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Geoscientific Model Development
Discussions

The Teddy-Tool v1.0: temporal disaggregation of daily climate model data for climate impact analysis

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Abstract

Climate models provide required input data for global or regional climate impact analysis in aggregated form, often on a daily basis to save space on data servers. Today, many impact models work with daily data, however, sub-daily climate information is getting increasingly important for more and more models from different sectors, such as the agricultural, the water, and the energy sector. Therefore, the open source Teddy-Tool (**te**mporal **d**isaggregation of **d**ail**y** climate model data) has been developed to disaggregate (temporally downscale) daily climate data to sub-daily hourly values for temperature, precipitation, humidity, longwave radiation, shortwave radiation, surface pressure and wind speed. Thereby, mass and energy are strictly preserved by the Teddy-Tool to exactly reproduce the daily values from the climate models. Here, we describe and document the temporal disaggregation, which is based on globally available bias-corrected hourly reanalysis WFDE5 data from 1980-2019 to take specific local and seasonal features of the diurnal course empirically into account. The physical dependency between variables is preserved, since the diurnal profile of all variables is taken from the same, most similar meteorological day of the historical reanalysis dataset. We perform a sensitivity analysis of different time window sizes used for finding the most similar meteorological day in the past. In addition, we perform a cross-validation, autocorrelation and extreme value analysis for 30 globally distributed samples around the world, representing different climate zones. The validation shows that Teddy is able to reproduce historical diurnal courses with high correlations >0.9 for all variables, except for wind speed (>0.75) and precipitation (>0.5). Consequently, sub-daily data provided by the Teddy-Tool could make climate impact assessments more robust and reliable.

Introduction

Sub-daily climate data is becoming increasingly important in climate impact analysis. This type of data, which captures variations in temperature, precipitation, and other weather variables at intervals of less than a day, can provide a more detailed representation of local and regional climate conditions and temporal variations. This information can be crucial for evaluating the impacts of climate change on various sectors, such as agriculture, water resources, energy production, and human health (Golub et al., 2022; Trinanes and Martinez-Urtaza, 2021; Colón-González et al., 2021; Tittensor et al., 2021; Byers et al., 2018; Jägermeyr et al., 2021; Poschlod and Ludwig, 2021; Degife et al., 2021). A better representation of the diurnal course of temperature, extreme precipitation events, and other weather variables are also important for adaptation assessments which depend on behavior or processes with high temporal dynamics, such as the energy demand, labor activity, the heat stress of crops or flood events (Minoli et al., 2022; Zabel et al., 2021; Reed et al., 2022; Orlov et al., 2021; Franke et al., 2022).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Research has shown that using sub-daily climate data can result in more robust and reliable impact assessments compared to using daily data (Orlov et al. 2023).

Today, most climate model data are available for download at daily resolution because of the high storage requirements for sub-daily climate data. However, the demand for sub-daily data is increasing due to lower costs for storage and computing resources. Different methods exist to disaggregate available daily climate data to sub-daily, most often hourly values. These can be roughly divided into statistical methods, weather generators, and mechanistic approaches, although mixed forms also exist (Förster et al., 2016).

Mechanistic methods use regional climate models to dynamically downscale atmospheric conditions in time and space, usually for a limited area (Vormoor and Skaugen, 2013; Liu et al., 2011; Kunstmann and Stadler, 2005). Weather generators generate synthetic sequences of hourly weather variables by using random number generators that match statistics (Ailliot et al., 2015; Mezghani and Hingray, 2009). Various statistical methods exist for temporal disaggregation of daily climate data, ranging from simple interpolations or deterministic approaches to non-parametric approaches and methods that derive statistical relationships from historical data (Breinl and Di Baldassarre, 2019; Debele et al., 2007; Förster et al., 2016; Görner et al., 2021; Liston and Elder, 2006; Park and Chung, 2020; Verfaillie et al., 2017; Poschlod et al., 2018; Zhao et al., 2021). Each of these methods has its own advantages and limitations, and the choice of method depends on factors such as the specific needs of the impact assessment, the quality of the available data, and computational resources.

