Harmonized European Long-Term Climate Data for Assessing the Effect of Changing Temporal Variability on Land–Atmosphere CO₂ Fluxes*

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ABSTRACT

Temporal variability of meteorological variables and extreme weather events is projected to increase in many regions of the world during the next century. Artificial experiments using process-oriented terrestrial ecosystem models make it possible to isolate effects of temporal variability from effects of gradual climate change on terrestrial ecosystem functions and the system state. Such factorial experiments require two long-term climate datasets: 1) a control dataset that represents observed and projected climate and 2) a dataset with the same long-term mean as the control dataset but with altered short-term variability. Using a bias correction method, various climate datasets spanning different periods are harmonized and then combined with the control dataset with consistent time series for Europe during 1901–2100. Then, parameters of a distribution transformation function are estimated for individual meteorological variables to derive the second climate dataset, which has similar long-term means but reduced temporal variability. The transformation conserves the number of rainy days within a month and the shape of the daily meteorological data distributions, which is important to ensure that, for example, drought duration does not modify the suitability of localized vegetation type to precipitation regimes. The median absolute difference between daily data of both datasets is 5% to 20%. On average, decadal extreme values are reduced by 2% to 35%. Driving a terrestrial ecosystem model with both climate datasets shows a general higher gross primary production under reduced temporal climate variability. This effect of climate variability on productivity demonstrates the potential of the climate datasets for studying various effects of temporal variability on ecosystem state and functions over large domains.

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1. Introduction

The anthropogenic change of greenhouse gas concentrations in the atmosphere leads to a changing mean climate. This effect can be amplified or dampened by positive or negative climate–carbon cycle feedback mechanisms (e.g., Cox et al. 2000; Friedlingstein et al. 2006; Heimann and Reichstein 2008). In addition to the mean, the variance of meteorological variables can change over time. While air temperature temporal variability

might decrease in future at the global scale (Huntingford et al. 2013), global and regional climate modeling results suggest an increase of the temporal variance of air temperature, precipitation, and other meteorological variables, and hence an increase of extreme meteorological events, at regional to local scales and up to 2100 (Easterling et al. 2000; Schär et al. 2004; Fischer and Schär 2010; Seneviratne et al. 2012). In general, there are three possibilities of how the distribution of meteorological variables can change: 1) a change in the mean while the distribution width remains constant, 2) a change in the variance while the mean remains the same, and 3) a change in both mean and variance (Katz and Brown 1992; Meehl et al. 2000). In the first and last case, (much) more extreme events in one direction are expected while in the second case, more extreme events at both ends of the range will occur. In addition, alteration of higher statistical moments will also affect the frequency of extreme meteorological events.

Therefore, there has been a new focus on the impacts of a changing variability of climate and frequency of extreme meteorological events on carbon, water, and nutrient cycles (Medvigy et al. 2010; Seneviratne et al. 2012; Reichstein et al. 2013). For instance, can more often extreme meteorological conditions in the future alter an otherwise positive effect of an increasing mean temperature on ecosystem productivity? Severe droughts, heat waves, storms, floods, and frosts can affect the carbon balance directly via effects on productivity or respiration or indirectly via effects on disturbances and vegetation changes (Reichstein et al. 2013). In addition to severe meteorological extreme events that alter ecosystem state variables dramatically (e.g., by disturbance), the changing temporal variability of meteorological variables will have effects on the carbon balance because terrestrial ecosystems respond to daily or even subdaily meteorological conditions and response functions are nonlinear. For example, the curvature of the light-response function of photosynthesis is concave (Harvey 1979). This means that we expect higher gross primary productivity under lower temporal variability conditions and conserved mean (case 2 above). In contrast, the curvature of the temperature-response function of ecosystem respiration is convex (Lloyd and Taylor 1994), and hence respiration is expected to be lower under lower temporal variability conditions and conserved mean. From these two examples alone we would expect a lower net ecosystem production under conditions with higher variability and conserved mean. However, in reality there are many of such nonlinear response functions of ecosystem processes to environmental factors, and hence the net effect of changing temporal climate variability on the carbon balance is unclear.

To address such questions from a theoretical modeling perspective, a climate dataset is required that shows a long-term mean similar to the control set while the day-to-day and year-to-year variability is altered (case 2 above). Then, such a dataset can be used in factorial modeling experiments to perform large-scale and long-time experiments using prognostic terrestrial ecosystem models. Changing the variance of the data is also expected to affect high and low extreme values. However, even when, for example, temperature is reduced by 20% during a 2-week period of extreme high temperature in summer, still this can be an extreme drought affecting the ecosystem function. It is not our aim to specifically reduce the number of extreme events by the proposed methods, although they will be clearly affected.

To perform factorial model experiments, first the ecosystem model's carbon pools need to be brought into equilibrium with preindustrial carbon dioxide concentrations and preindustrial climate using a spinup procedure. Then, transient model simulations until 2100 or longer can be performed using changing CO₂ and climate data. If the respective climate time series contained an abrupt offset, then the ecosystem states would drift toward another hypothetical preindustrial equilibrium. Such drift would overlay climate change-induced trends and lead to invalid conclusions. Hence, it is important to use time series of climate data that are most harmonized for prognostic ecosystem model applications. In addition, the climate data should reflect observations during past and recent time periods providing the opportunity of an ecosystem model evaluation using carbon pool and flux observations. Therefore, monthly climate anomalies have usually been extracted from climate model results and added to current observation-based climate grids in most previous modeling studies (e.g., Cramer et al. 2001; Schaphoff et al. 2006).

