 RCP8.5 runs. 24 (21) runs have a horizontal resolution of 50 (12) km.

	EUR-11 (~12 km horiz. resolution)		**EUR-44** (~50 km horiz. resolution)	
	RCM	**GCM**	**RCM**	**GCM**
RCP2.6 (8)	HIRHAM5	EC-EARTH	RACMO22E	HadGEM2-ES
	REMO2009	MPI-ESM-LR	RCA4	HadGEM2-ES
	RCA4	EC-EARTH	RCA4	MPI-ESM-LR
			RCA4	MIROC5
			RCA4	NorESM1-M
RCP4.5 (16)	CCLM4-8-17	EC-EARTH	RACMO22E	EC-EARTH
	CCLM4-8-17	HadGEM2-ES	RACMO22E	HadGEM2-ES
	CCLM4-8-17	MPI-ESM-LR	RCA4	CanESM2
	HIRHAM5	EC-EARTH	RCA4	CSIRO-Mk3-6-0
	REMO2009	MPI-ESM-LR	RCA4	MIROC5
	RCA4	EC-EARTH	RCA4	NorESM1-M
	RCA4	IPSL-CM5A-MR	RCA4	GFDL-ESM2M
	RCA4	HadGEM2-ES		
	RCA4	MPI-ESM-LR		
RCP8.5 (21)	CCLM4-8-17	EC-EARTH	RegCM4-3	HadGEM2-ES
	CCLM4-8-17	HadGEM2-ES	RACMO22E	HadGEM2-ES
	CCLM4-8-17	MPI-ESM-LR	RACMO22E	EC-EARTH
	HIRHAM5	EC-EARTH	RCA4	CanESM2
	REMO2009	MPI-ESM-LR	RCA4	CSIRO-Mk3-6-0
	RCA4	EC-EARTH	RCA4	MIROC5
	RCA4	IPSL-CM5A-MR	RCA4	NorESM1-M
	RCA4	HadGEM2-ES	RCA4	GFDL-ESM2M
	RCA4	MPI-ESM-LR	CCLM5-0-6	EC-EARTH
			CCLM5-0-6	MIROC5
			CCLM5-0-6	MPI-ESM-LR
			CCLM5-0-6	HadGEM2-ES

Begert et al., 2019). In addition, the climate trend curve nicely tracks the nonlinear evolution of the Swiss mean temperature. Fig. 4b shows the evolution of the sea level in the Netherlands. The 2021 CM was about 27 cm higher than the mean sea level at the beginning of the recordings in 1890. In contrast to the temperature evolution, the change in time has been quite linear. The highly variable local annual precipitation at the station of Zürich/Fluntern is shown in Fig. 4c. The CM for 2022 is estimated as 1004 $\pm$ 116 mm. In contrast to the temperature example in Fig. 4a, the 95 % confidence interval includes the 1991–2020 climate normal value of 1108 mm suggesting that the normal is still a reasonable CCM estimate. The long-term evolution shows a small tendency for increases but a pronounced decline in the last 25 years.

Fig. 4d depicts the evolution of the highly variable drought indicator "precipitation deficit" (maximum of cumulative potential evaporation minus precipitation from April to September, cf. Beersma and Buishand, 2004) in the Netherlands since 1906. In the 20th century, the values have been relatively stable over time, fluctuating around 150 mm. In the last two decades however, there is a tendency towards increasing drought (larger deficits) with a 2022 CM of 200 $\pm$ 43 mm. In Fig. 4e, the highly nonlinear long-term evolution of local sunshine duration in Bern/Liebefeld is shown. The 2022 CM of 2036 $\pm$ 106 h is considerably higher than the recent 1991–2020 normal (1797 h) and the climate trend line nicely traces the long-term evolution. Finally, Fig. 4f illustrates the strongly (nearly-linearly) increasing of absolute humidity in Genève/Cointrin since 1959. It reached a 2022 CM of 7.97 $\pm$ 0.17 g m^{-3}, an increase of about 10 % in the period 1959–2022.

In all cases, the LO42 climate trend line nicely illustrates the smoothed evolution regardless of whether it is linear or nonlinear. Note that the climate trend line (by construction) closely follows the 30-year moving average. It is also more representative for the temporally local behavior than the classical moving average which sometimes shows fast quite unrealistic year-to-year variability (e.g. Fig. 4d in the early 1960s).