Here, we introduce the Teddy-Tool (**te**mporal **d**isaggregation of **d**ail**y** climate model data), which uses statistical methods for temporal disaggregation of daily climate model data. Existing statistical approaches are often only valid for a specific location and cannot be applied globally. In addition, available disaggregation tools often focus on only one variable and therefore do not consider physical interdependencies between different variables, such as precipitation, humidity, temperature, and radiation. Teddy has been specifically developed as a globally applicable tool for climate impact studies. For this purpose, Teddy strictly preserves mass and energy of daily climate model data for each variable throughout the disaggregation procedure. Teddy additionally aims at taking regional and seasonal climate characteristics into account and considers the physical consistency between variables.

In principal, the Teddy-Tool can be used with any climate input, but has particularly been used so far with bias corrected daily CMIP6 climate data (Eyring et al., 2016) for historical time periods and future scenarios from the ISIMIP (Inter-Sectoral Impact Model Intercomparison Project), which provides bias corrected and trend-preserved climate data (Lange, 2019) and offers a framework for consistently projecting the impacts of climate change across affected sectors and spatial scales (Warszawski et al., 2014). To guarantee cross-sectoral consistency, all sectors are provided with the same climate data. Within ISIMIP, some models from different sectors have expressed their need for sub-daily climate data, including the agricultural and the energy sector. Teddy represents an easy-to-use tool that can be applied for climate impact assessments in different sectors that allows a physically consistent temporal disaggregation of the daily ISIMIP climate model data. The Teddy-Tool has been written in Matlab and is available open source via Zenodo (https://doi.org/10.5281/zenodo.7679149).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

1. Temporal disaggregation

Teddy uses an empirical approach, which applies the region-specific diurnal course from the most similar day in the past to daily climate model data for a day of interest. Teddy has been developed specifically to disaggregate daily bias-corrected climate model data from the ISIMIP project at 0.5° spatial resolution for air temperature (tas), humidity (hurs), shortwave radiation (rsds), longwave radiation (rlds), air pressure (ps), windspeed (sfcwind), and precipitation (pr) (Lange, 2019). For air temperature, the daily maximum and minimum values (tasmax, tasmin) are additionally provided. ISIMIP provides data for different historical and future time periods and scenarios for the climate models GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. As a reference, globally available hourly bias-corrected reanalysis WFDE5 data (1980-2019) are used at 0.5° spatial resolution to identify the most similar meteorological day in the past for a specific location (Cucchi et al., 2020). The diurnal profile of the most similar day is subsequently applied to the daily climate model data for each of the variables. In the following, the procedure is explained:

In a first precalculation step, in order to minimize computational resources, hourly WFDE5 data are aggregated to daily values and stored as NetCDF files. The daily aggregation uses mean values for all variables and daily sums for precipitation. In addition, rainfall and snowfall fluxes must be summed up for WFDE5. Daily maximum and minimum temperature are calculated from the hourly data. Units of climate inputs are converted to match the Teddy output (see Tab. 1). For the conversion of specific humidity to relative humidity, the Buck equation is applied (Buck, 1981).

Table 1: Variables and units of used hourly (h) and daily (d) climate data and the Teddy output. For WFDE5, the specific variable name is provided in brackets. WFDE5 variables have instantaneous values, while SWdown, LWdown, Rainf and Snowf have average values over the next hour at each time step.