For the purpose of running a land surface scheme, a full range of climatic variables, including longwave radiation, wind speed, and specific humidity in addition to temperature, shortwave radiation, and precipitation, needs to be provided at high temporal resolution. Therefore, an alternative approach is to use bias-corrected reanalysis data or bias-corrected climate model results (Sheffield et al. 2006; Weedon et al. 2011). For deriving such a climate dataset, we make use of the statistical bias correction methodology described in Piani et al. (2010) and apply it to temperature, precipitation, shortwave and longwave downward radiation flux, wind speed, surface pressure, and specific humidity. This bias correction is based on a fitted histogram equalization function that is defined daily. The method has been successfully applied within the EU project Water and

Global Change (WATCH) for deriving bias-corrected temperature and precipitation datasets during 1990–99 (Piani et al. 2010). We extend the approach for deriving grids of a full range of required climatic variables with high spatial resolution and daily temporal resolution spanning the period 1901–2100. This dataset reflects as much as possible observed climate during recent times, and the time series are harmonized such that jumps due to different underlying original climate datasets are avoided. Such long-term datasets can serve as the control for artificial model experiments as mentioned above. It is also the basis for an alternative long-term dataset with altered short-term variability but conserved long-term mean. This second dataset will be derived from the first one by a power-law transformation, and it will be useful for detailed studies on effects of climate variability and extreme events on terrestrial ecosystem functions. Such effects will be demonstrated by running the terrestrial ecosystem model JSBACH (Jena Scheme of Biosphere–Atmosphere Coupling in Hamburg; Raddatz et al. 2007) using both climate datasets.

2. Methods

a. Climate datasets

In this section we describe the control climate dataset for Europe ranging from 29° to 71°N and −24° to 45°E during 1901–2100 that we derived from combining several other climate datasets. This dataset can be used to run terrestrial ecosystem models, and it is also used to derive a dataset with reduced temporal variability (see section 2b). The following steps have been applied to produce consistent time series during 1901–2100:

- (i) 1901–78. For this time period the WATCH forcing data Weedon et al. (2011) are used. The WATCH forcing data are based on 40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40) data and span the period 1901–2001 with daily temporal resolution. The ERA-40 reanalysis data have been scaled to a grid cell size of 0.5° (Weedon et al. 2011) in the EU project WATCH (www.eu-watch.org/). The reanalysis data also have been bias corrected in several ways (Weedon et al. 2011).
- (ii) 1979–2010. This period is covered by Interim ECMWF Re-Analysis (ERA-Interim) data (Dee et al. 2011). We obtained daily data with a grid cell size of 0.5° from ECMWF. The reanalysis data were bias-corrected against the WATCH forcing data described above using an overlapping period of 1979–2001 and following the standard procedure described in Piani et al. (2010). Ideally, this approach

conserves statistical moments of the distribution (e.g., the mean and variance). In addition, the number of rainy days remains unchanged. The WATCH forcing data serve as the reference dataset since they have already been bias corrected against other climatic datasets (Weedon et al. 2011).

- (iii) The spatial resolution of datasets (i) and (ii) above was further improved to a grid cell size of 0.25° for having the spatial resolution comparable with the one from the regional climate model outputs [see item (iv) below]. This was reached by imposing the 0.1° subgrid variability from the Climate Research Unit (CRU) CL 2.0 dataset (New et al. 2002) on the 0.5° datasets (i) and (ii) above for each meteorological variable. For each large 0.5° grid cell, the anomalies of the finer 0.1° values within this 0.5° grid cell were estimated. Then, these anomalies were added to the original 0.5° value in order to obtain a dataset at 0.1° spatial resolution, which equals the datasets (i) and (ii) above at 0.5° spatial resolution. This dataset was further aggregated to the final 0.25° resolution using a trilinear interpolation method.

Since CRU CL 2.0 does not contain surface pressure (P) but a digital elevation map (h) we applied an altitude-based correction for scaling this variable following

$$P = 101\,325(1 - h \cdot 2.255\,77 \times 10^{-5})^{5.255\,88}. \quad (1)$$

In addition, CRU CL 2.0 contains relative humidity instead of specific humidity, which we needed for the final dataset. Therefore, we calculated specific humidity (SH) from pressure P by using information about height h and air temperature T . We first derived the saturated water vapor pressure as follows:

$$e(T) = 611.2 \exp\left(\frac{17.67T}{243.15 + T}\right). \quad (2)$$

This leads to the mixing ratio (MR)

$$\text{MR} = 0.622 \exp\left[\frac{e(t)}{P - e(t)}\right], \quad (3)$$

which is then used to obtain specific humidity following

$$\text{SH} = \frac{\text{MR}}{1 + \text{MR}}. \quad (4)$$

CRU CL 2.0 also does not contain minimum and maximum daily air temperature but mean daily temperature and the diurnal temperature range. Therefore, we first obtained datasets of minimum

and maximum daily temperature by mapping the relative difference of Tmin and Tmax to Tmean from the WATCH forcing data or bias-corrected ERA-Interim data to the CRU diurnal temperature range, and added this result to the CRU CL 2.0 mean daily temperature.

The CRU CL 2.0 dataset and Eqs. (1)–(4) will only determine the spatial variability of meteorological variables within a 0.5° area, that is, how a 0.5° average is represented by grid cells at 0.25° resolution. Aggregated values at 0.5° will equal the values from datasets described in (i) and (ii) above.

(iv) 2011–2100. To extend the dataset from 2011 until 2100 results of the regional climate model REMO during 1970–2100 have been used. ECHAM5 fields served as boundary conditions and the Special Report on Emissions Scenarios (SRES) A1B carbon dioxide emission scenario have been applied. These data were provided by the EU project ENSEMBLES (<http://ensembles-eu.org/>) and already came with a 0.25° spatial and daily temporal resolution. The same bias-correction method as in (ii) has been applied to the full dataset (1970–2100) and 1970–2010 was chosen as the overlapping period.

b. Transformation function and its parameter estimation

The aim is to transform the distribution of the original data x into a distribution of data $f(x)$ such that the mean is conserved but the variance is higher or lower. For such, one can use the transformation function

$$f(x) = cx^\alpha. \quad (5)$$

An analytical solution of the parameters c and α is possible when using a Taylor approximation of $f(x)$ around the mean μ of the actual data x :

$$f(x) \approx f(\mu) + f'(\mu)(x - \mu). \quad (6)$$

The expected value of $f(x)$ approximates to $f(\mu)$:

$$\begin{aligned} E[f(x)] &\approx E[f(\mu) + f'(\mu)(x - \mu)] \\ &= E[f(\mu)] + f'(\mu)E(x - \mu) = f(\mu). \end{aligned} \quad (7)$$