5.2. Alternative anomalies and event classification

The deviation from the CCM – an alternative kind of anomalies – can be used to judge and classify events with respect to the climate conditions the event took place. This allows a fairer event classification than using anomalies with respect to the potentially biased classical normal values (cf. Gubler et al. (2023) classifying daily temperature extremes). The example for the annual Swiss mean temperature in Fig. 5 shows that the years with the most positive deviation from the CCM in decreasing order are 1947, 1961, 1994, 1921 and 1920. The years with the most negative deviation from the CCM are 1956, 2010, 1940, 1879 and 1941. The year 2022 is currently clearly the warmest year on record since 1864 (around 0.5 °C warmer than the previous record holder 2018). It was 0.88 °C warmer than the expected 2022 CM. Together with 1949 and 1898, this is the sixth largest positive deviation from the climate trend line in the time series. The deviation approximately corresponds to the 95th percentile in the distribution of the deviations. This relates to an approximate return period of about 20 years, making the year 2022 an exceptionally warm but not very extreme year in the current climate.

6. Conclusions and outlook

A transparent criteria-based assessment and method selection has been applied to estimate the current climate mean (CCM) in a changing climate based on past climate data. Besides performance, i.e. how close a method is with respect to a CCM benchmark based on climatological convention (i.e., a centered 30-year mean), we assess several additional criteria such as its flexibility to represent trends adequately, its wide applicability to a large range of climate variables and its simplicity in terms of use and communication. A carefully customized smooth nonlinear climate trend line based on local linear regression (1st order LOESS) turns out to be particularly promising in the overall assessment. It is already operationally used at KNMI (https://www.knmi.nl/klimaat) and will be implemented at MeteoSwiss in 2024 on an operational basis to complement the current climate monitoring products and climate services. Beside visualization purposes (e.g. trend lines in climate dashboards), potential modern climate services include the computation of up-to-date change signals, the classification of weather and climate extremes, or calculating an alternative kind of climate anomalies with respect to the climate trend line. Time will show which of the applications presented here will prove themselves in operational use. In order to increase the comparability and objectivity of climate monitoring results, we strongly recommend in-depth discussions at the international level with the aim to better harmonize the current methods and procedures for describing climate trends and estimating CCMs. This study suggests that local linear regression is a potential candidate but additional analyses are necessary to better determine its limitations. In the long-run, it would be interesting to define a regional/local current climate mean centered on today as recently proposed by Betts et al. (2023) to monitor the global 1.5 °C or 2 °C target. To achieve this goal, the recent observations must be linked with reliable forecasts for the next 1–2 decades. Until this becomes possible on the regional/local scale, the local linear regression approach based on past observations – that we identify as the best performing method here – can be a good solution.

CRediT authorship contribution statement

Simon C. Scherrer: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft. **Cees de Valk:** Methodology, Resources, Software, Writing – review & editing. **Michael Begert:** Software, Writing – review & editing. **Stefanie Gubler:** Writing – review & editing. **Sven Kotlarski:** Conceptualization, Writing – review & editing. **Mischa Croci-Maspoli:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Code and data availability

The code to compute the CCM based on local linear regression is available at https://gitlab.com/cees.de.valk/trend_knmi. The HadCRUT5.0.1.0 and CRUTEM.5.0.1.0 data are publicly available from the Met Office. The Swiss mean temperature data is freely available from doi: 10.18751/Climate/Timeseries/CHTM/1.3. Other Swiss observational data and the CH2018 scenario data is available from MeteoSwiss upon request. The KNMI observational data used is available via https://www.knmi.nl/klimaat.

Appendix A: Implementation details and optimal parameter determination

In this section we present some details of the technical implementation of some of the CCM approaches (cf. Table A1) and investigate the effect of the parameter choice on the CCM error statistics for the different approaches. Of the approaches presented in Table 1, M30.upd.10 and MA30 are WMO standards and have fixed parameters. The equally weighted moving average (MA), linear trend (LT), cubic spline (SP), Gaussian kernel smoother (KS) and local linear regression (1st order LOESS, LO) all have one free parameter that can be optimized in terms of CCM error behavior with respect to the centered 30-year mean benchmark (cf. section performance metrics in the main text). For MA, the parameter is the averaging window length w_{MA}. For LT, it is the trend window length w_{LT}. For KS, it is the smoothing bandwidth bw_{KS}. For SP, it is the degree of freedom df_{SP} and for LO, it is the trend window length w_{LO}. Three error metrics used here are the bias, the mean square error (MSE) and the mean absolute error (MAE).