Variable	WFDE5 (h)	ISIMIP Climate Model (d)	Teddy (flexible)
tas	K (Tair)	K	K
tasmin	-	K	-
tasmax	-	K	-
hurs/huss	kg/kg (Qair)	%	%
rsds	W m^{-2} (SWdown)	W m^{-2}	W m^{-2}
rlds	W m^{-2} (LWdown)	W m^{-2}	W m^{-2}
pr	kg m^{-2} s^{-1} (Rainf+Snowf)	kg m^{-2} s^{-1}	mm $timestep^{-1}$
ps	Pa (PSurf)	Pa	hPa
sfcwind	m s^{-1} (Wind)	m s^{-1}	m s^{-1}

After reading the daily climate model data for the selected location (latitude/longitude) that determines a specific grid cell at 0.5° resolution, the daily mean values of all ISIMIP variables (see Tab. 1) are compared to the aggregated daily values of WFDE5 for a specific time step in order to identify

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

the most similar meteorological day. For the comparison, a day-of-year (DOY) window can be selected by the user that allows for a selection of days around the DOY of the actual time step. By default, the DOY window size is set to 11, which means a sequence of ± 11 days around the actual DOY. As a result, 23 days are selected from each of the 40 WFDE5 reference years (1980-2019). These 920 days now serve as the basic population for further calculations (Fig. 1). In a next step, the climate model day of interest and the basic population of 920 WFDE5 days are classified according to their precipitation state. As climate models tend to produce too many days with low-intensity precipitation called "drizzle bias" (Chen et al., 2021), days with aggregated daily precipitation values below 1 mm per day are considered as dry days (Sun et al., 2006). Depending on the precipitation state of the previous day, the day of interest and the following day, there are eight classes: dry-dry-dry, dry-dry-wet, wet-dry-dry, wet-dry-wet, dry-wet-dry, dry-wet-wet, wet-wet-dry, and wet-wet-wet. This step is included to better reproduce the inter-day connectivity of precipitation (Li et al., 2018). Only days with the same precipitation class as the climate model day of interest are selected for the further course. Next, the absolute error between daily climate model and aggregated daily WFDE5 data for each variable is calculated for the remaining basic population and ranked in ascending order. The ranks over all variables are cumulated for each day of the basic population. The most similar meteorological day is determined as the day with the lowest cumulated ranks (Fig. 1). Finally, the hourly values are taken from the most similar day of the WFDE5 reference dataset for each variable and divided by the WFDE5 daily mean value of the selected day, in order to refer to relative diurnal profiles without absolute variations (Fig. 1). The hourly profile is then applied for each variable to the daily mean value from the climate model. Thus, the daily mean is conserved.

For temperature, the resulting hourly temperature is further scaled between the provided minimum and maximum. The scaling is performed in a way that the daily mean value is preserved with an accuracy of four decimals. Relative humidity is limited to 100%, again under preserving the daily mean value.

Large selected DOY windows increase the basic population, but on the other sight might distort climatic characteristics with a strong seasonal course such as shortwave radiation values for the actual DOY. Therefore, we preprocessed hourly potential (cloud free) solar radiation for each DOY globally at 0.5° spatial resolution. This data is used as upper bound to limit the resulting hourly values for the corresponding DOY, while the daily mean value is preserved.