Since we aim for keeping the mean constant $\{E[f(x)] = \mu$ hence $f(\mu) = \mu\}$, we can estimate c as follows:

$$f(\mu) \approx \mu, \quad (8)$$

$$c\mu^\alpha = \mu, \quad (9)$$

$$c = \mu^{1-\alpha}. \quad (10)$$

A similar calculation can be done for the variance of $f(x)$:

$$\begin{aligned} \text{Var}[f(x)] &\approx E[f(\mu) + f'(\mu)(x - \mu) - \mu]^2 \\ &= E\{[f'(\mu)(x - \mu)]^2\} = f'(\mu)^2 \text{Var}(x). \end{aligned} \quad (11)$$

We want to estimate parameters c and α such that the new variance $\text{Var}[f(x)]$ is a multiple (k) of the variance of the original data $\text{Var}(x)$, hence

$$f'(\mu)^2 \text{Var}(x) = k \text{Var}(x), \quad (12)$$

$$k = f'(\mu)^2, \quad (13)$$

$$k = c^2 \alpha^2 \mu^{2\alpha-2}. \quad (14)$$

Combining Eq. (14) with Eq. (10) leads to α :

$$k = \alpha^2, \quad (15)$$

$$\alpha = \sqrt{k}. \quad (16)$$

The variance factor k will be defined (section 2c) and the mean μ is known. Then, α is estimated using Eq. (16), and c is subsequently determined using Eq. (10).

c. Practical implementation—A specific example

In this study we perform the transformation on the specific climate dataset described in section 2a. This dataset will be called control (CNTL) in the following. It contains the following measures at daily resolution: minimum air temperature, maximum air temperature, precipitation, downward shortwave radiation, downward longwave radiation, specific humidity, wind speed, and surface pressure.

In Europe, most of the variance during a year is generally induced by the large seasonal cycle. However, we are not interested in altering a seasonal cycle of meteorological variables that is typical for a specific place, and to which the ecosystem has adapted over a long time. Therefore, we first subtract the mean seasonal cycle from the climate data and then perform the transformation (section 2b) on the anomalies. Afterward, the mean seasonal cycle is added to these transformed anomalies. For the seasonal cycle removal and the transformation, a 10-yr moving window is used. In this way, a high impact of specific climatic conditions of a certain year on the parameters α and c is avoided. On the other hand, a 10-yr moving window is narrow enough to keep any long-term trend in meteorological variables, such as rising temperature.

The mean seasonal cycle is removed as follows. For each day of the year the mean of 10 values within the 10-yr

moving window is subtracted from the value of the particular day. For precipitation and wind, we calculate the mean seasonal cycle using monthly data because the more stochastic characteristic of these data does not allow estimating a stable climatology at daily resolution. These mean seasonal cycles are also subtracted from daily data.

The transformation is performed using $k = 0.25$ (i.e., the aim is to reduce the temporal variability of CNTL). On purpose, we estimate parameters such that variability is reduced because it ensures that the altered ranges of values are within the decadal envelope of variability from CNTL. This leads to a dataset that we will call REDVAR in the following. It has the same spatial and temporal resolution, and covers the same domain as CNTL.

d. Data evaluation procedure

The aim of the bias correction method is to produce a time series for the period 1901–2100 (CNTL) that does not contain jumps just because different periods are based on different climate datasets. Validation of the bias correction method will be done by comparing the bias-corrected dataset with the respective reference dataset during the overlapping time period 1981–2000. Continental-scale difference plots of mean annual climate variables and mean seasonal climate variables will be shown. In addition, detailed time series of annual values, regression analyses, and the long-term probability density function will be compared at European locations with a strong climate gradient in Finland, Germany, and Portugal.

Validation of the data transformation to the dataset with reduced temporal variability but conserved long-term mean includes a continental-scale analysis of the median absolute difference of daily data during 1981–2000, and a comparison of mean annual and seasonal climate variables between the datasets during these time periods. In addition, gridpoint time series of variables of reduced variability versus control climate will be analyzed at different time scales. Also, the probability density function of daily climate variables during 1981–2010 will be compared. The relationships among air temperature, shortwave radiation, and precipitation will be evaluated by respective regression analyses.

The median absolute difference of two datasets $MAD(x, y)$ is defined as

$$MAD(x, y) = \text{median}(|x_i - y_i|). \quad (17)$$

To analyze differences in extreme values of both datasets, decadal minimum and maximum values are calculated during 1901–2100. Such decadal time series are compared at four European locations. In addition,

99th percentiles of annual maximum values and first percentiles of annual minimum values during each decade of the period 1901–2100 are calculated for each grid cell. Then, an average of these 20 extreme values are taken and the ratio between REDVAR and CNTL dataset results analyzed w.r.t. a reduction of extreme meteorological conditions in the reduced variability dataset.

e. Terrestrial ecosystem model application

To demonstrate the potential of the climate datasets for studying effects of temporal climate variability and extreme events on ecosystem functions we are using the terrestrial ecosystem model JSBACH (Raddatz et al. 2007). This one-dimensional model simulates land–atmosphere exchanges of energy, water, and carbon dioxide at 30-min temporal resolution. Representation of canopy processes are based on the Biosphere Energy-Transfer and Hydrology model (BETHY; Knorr 2000) but phenology and a simple carbon cycle scheme including several pools for vegetation, litter, and soil carbon have also been added (Raddatz et al. 2007). JSBACH has been driven by both the CNTL and REDVAR climate datasets at three locations in Europe. Carbon pools have been brought into equilibrium by a 1000-yr spinup procedure using climate from the period 1901–30 and atmospheric carbon dioxide concentration from year 1901 (296 ppm). Then, the model was run with transient climate and transient atmospheric carbon dioxide concentration during 1901–2100. The global atmospheric carbon dioxide concentration followed for the historical period (1901–2010) the Coupled Model Intercomparison Project phase 5 (CMIP5) protocol (Meinshausen et al. 2011) and for the period 2011–2100 the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) SRES A1B scenario (http://www.ipcc-data.org/observ/ddc_co2.html).