Fig. A1 shows the error metrics for the CCM of annual Swiss mean temperature. They are aggregated for all 64 end years of the future (2021–2084) and the same number of end years of the past looking backward from 2020 (1957–2020). In the scientific literature, the optimal parameter choice is often determined where the MSE reaches a minimum (cf. dots and printed MSE values in Fig. A1, center panels). For MA, KS and SP the minima are well confined and the optimal parameter of the observational period is mostly similar to the one of the future intermediate- (RCP4.5) or high-emission (RCP8.5) scenario. It is also reasonably close to the parameter chosen by other authors or institutions (w_{MA} = 10 years, cf. IPCC, 2021; df_{SP} = 6, cf. Rigal et al., 2019). The CCM error characteristics for LT and LO look very similar. This is not astonishing since we use a first order (linear) LOESS and the only difference between the two is the weighting scheme of the input data points (cf. de Valk, 2020). The MSE values of LT and LO are in general low. While for the observational period, the 20 (LT) and 30 (LO) year windows achieve the minimum MSE, the optimal windows are larger for the future scenarios (w_{LT}: 36/38 (RCP2.6/RCP8.5) or even 58 years (RCP4.5) and w_{LO}: 55 (RCP2.6/RCP8.5) or 80 years (RCP4.5)). The windows used operationally by the Copernicus Climate Service (w_{LT} = 30 years) and KNMI (w_{LO} = 42 years) show MSE values close to the optimized minima for the observational and the three future scenario periods.

Note that for the past period 1957–2020, all CCM approaches with optimized parameters work similarly well (MSE = 0.039–0.049 $^\circ C^2$, cf. Table A2). For the scenario period 2021–2084, the performance between the approaches differs considerably. For the low-emission scenario RCP2.6, MA (w_{MA} = 16 years) and KS (bw_{KS} = 24 years) work best (MSE = 0.022 $^\circ C^2$) while for intermediate-emission RCP4.5 and high-emission RCP8.5 LO (w_{LO} = 55 / 80 years) performs best (MSE = 0.028 and 0.041 $^\circ C^2$) but LT and SP show only somewhat higher MSE values. Note that the MSE is much higher (MSE > 0.1 $^\circ C^2$) for MA and KS in the high-emission RCP8.5 scenario.

Appendix B: EURO-CORDEX simulations

See Table B1

References

Arguez, A., Vose, R.S., 2011. The Definition of the Standard WMO Climate Normal: The Key to Deriving Alternative Climate Normals. Bull. Am. Meteorol. Soc. 92, 699–704. https://doi.org/10.1175/2010BAMS2955.1.

Arguez, A., Vose, R.S., Dissen, J., 2013. Alternative Climate Normals: Impacts to the Energy Industry. Bull. Am. Meteorol. Soc. 94, 915–917. https://doi.org/10.1175/BAMS-D-12-00155.1.

Beersma, J.J., Buishand, T.A., 2004. Joint probability of precipitation and discharge deficits in the Netherlands. Water Resour Res 40, W12508. https://doi.org/10.1029/2004WR003265.

Begert, M., Frei, C., 2018. Long-term area-mean temperature series for Switzerland—Combining homogenized station data and high resolution grid data. Int J Clim 38, 2792–2807. https://doi.org/10.1002/joc.5460.

Begert, M., Stöckli, R., Croci-Maspoli, M., 2019. Klimaentwicklung in der Schweiz - Vorindustrielle Referenzperiode und Veränderung seit 1864 auf Basis der Temperaturmessung. Fachbericht MeteoSchweiz 274, 23 pp, [available at www.meteoswiss.ch].

Betts, R.A., Belcher, S.E., Hermanson, L., Klein Tank, A., Lowe, J.A., Jones, C.D., Morice, C.P., Rayner, N.A., Scaife, A.A., Stott, P.A., 2023. Approaching 1.5 °C: how will we know we've reached this crucial warming mark? Nature 624, 33–35. https://doi.org/10.1038/d41586-023-03775-z.

Boer, G.J., Smith, D.M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirtman, B., Kushnir, Y., Kimoto, M., Meehl, G.A., Msadek, R., Mueller, W.A., Taylor, K.E., Zwiers, F., Rixen, M., Ruprich-Robert, Y., Eade, R., 2016. The Decadal Climate Prediction Project (DCPP) contribution to CMIP6. Geosci Model Dev 9, 3751–3777. https://doi.org/10.5194/gmd-9-3751-2016.