In a final step, hourly values can again be aggregated to the time step set by the user (possible: 1, 2, 3, 4, 6, 8, 12).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions
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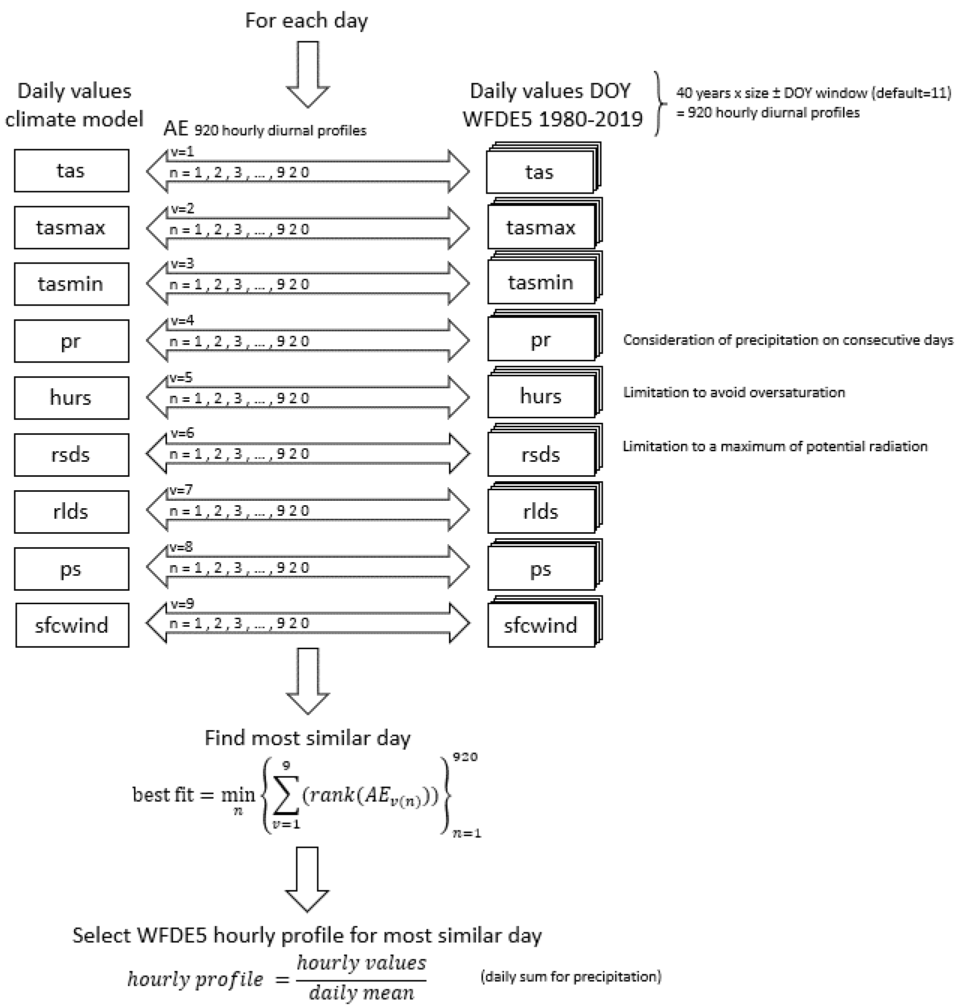

Figure 1: Procedure to identify the most similar meteorological day in the population of reference data for the default DOY window of ± 11 days around the actual DOY.

In rare cases, precipitation cannot be distributed, due to failing precipitation in the reference data. To handle this exception, several options are implemented. First, the DOY window is automatically expanded to +- 50 days around the actual DOY. If this doesn't help, a linear regression between the precipitation amount and the duration is performed for the specific location across the entire data spectrum. The linear regression determines the usual duration of the selected precipitation event. Subsequently, an hour is randomly selected for the start of the precipitation event. In order to reduce possible physical inconsistencies with other variables that could lead to implications in impact models, the precipitation is only distributed to hours at nighttime (without solar radiation).

Precipitation values below 1 mm day^{-1} are also disaggregated to sub-daily values in order to ensure mass and energy conservation. If no historical precipitation event is found for this case, precipitation

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Open Access
Discussions

noise is randomly distributed to an hour at nighttime. If no hour without radiation occurs (e.g. high latitudes in northern summer), the precipitation is distributed to local midnight.

The calculation procedure can be performed either for universal time (UT) or for local solar time (LST). The latter divides the world into equal time zones of 15° with the central time zone (+-7.5°) at Greenwich.

2. Validation

In a first step, a cross-validation is carried out for 30 globally distributed samples (Fig. 2) for the year 2010. Therefore, WFDE5 data for 2010 aggregated to daily values serves as an input. The same year is excluded from the basic population during the cross-validation. As a result, it can be tested how well WFDE5 hourly values for the year 2010 are reproduced with the basic population of all other years. The 30 samples are chosen to represent globally relevant agricultural production regions in different climate zones (Fig. 2). To evaluate the sensitivity of the different DOY window sizes, we run the cross-validation with different DOY window sizes, ranging from 1 to 25, in steps of two, including the option to disable the DOY window (DOY window size = 0). In order to additionally validate the performance for extreme events, we perform a second cross-validation for all available 40 years (1980-2019) with DOY window sizes of 11 and 25 for sample location 29, located in Southern Germany.