3. Results

a. Evaluation of the CNTL climate dataset

In Fig. 1 European maps of differences of mean annual climate variables between the bias-corrected ERA-Interim dataset and the WATCH forcing data during 1981–2000 are shown. Minimum and maximum daily air temperature differ by maximal 0.2°C . The long-term mean annual precipitation and mean shortwave radiation can differ by about 0.08 mm day^{-1} and 0.5 W m^{-2} , respectively. This shows the general similarity of the bias-corrected ERA-Interim climate data and the reference dataset, the WATCH forcing data, which is also true for longwave radiation, specific humidity, wind speed, and

FIG. 1. Difference between the bias-corrected ERA-Interim dataset and the WATCH forcing dataset (WFD). Shown are differences of 1981–2000 averages of daily data. See supplemental material for seasonal averages.

surface pressure (Fig. 1). There are a few interesting spatial patterns; for example, the bias-corrected ERA-Interim data show lower temperatures and higher radiation in Scandinavia, southern Germany, and southern France. However, differences are generally small. Results of seasonal averages agree with the finding from mean annual results above about the general similarity of the two datasets (see Figs. S1 and S2 in the supplemental material, available online at <http://dx.doi.org/10.1175/JCLI-D-13-00543.s1>). Differences between bias-corrected ERA-Interim and WATCH forcing data in summer and winter are of the same magnitude as mean annual differences (see supplemental Figs. S1 and S2). Despite the fact that differences are small, it is interesting to note that there is spatial correlation in the difference. The maps do not show a random distribution of differences but rather regional differences (e.g., the small overestimation of shortwave radiation in southern Scandinavia and Great Britain in summer; supplemental Fig. S1).

For the continental-scale evaluation of the bias correction of ECHAM5-REMO results, the same kind of difference maps are shown in Fig. 2 and in the supplemental Figs. S3 and S4. Here, the bias-corrected ERA-Interim data serve as the reference dataset. The remaining differences between these datasets are a bit higher than between the datasets shown in Fig. 1. However, the magnitude of difference is similar and both mean annual and mean seasonal results show that there is not a major bias anymore in the REMO dataset. The plots in Fig. 2 and in the supplemental material suggest that there exist more spatial pattern and regional differences between the bias-corrected REMO and bias-corrected ERA-Interim datasets than between the bias-corrected ERA-Interim and WATCH forcing data (Fig. 1 and supplemental material).

For a deeper evaluation of the bias-correction method, time series from three grid cells representing different climatic zones are analyzed in Fig. 3 and the supplemental Figs. S5–S11. Most of the original ERA-Interim variables are already quite similar to WATCH forcing data. However, the scatterplots and annual time series plots demonstrate how existing biases were corrected (Fig. 3c; see also the supplemental material), for example, for shortwave radiation (Fig. 3; see also supplemental Fig. S8), longwave radiation, specific humidity, wind speed (supplemental Figs. S9–S11), and temperatures in the Mediterranean (supplemental Figs. S5c and S6c).

The probability density functions in Fig. 3 and supplemental Figs. S5–S11 show the importance of bias correction method. The distributions of daily data are largely corrected. The improvement of the daily data probability function is important because it shows that

the variability and range of the daily data were also improved. This also has consequences for the standard deviation of daily data during a year, which is also improved in addition to mean values (Fig. 3; see also the supplemental material).

b. Comparison of CNTL and REDVAR datasets

1) DIFFERENCES BETWEEN CNTL AND REDVAR DAILY DATA

The transformation described in section 2b leads to daily values of meteorological variables differing from the ones in the CNTL dataset. Variability of daily data is much reduced while the general shape of the seasonal cycle is maintained (Fig. 4a; see also supplemental Figs. S12–S32). The reduction in daily variability is also seen by the comparison of probability density functions. REDVAR mean daily temperature shows a higher number of mean values than extreme minimum or maximum values (Fig. 4c). The temperature bimodality is caused by winter versus summer conditions. Small precipitation values occur much more often in the REDVAR dataset (Fig. 4d). In contrast, very large precipitation values are removed from the distribution (Fig. 4d). It is important to note that the type of distribution (bimodal normal distribution for temperature, exponential distribution for precipitation) remains unaltered. Also for the other variables, the REDVAR distributions are much narrower and medium-range values occur more often while the mode or modes are being maintained (supplemental Figs. S12–S32).

The variability reduction can also be seen at annual scale. Year-to-year variation of REDVAR variables is smaller than year-to-year variation of CNTL variables (Figs. 4e,f; supplemental Figs. S12–S32). However, a potential long-term trend like in the example of temperatures remains unaltered in the REDVAR dataset (Figs. 4e,g; see also supplemental material).

The continental-scale analysis of differences between REDVAR and CNTL datasets is done using maps of median absolute deviation of daily data during 1981–2000 (Fig. 5; supplemental Fig. S33). The median absolute deviation of daily minimum and daily maximum temperature ranges between 0.5° and 1.6°C in Europe with a clear gradient from maritime to continental regions (Figs. 5a,b). The absolute temperature difference between the two datasets is higher at continental regions because the daily temperature variability is higher there and the variability is reduced in relative terms. Daily values of shortwave radiation differ by about 4 to 12 W m⁻² (about 5% to 20%) between the two datasets (Fig. 5d). The median absolute deviation between CNTL and REDVAR daily precipitation values ranges

FIG. 2. Difference between the bias-corrected ENSEMBLES ECHAM5-REMO dataset and the bias-corrected ERA-Interim dataset. Shown are differences of 1981–2000 averages of daily data. See supplemental material for seasonal averages.

(a) Mean daily air temperature ($^{\circ}\text{C}$). Daily data shown in the first two plots, otherwise annual.

(b) Daily precipitation (mm/d). Daily data shown in the first two plots, otherwise annual.

(c) Mean daily short-wave radiation (W/m^2). Daily data shown in the first two plots, otherwise annual.

FIG. 3. Pixel-level evaluation of the bias correction method for a grid cell in central Germany at the overlapping period 1981–2000. Results from the datasets WATCH, ERA-Interim (ERA-I), bias-corrected ERA-Interim (BC ERA-I), ECHAM5-REMO (REMO), and bias-corrected ECHAM5-REMO (BC REMO) are shown. More variables and grid cells can be found in the supplementary material.