CH2018, 2018. CH2018 – Climate Scenarios for Switzerland, Technical Report. National Centre for Climate Services, Zurich, 271 pp, ISBN: 978-3-9525031-4-0 [available at www.klimaszenarien.ch].

Chambers, J.M., Hastie, T.J., 1992. Statistical Models in S. Wadsworth & Brooks/Cole. 608 pp. ISBN 0-534-16765-9.

Cheng, L., Foster, G., Hausfather, Z., Trenberth, K.E., Abraham, J., 2022. Improved Quantification of the Rate of Ocean Warming. J. Clim. 35, 4827–4840. https://doi.org/10.1175/JCLI-D-21-0895.1.

Clarke, D.C., Richardson, M., 2021. The benefits of continuous local regression for quantifying global warming. Earth Space Sci. 8, e2020EA001082 https://doi.org/10.1029/2020EA001082.

Cleveland, W.S., 1979. Robust locally weighted regression and smoothing scatterplots. J. Am. Stat. Assoc. 74, 829–836. https://doi.org/10.2307/2286407.

Cleveland, W.S., Devlin, S.J., 1988. Locally weighted regression: an approach to regression analysis by local fitting. J. Am. Stat. Assoc. 83, 596–610. https://doi.org/10.1080/01621459.1988.10478639.

Copernicus Climate Change Service (C3S), 2021. Global temperature trend monitor - User guide [available at https://datastore.copernicus-climate.eu/documents/app-c3s-global-temperature-trend-monitor/C3S_Application-Documentation-Global_temperature_trend_monitor_v1.0_TNS_FV_v3.5.pdf].

de Valk, C.F., 2020. Standard method for determining a climatological trend. KNMI Technical report. 389, 33 pp [available at https://cdn.knmi.nl/system/ckeditor_assets/attachments/161/TR389.pdf].

Efron, B., Tibshirani, R.J., 1994. An introduction to the bootstrap. Chapman and Hall/CRC Press, New York, p. 456 pp. https://doi.org/10.1201/9780429246593.

Feigenwinter, I., Kotlarski, S, Casanueva, A., Fischer, A.M., Schwierz, C., Liniger, M.A., 2018. Exploring quantile mapping as a tool to produce user-tailored climate scenarios for Switzerland. MeteoSwiss Technical Report. 270, 44 pp [available from www.meteoswiss.ch].

Fischer, A.M., et al., 2022. Climate Scenarios for Switzerland CH2018 – approach and implications. Clim. Serv. 26, 100288 https://doi.org/10.1016/j.cliser.2022.100288.

Gasser T., Müller, H.G., 1979. Kernel estimation of regression functions. In: Gasser, T., Rosenblatt, M. (Eds.), Smoothing Techniques for Curve Estimation. Lecture Notes in Mathematics. 757. Springer, Berlin, Heidelberg, pp. 23–68. https://doi.org/10.1007/BFb0098489.

Gubler, S., Fukutome, S., Scherrer, S.C., 2023. On the statistical distribution of temperature and the classification of extreme events considering season and climate change—an application in Switzerland. Theor. Appl. Climatol. 153, 1273–1291. https://doi.org/10.1007/s00704-023-04530-0.

Hart, J.D., Wehrly, T.E., 1992. Kernel regression when the boundary region is large, with an application to testing the adequacy of polynomial models. J. Am. Stat. Assoc. 87, 1018–1024. https://doi.org/10.1080/01621459.1992.10476257.

Hawkins, E., Frame, D., Harrington, L., Joshi, M., King, A., Rojas, M., Sutton, R., 2020. Observed emergence of the climate change signal: From the familiar to the unknown. Geophys. Res. Lett. 47, e2019GL086259 https://doi.org/10.1029/2019GL086259.

IPCC, 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou B. (eds.)]. Cambridge University Press. https://doi.org/10.1017/9781009157896.

Jacob, D., et al., 2014. EURO-CORDEX: new high-resolution climate change projections for European impact research. Reg. Environ. Change 14, 563–578. https://doi.org/10.1007/s10113-013-0499-2.

Jacob, D., et al., 2020. Regional climate downscaling over Europe: perspectives from the EURO-CORDEX community. Reg Environ Change 20. https://doi.org/10.1007/s10113-020-01606-9.