FIG. 4. Pixel-level comparison between CNTL and REDVAR datasets for a grid cell in central Germany. Mean daily air temperature ($^{\circ}\text{C}$) and daily precipitation (mm day^{-1}) are shown on the left- and right-hand side, respectively. First two rows: daily data, third row: annual data, fourth row: 30-yr running mean. JJA results represent June–August averages. More variables and grid cells can be found in the supplementary material.

FIG. 5. Median absolute deviation between daily reduced variability and control data during 1981–2000. See supplemental material for more variables.

between 0.1 and 0.6 mm day^{−1} during 1981–2000 (Fig. 5c), which is a relative difference of about 10% to 20%. The precipitation difference is highest in coastal regions, in particular in the Mediterranean (Fig. 5c).

2) COMPARISON OF CNTL AND REDVAR LONG-TERM AVERAGES

The REDVAR and CNTL 30-yr running means during 1961–2100 are very similar (Figs. 4g,h; supplemental Figs. S12–S32). In addition, the long-term averages of seasonal values differ only marginally (Figs. 4g,h; supplemental Figs. S12–S32), that is, the temporal variability reduction has not altered a seasonal cycle. Both datasets show the same long-term dynamics of annual and seasonal averages, such as an increase of air temperature in central Germany (Fig. 4g). Interestingly, annual precipitation is projected to increase whereas summer precipitation is projected to decrease in central

Germany after 2060 (Fig. 4h). Such long-term dynamics remain consistent between both REDVAR and CNTL datasets.

The long-term similarity of both datasets CNTL and REDVAR is also seen for the whole continent in general. Long-term averages of meteorological variables compare well during 1981–2000 (Fig. 6). Deviations between the two datasets are marginal; for example, mean annual minimum and maximum temperatures differ less than 0.06°C, mean annual precipitation differs less than 0.02 mm day^{−1}, and mean annual shortwave radiation differs less than 0.25 W m^{−2}. Such differences can be neglected. It is important to note that not only annual average values agree with each other but also seasonal averages during 1981–2000 are similar between the two datasets (supplemental Figs. S34 and S35). Long-term June–August (JJA) averages differ between CNTL and REDVAR about 2 times more than long-term

FIG. 6. Difference between REDVAR and CNTL datasets. Shown are differences of 1981–2000 averages of daily data. See supplemental material for seasonal averages.

FIG. 7. Scatterplots of some daily climate variables for a grid cell in central Germany during 1981–2000. More variables and grid cells can be found in the supplementary material.

annual averages but the differences are still negligible (cf. supplemental material Fig. S34 and Fig. 6 herein).

3) RELATIONSHIPS BETWEEN CLIMATE VARIABLES

The scatterplots in Fig. 7 show relationships between daily air temperature and respectively precipitation and shortwave radiation for both datasets CNTL and REDVAR at a grid cell representing a location in central Germany during 1981–2000. More of such scatterplots for other locations can be found in the supplemental Figs. S36–S38. The relationships between precipitation or shortwave radiation and air temperature are similar for CNTL and REDVAR (Fig. 7). Importantly, the reduction of temporal variability led to values that lay within the wider climate space of the control dataset.

4) EVALUATION OF EXTREME VALUES

As could be already seen from the probability density function of the variables [e.g., in section 3b(1)], the transformation leads to higher values at the lower end of the range and lower values at the higher end of the range. This is even more clearly visible when looking at the time series of decadal minimum or maximum values in Fig. 8 (supplemental material Figs. S39–S44 for other locations). Decadal maximum extremes of daily minimum or maximum temperature are lower in the REDVAR dataset while decadal minimum extremes of temperatures are only slightly higher in REDVAR compared to CNTL (Figs. 8a–d; also see the supplemental material). Other REDVAR variables usually show an increase in decadal minimum extremes and a decrease in decadal maximum extremes (Fig. 8 and supplemental material) in comparison to CNTL variables.

For a quantification of the differences in mean decadal extreme values for whole of Europe, maps of ratios of mean extreme values were derived as described in section 2d. REDVAR mean decadal extreme values are usually 2% to 35% “less extreme” than CNTL mean decadal extreme values (Fig. 9).

c. Effects of temporal climate variability on ecosystem functioning

The effects of reduced day-to-day and year-to-year variability of meteorological variables on ecosystem functions are exemplified by a comparison of JSBACH model results of annual gross primary production (GPP) at different locations in Europe (Finland, Germany, Portugal) during 1960–2100 in Fig. 10. The ecosystem model was run with both climate datasets CNTL and REDVAR. Rising atmospheric carbon dioxide concentration and projected climate change led to an increase of GPP in most locations. The long-term trend is visible in both model experiments. The comparison of the annual results (thin lines) shows that REDVAR-driven JSBACH results of GPP are similar to CNTL-driven results in some years but usually REDVAR-driven results are higher. This leads to a positive offset of the 30-yr running mean curves of about 5%–10%.

4. Discussion

In this paper two long-term and high-resolution climate datasets for Europe are presented. One dataset (CNTL) represents climate, which is close to observations during the period 1958–2010 followed by projected climate until 2100 by using regional climate model results and the SRES A1B emission scenario. A bias correction

FIG. 8. Decadal extreme values during 1901–2100 for CNTL and REDVAR datasets or a grid cell in central Germany. See supplemental material for more variables and other locations.

FIG. 9. Selected maps of the ratio of REDVAR vs CNTL mean decadal extremes during 1901–2100. Decadal extreme values are represented by 99th or first percentiles of maximum or minimum annual values.

method based on a fitted histogram equalization function on daily data (Piani et al. 2010) has been applied to ensure similar average and variability between the different datasets comprising the long time series. The second dataset was derived from this control dataset by applying a statistical transformation of the daily residuals to a mean seasonal cycle, which reduces the temporal variability and extreme weather events while keeping the mean seasonal cycle and the long-term annual and seasonal average climate constant. Terrestrial ecosystem models can be driven by such climate datasets to investigate the effects of climate variability and extreme weather events on ecosystem functions in addition to a gradual change in climate.

The approach described in Piani et al. (2010) has been applied successfully to replace and extend the WATCH forcing data (originally 1901–2001) during 1979–2010 by using ERA-Interim reanalysis results. The WATCH forcing data are based on ERA-40 reanalysis results but

corrected in various ways to represent observed climate (Weedon et al. 2011). This dataset is used for the period 1901–77. It can be considered to represent observed meteorological events, seasonal cycles, and climate trends since 1958 (Weedon et al. 2011), whereas before that year it has been constructed to have similar subdaily to seasonal statistical characteristics instead of representing particular historical meteorological events (Weedon et al. 2011).

It is important to drive a terrestrial ecosystem model with as consistent as possible climate data during the period 1981–2010 when most observational datasets, such as tall tower atmospheric carbon dioxide concentrations or remote sensing land surface products, are available for model evaluation. Therefore, we decided to use bias-corrected ERA-Interim data for the whole available period 1979–2010 instead of having a change from ERA-40-based WATCH forcing data to bias-corrected ERA-Interim data in 2002. The validity of the

FIG. 10. JSBACH model results of gross primary production (GPP; $\text{gC m}^{-2} \text{a}^{-1}$) for specific locations in Finland (FI-Hyy), central Germany (DE-Hai), and Portugal (PT-Mi1) during 1960–2100 using both CNTL and REDVAR climate datasets. The right panel shows the REDVAR–CNTL difference. Thin and thick lines represent annual and 30-yr running mean values, respectively.

bias correction method and the properties of the ERA-Interim reanalysis data support this decision (section 3a).

REMO regional model results provided through the EU project ENSEMBLES have been bias corrected for

representing the time period 2011–2100. In particular for this dataset, not only could long-term bias could be removed, but the bias correction approach also improved the shape of the probability distribution and the

standard deviation of daily data (Fig. 3 and supplemental material). This is particularly important when having a modeling study on climate variability effects on ecosystem functions in mind. However, REMO model results of shortwave radiation over Europe show a very high day-to-day variability that cannot be corrected with the applied bias correction approach. The same bias correction method will also be applied to other regional model results from the ENSEMBLES project in future. This will ensure the possibility to drive terrestrial ecosystem models with an ensemble of climate datasets using various regional model climate outputs. The ensemble of results will ensure that single effects from such problems with individual datasets can be neglected in an ensemble mean.

The variance of the meteorological variables can be strongly influenced by a seasonal cycle. When producing the REDVAR dataset our aim was to leave the seasonal cycle unaltered. Therefore, the transformation has been performed on anomalies to a mean seasonal cycle in a 10-yr moving window approach. This is why the daily data of the reduced variability time series are only about 5% to 20% different from the daily data of the control time series even when $k = 0.25$ was chosen (cf. sections 2b and 2c), mainly due to the reduction of high or low values and a general redistribution of the residuals toward the mean. The transformation conserves not only long-term annual and seasonal means but also the general type of the probability density function. For instance, precipitation data follow an exponential distribution, and temperature and shortwave radiation show a bimodal distribution being the sum of two normal distributions. This remains true for the transformed dataset. Power spectra (see the supplemental material) for several variables and locations always show identical peaks at $1/(365 \text{ days})$, which clarifies that both CNTL and REDVAR have identical mean seasonal cycles.

The transformation following Eq. (5) maintains zero values, which is important for keeping precipitation-free time periods. That means that if there are two months without precipitation in the control dataset, then these months will also have no precipitation in the reduced variability dataset. With this approach, we make sure that rain-free periods (e.g., in the Mediterranean) to which ecosystems are already adapted are also present in the transformed dataset, and that we do not change the overall precipitation regime throughout a year. That also means, on the other hand, that if an abnormal drought with exactly zero precipitation during two months in summer occurs, this drought will not be removed in the transformed dataset. Still, variability of the meteorological variables will be different and the variability effect on ecosystem functions can be studied using CNTL and REDVAR.

By using the methods described in this paper, it is equally possible to derive a dataset with increased instead of decreased climate temporal variability and conserved long-term mean. These properties were also important for applications with a terrestrial ecosystem model. For this, one would need to basically set $k > 1$. Initial tests with $k = 1.25$ showed results (not shown) that seem to be reasonable and promising. However, increasing the temporal climate variability can easily lead to unrealistic climatic situations. For example, the method could produce downward radiation that is physically not possible or temperatures that have never been observed. However, the range of values of the transformed dataset presented in this paper is always narrower than the one of the control climate dataset. This characteristic avoids any trivial derivation of unrealistic climate variables.

By using a 10-yr moving window approach, the distribution of the climate data is altered in a way such that the long-term mean (30-yr) is conserved. Such datasets are suited for studying general effects of climate variability on terrestrial ecosystem functions using prognostic models. The moving window approach ensures a large data basis for estimating the transformation parameters; that is, the reference distribution represents a long-term average distribution of the meteorological variable of interest. However, REDVAR climate differs from CNTL climate in both day-to-day and year-to-year variability. Therefore, these datasets will be not suited to address specific questions about the impact of temporal variability on the carbon cycle at different temporal scales. For that, it would be important to perform the transformation for each individual year ensuring a constant year-to-year variability. Then, adjustment of state variables and relocation of fluxes would be possible only within one specific season. This is a very strong constraint on the algorithm, which will lead to more similarities of the altered dataset to the control one.

For reducing the temporal climate variability, we applied a transformation function that is approximated by a Taylor series around the mean. This series was cut after the second term (section 2b). The analytical solution of the transformation parameters c and α by cutting the Taylor series after the third term is also possible and can be found in the appendix. Its application at the three European sites resulted in parameter values differing at the second most decimal place and hence in marginally different overall results (not shown). Therefore, the simpler Eq. (6) instead of Eq. (A2) has been used, also for computing time reasons.

By driving the terrestrial ecosystem model JSBACH with both climate datasets CNTL and REDVAR, the effects of temporal climate variability and extreme

meteorological events on gross primary productivity in addition to effects of gradual climate change and rising atmospheric carbon dioxide concentration were studied (section 3c). The aim of this model application was to demonstrate the usefulness of the climate datasets for such artificial model experiments, in particular the usefulness of the assumptions described in section 2c. Higher photosynthetic rates under reduced climate variability can have several causes but one is the curvature of the light-response curve of net assimilation. Reduction of very high radiation levels leads to only a marginal reduction in productivity while increasing low radiation levels results in a large increase of productivity. Since the temperature response function of respiration is nonlinear in the opposite direction (convex), net ecosystem production, being the difference between gross primary production and ecosystem respiration, is expected to be higher under reduced temporal climate variability and conserved mean. However, these response functions are only two examples among many, and on larger spatial and temporal scales climate variability effects on water availability and disturbances will have additional effects on ecosystem state variables and ecosystem functioning (Reichstein et al. 2013). Such questions will be addressed by future modeling studies using the climate datasets described here.