Kaspar, F., Friedrich, K., Imbery, F., 2023. Observed temperature trends in Germany: Current status and communication tools. Meteorol Zeitschrift 32, 279–291. https://doi.org/10.1127/metz/2023/1150.

Keizer, I., Le Bars, D., de Valk, C., Jüling, A., van de Wal, R., Drijfhout, S., 2023. The acceleration of sea-level rise along the coast of the Netherlands started in the 1960s. Ocean Sci. 19, 991–1007. https://doi.org/10.5194/os-19-991-2023.

Krakauer, N.Y., Devineni, N., 2015. Up-to-date probabilistic temperature climatologies. Environ. Res. Lett. 10, 024014 https://doi.org/10.1088/1748-9326/10/2/024014.

Lenssen, N., Schmidt, G., Hansen, J., Menne, M., Persin, A., Ruedy, R., Zyss, D., 2019. Improvements in the GISTEMP uncertainty model. J. Geophys. Res. Atmos. 124, 6307–6326. https://doi.org/10.1029/2018JD029522.

Livezey, R.E., Vinnikov, K.Y., Timofeyeva, M.M., Tinker, R., van den Dool, H.M., 2007. Estimation and extrapolation of climate normals and climatic trends. J. Appl. Meteor. Climatol. 46, 1759–1776. https://doi.org/10.1175/2007JAMC1666.1.

Mann, M.E., 2004. On smoothing potentially non-stationary climate time series. Geophys. Res. Lett. 31, L07214. https://doi.org/10.1029/2004GL019569.

Mann, M.E., 2008. Smoothing of climate time series revisited. Geophys. Res. Lett. 35, L16708. https://doi.org/10.1029/2008GL034716.

Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D.P., Stouffer, R.J., 2008. Stationarity is dead: whither water management? Science 319, 573–574. https://doi.org/10.1126/science.1151915.

Morice, C.P., Kennedy, J.J., Rayner, N.A., Winn, J.P., Hogan, E., Killick, R.E., et al., 2021. An updated assessment of near-surface temperature change from 1850: the HadCRUT5 data set. J. Geophys. Res.: Atmos. 126, e2019JD032361 https://doi.org/10.1029/2019JD032361.

Osborn, T.J., Jones, P.D., Lister, D.H., Morice, C.P., Simpson, I.R., Harris, I.C., 2021. Land surface air temperature variations across the globe updated to 2019: the CRUTEM5 dataset. J. Geophys. Res. 126, e2019JD032352 https://doi.org/10.1029/2019JD032352.

Rigal, A., Azaïs, J.-M., Ribes, A., 2019. Estimating daily climatological normals in a changing climate. Clim. Dyn. 53, 275–286. https://doi.org/10.1007/s00382-018-4584-6.

Scherrer, S.C., Appenzeller, C., Liniger, M.A., 2006. Temperature trends in Switzerland and Europe: implications for climate normals. Int. J. Clim. 26, 565–580. https://doi.org/10.1002/joc.1270.

Steinacker, R., 2021. How to correctly apply Gaussian statistics in a non-stationary climate? Theor. Appl. Climatol. 144, 1363–1374. https://doi.org/10.1007/s00704-021-03601-4.

Student, 1908. The probable error of a mean. Biometrika 6, 1–25. https://doi.org/10.2307/2331554.

Trewin, B., 2022. Assessing internal variability of global mean surface temperature from observational data and implications for reaching key thresholds. J. Geophys. Res.: Atmos. 127, e2022JD036747 https://doi.org/10.1029/2022JD036747.

United Nations, 2015. Paris Agreement. Retrieved from https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

Wilks, D.S., 2013. Projecting ‘‘normals’’ in a nonstationary climate. J. Appl. Meteorol. Climatol. 52, 289–302. https://doi.org/10.1175/JAMC-D-11-0267.1.

Wilks, D.S., Livezey, R.E., 2013. Performance of alternative normals for tracking climate changes, using homogenized and nonhomogenized seasonal U.S. surface temperatures. J. Appl. Meteorol. Climatol. 52, 1677–1687. https://doi.org/10.1175/JAMC-D-13-026.1.

WMO, 2007. The Role of Climatological Normals in a Changing Climate. WMO Tech. Doc. 1377, 130 pp [available at https://library.wmo.int/doc_num.php?explnum_id=4546].

WMO, 2017. WMO Guidelines on the Calculation of Climate Normals. WMO-No. 1203, 29 pp [available at https://library.wmo.int/doc_num.php?explnum_id=4166].