5. Conclusions

By using a simple nonlinear transformation function a climate dataset can be transformed into another one with an altered temporal variability but conserved long-term mean. The respective transformation parameters can be obtained from the variability reduction factor and the mean by using a Taylor approximation of the transformation function. The resulting dataset with altered temporal variability can be used for factorial experiments with a process-oriented terrestrial ecosystems model for separating effects of climate variability from effects of gradual climate change on terrestrial ecosystem functions. The long-term annual and seasonal means of the dataset with reduced variability are similar to the ones of the control dataset. Therefore, differences in ecosystem model results of long-term averages of ecosystem functions using control and reduced variability datasets will not be due to differences in the long-term mean of climate variables but to the altered variability.

By using both a harmonized long-term climate dataset (control) and a reduced temporal variability climate dataset in an artificial model experiment, a terrestrial ecosystem model predicts 5%–10% higher long-term mean gross primary production under reduced variability compared to the control experiment. This means

that the projected increasing climate variability will lead to less productivity and primary carbon uptake by the terrestrial biosphere, partly compensating fertilization effects of rising atmospheric carbon dioxide concentration and effects of gradual climate change.

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APPENDIX

Analytical Solution of Transformation Parameters Given Three Terms of the Taylor Series Approximation

The aim is to transform the distribution of the original data x into a distribution such that the long-term mean is conserved but the variance of $f(x)$ is higher or lower. For such, one can use the transformation function

$$f(x) = cx^\alpha. \quad (\text{A1})$$

In this appendix we present the analytical solution of parameters c and α when using the first three terms of the Taylor series approximation around the mean μ :

$$f(x) \approx f(\mu) + f'(\mu)(x - \mu) + \frac{1}{2}f''(\mu)(x - \mu)^2. \quad (\text{A2})$$

For doing such, we will need the first and the second derivative of function f :

$$f'(x) = c\alpha x^{\alpha-1}, \quad (\text{A3})$$

$$f''(x) = c\alpha(\alpha - 1)x^{\alpha-2}. \quad (\text{A4})$$

Then, analogous to section 2b, the first two moments of $f(x)$ approximate to

$$E[f(x)] \approx f(\mu) + \frac{1}{2}f''(\mu)\sigma^2, \quad (\text{A5})$$

$$\text{Var}[f(x)] \approx f'(\mu)^2\sigma^2, \quad (\text{A6})$$

where μ and σ are the actual mean and standard deviation of the data x .

During the transformation of the distribution we aim for keeping the mean constant, that is,

$$E[f(x)] = \mu, \quad (\text{A7})$$

$$f(\mu) + \frac{1}{2} f''(\mu) \sigma^2 = \mu, \quad (\text{A8})$$

$$c\mu^\alpha + \frac{1}{2} c\alpha(\alpha-1)\mu^{\alpha-2}\sigma^2 = \mu. \quad (\text{A9})$$

The main objective was to alter the variance of a factor k during the transformation of the distribution, that is,

$$\text{Var}[f(x)] = k\sigma^2, \quad (\text{A10})$$

$$f'(\mu)^2 \sigma^2 = k\sigma^2, \quad (\text{A11})$$

$$(c\alpha\mu^{\alpha-1})^2 \sigma^2 = k\sigma^2, \quad (\text{A12})$$

$$c^2 \alpha^2 \mu^{2\alpha-2} = k, \quad (\text{A13})$$

which can be rearranged to

$$c = \sqrt{\frac{k}{\alpha^2 \mu^{2\alpha-2}}}, \quad (\text{A14})$$

$$= \frac{k^{1/2}}{\alpha \mu^{\alpha-1}}. \quad (\text{A15})$$

Putting Eq. (A15) into Eq. (A9) gives the following calculation of α :

$$\frac{k^{1/2} \mu^\alpha}{\alpha \mu^{\alpha-1}} + \frac{1}{2} \frac{k^{1/2}}{\alpha \mu^{\alpha-1}} \alpha(\alpha-1) \mu^{\alpha-2} \sigma^2 = \mu, \quad (\text{A16})$$

$$\frac{k^{1/2}}{\alpha} + \frac{1}{2} \frac{k^{1/2}}{\mu^2} (\alpha-1) \sigma^2 = 1, \quad (\text{A17})$$

$$\frac{k^{1/2}}{\alpha} + \frac{1}{2} \frac{\alpha^2}{\alpha} \frac{k^{1/2}}{\mu^2} \sigma^2 - \frac{\alpha}{\alpha} \left(\frac{1}{2} \frac{k^{1/2}}{\mu^2} \sigma^2 + 1 \right) = 0, \quad (\text{A18})$$

$$\alpha^2 \frac{k^{1/2}}{\mu^2} \sigma^2 - \alpha \left(\frac{1}{2} \frac{k^{1/2}}{\mu^2} \sigma^2 + 1 \right) + k^{1/2} = 0. \quad (\text{A19})$$

Let us define $a = [(1/2)(k^{1/2}/\mu^2)]\sigma^2$. Then, the last equation reads as

$$\alpha^2 - \alpha \frac{a+1}{a} + \frac{k^{1/2}}{a} = 0. \quad (\text{A20})$$

This equation has two potential solutions:

$$\alpha_{1,2} = \frac{a+1}{2a} \pm \left[\frac{\left(\frac{a+1}{a} \right)^2}{4} - \frac{k^{1/2}}{a} \right]^{1/2}. \quad (\text{A21})$$

REFERENCES

- Cox, P., R. Betts, C. Jones, S. Spall, and I. Totterdell, 2000: Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature*, **408**, 184–187, doi:[10.1038/35041539](https://doi.org/10.1038/35041539).
- Cramer, W., and Coauthors, 2001: Global response of terrestrial ecosystem structure and function to CO₂ and climate change: Results from six dynamic global vegetation models. *Global Change Biol.*, **7**, 357–373, doi:[10.1046/j.1365-2486.2001.00383.x](https://doi.org/10.1046/j.1365-2486.2001.00383.x).
- Dee, D., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597, doi:[10.1002/qj.828](https://doi.org/10.1002/qj.828).
- Easterling, D., G. Meehl, C. Parmesan, S. Changnon, T. Karl, and L. Mearns, 2000: Climate extremes: Observations, modeling, and impacts. *Science*, **289**, 2068–2074, doi:[10.1126/science.289.5487.2068](https://doi.org/10.1126/science.289.5487.2068).
- Fischer, E. M., and C. Schär, 2010: Consistent geographical patterns of changes in high-impact European heatwaves. *Nat. Geosci.*, **3**, 398–403, doi:[10.1038/ngeo866](https://doi.org/10.1038/ngeo866).
- Friedlingstein, P., and Coauthors, 2006: Climate-carbon cycle feedback analysis: Results from the C⁴MIP model intercomparison. *J. Climate*, **19**, 3337–3353, doi:[10.1175/JCLI3800.1](https://doi.org/10.1175/JCLI3800.1).
- Harvey, G. W., 1979: Photosynthetic performance of isolated leaf cells from sun and shade plants. *Carnegie Inst. Wash. Yearb.*, **79**, 161–164.
- Heimann, M., and M. Reichstein, 2008: Terrestrial ecosystem carbon dynamics and climate feedbacks. *Nature*, **451**, 289–292, doi:[10.1038/nature06591](https://doi.org/10.1038/nature06591).
- Huntingford, C., P. D. Jones, V. N. Livina, T. M. Lenton, and P. M. Cox, 2013: No increase in global temperature variability despite changing regional patterns. *Nature*, **500**, 327–330, doi:[10.1038/nature12310](https://doi.org/10.1038/nature12310).
- Katz, R. W., and B. G. Brown, 1992: Extreme events in a changing climate: Variability is more important than averages. *Climatic Change*, **21**, 289–302, doi:[10.1007/BF00139728](https://doi.org/10.1007/BF00139728).
- Knorr, W., 2000: Annual and interannual CO₂ exchanges of the terrestrial biosphere: Process-based simulations and uncertainties. *Global Ecol. Biogeogr.*, **9**, 225–252, doi:[10.1046/j.1365-2699.2000.00159.x](https://doi.org/10.1046/j.1365-2699.2000.00159.x).
- Lloyd, J., and J. A. Taylor, 1994: On the temperature dependence of soil respiration. *Funct. Ecol.*, **8**, 315–323, doi:[10.2307/2389824](https://doi.org/10.2307/2389824).
- Medvigy, D., S. C. Wofsy, J. W. Munger, and P. R. Moorcroft, 2010: Responses of terrestrial ecosystems and carbon budgets to current and future environmental variability. *Proc. Natl. Acad. Sci. USA*, **107**, 8275–8280, doi:[10.1073/pnas.0912032107](https://doi.org/10.1073/pnas.0912032107).
- Meehl, G. A., and Coauthors, 2000: An introduction to trends in extreme weather and climate events: Observations, socioeconomic impacts, terrestrial ecological impacts, and model projections. *Bull. Amer. Meteor. Soc.*, **81**, 413–416, doi:[10.1175/1520-0477\(2000\)081<0413:AITTIE>2.3.CO;2](https://doi.org/10.1175/1520-0477(2000)081<0413:AITTIE>2.3.CO;2).
- Meinshausen, M., and Coauthors, 2011: The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic Change*, **109**, 213–241, doi:[10.1007/s10584-011-0156-z](https://doi.org/10.1007/s10584-011-0156-z).
- New, M., D. Lister, M. Hulme, and I. Makin, 2002: A high-resolution data set of surface climate over global land areas. *Climate Res.*, **21**, 1–25, doi:[10.3354/cr021001](https://doi.org/10.3354/cr021001).
- Piani, C., G. Weedon, M. Best, S. Gomes, P. Viterbo, S. Hagemann, and J. Haerter, 2010: Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *J. Hydrol.*, **395**, 199–215, doi:[10.1016/j.jhydrol.2010.10.024](https://doi.org/10.1016/j.jhydrol.2010.10.024).

- Raddatz, T., and Coauthors, 2007: Will the tropical land biosphere dominate the climate–carbon cycle feedback during the twenty-first century? *Climate Dyn.*, **29**, 565–574, doi:[10.1007/s00382-007-0247-8](https://doi.org/10.1007/s00382-007-0247-8).
- Reichstein, M., and Coauthors, 2013: Climate extremes and the carbon cycle. *Nature*, **500**, 287–295, doi:[10.1038/nature12350](https://doi.org/10.1038/nature12350).
- Schaphoff, S., W. Lucht, D. Gerten, S. Sitch, W. Cramer, and I. C. Prentice, 2006: Terrestrial biosphere carbon storage under alternative climate projections. *Climatic Change*, **74**, 97–122, doi:[10.1007/s10584-005-9002-5](https://doi.org/10.1007/s10584-005-9002-5).
- Schär, C., P. Vidale, D. Lüthi, C. Frei, C. Häberli, M. Liniger, and C. Appenzeller, 2004: The role of increasing temperature variability in European summer heatwaves. *Nature*, **427**, 332–336, doi:[10.1038/nature02300](https://doi.org/10.1038/nature02300).
- Seneviratne, S., and Coauthors, 2012: Changes in climate extremes and their impacts on the natural physical environment. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*, C. Field et al., Eds., Cambridge University Press, 109–230.
- Sheffield, J., G. Goteti, and E. F. Wood, 2006: Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *J. Climate*, **19**, 3088–3111, doi:[10.1175/JCLI3790.1](https://doi.org/10.1175/JCLI3790.1).
- Weedon, G., and Coauthors, 2011: Creation of the WATCH forcing data and its use to assess global and regional reference crop evaporation over land during the twentieth century. *J. Hydrometeor.*, **12**, 823–848, doi:[10.1175/2011JHM1369.1](https://doi.org/10.1175/2011JHM1369.1).