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

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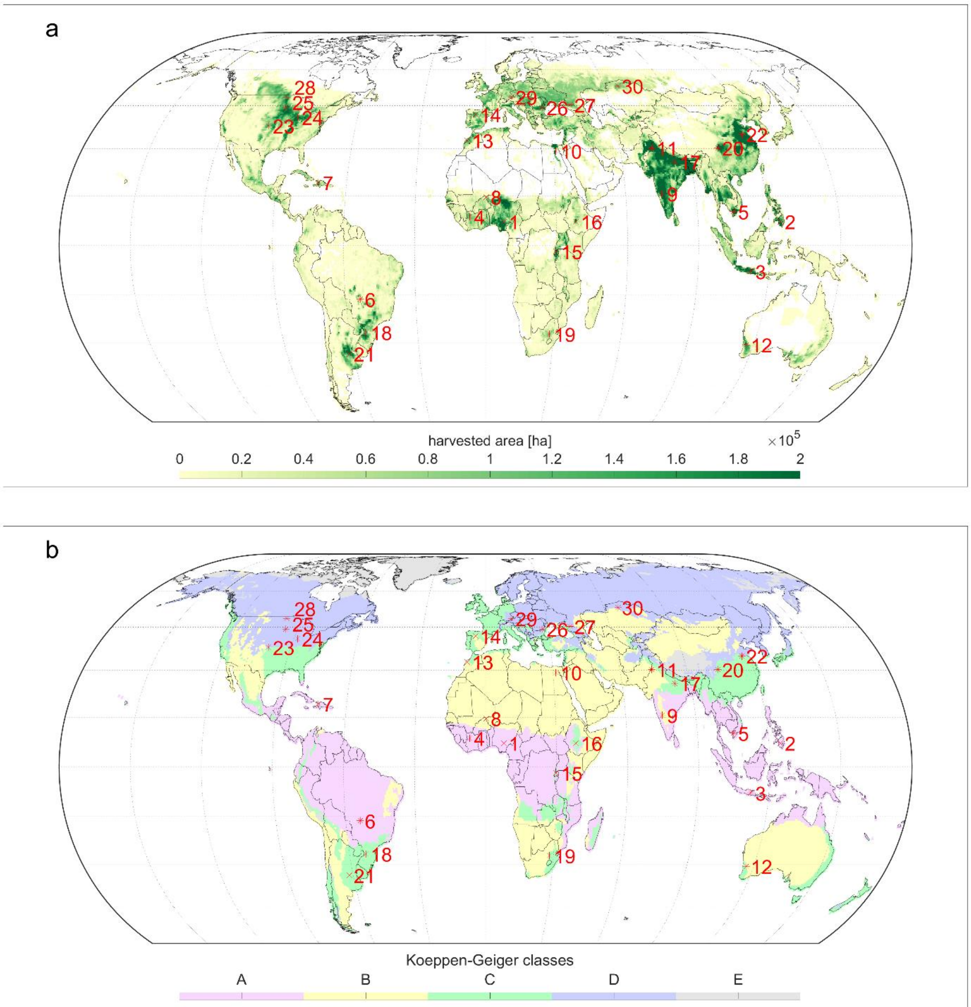

Figure 2: Distribution of 30 global samples used for the cross-validation on (a) annual total harvested area of rainfed and irrigated crops in hectare per pixel at a 30 arc-minute grid (Portmann et al., 2010) and (b) for Koeppen-Geiger climate zones calculated for 1980-2019 WFDE5 temperature and precipitation values (Beck et al., 2018). Samples are ordered by climate zone affiliation and their distance to the equator.

As an example for sample location 16 in Ethiopia, Fig. 3 shows the results of the temporal disaggregation series for the cross-validation for a 10-day time series in 2010 in comparison with the daily climate input and the original hourly WFDE5 data. The hourly courses show high correlations for the randomly selected time series for all variables (Fig. 3 and scatterplots in Fig. 4 for the entire year).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions
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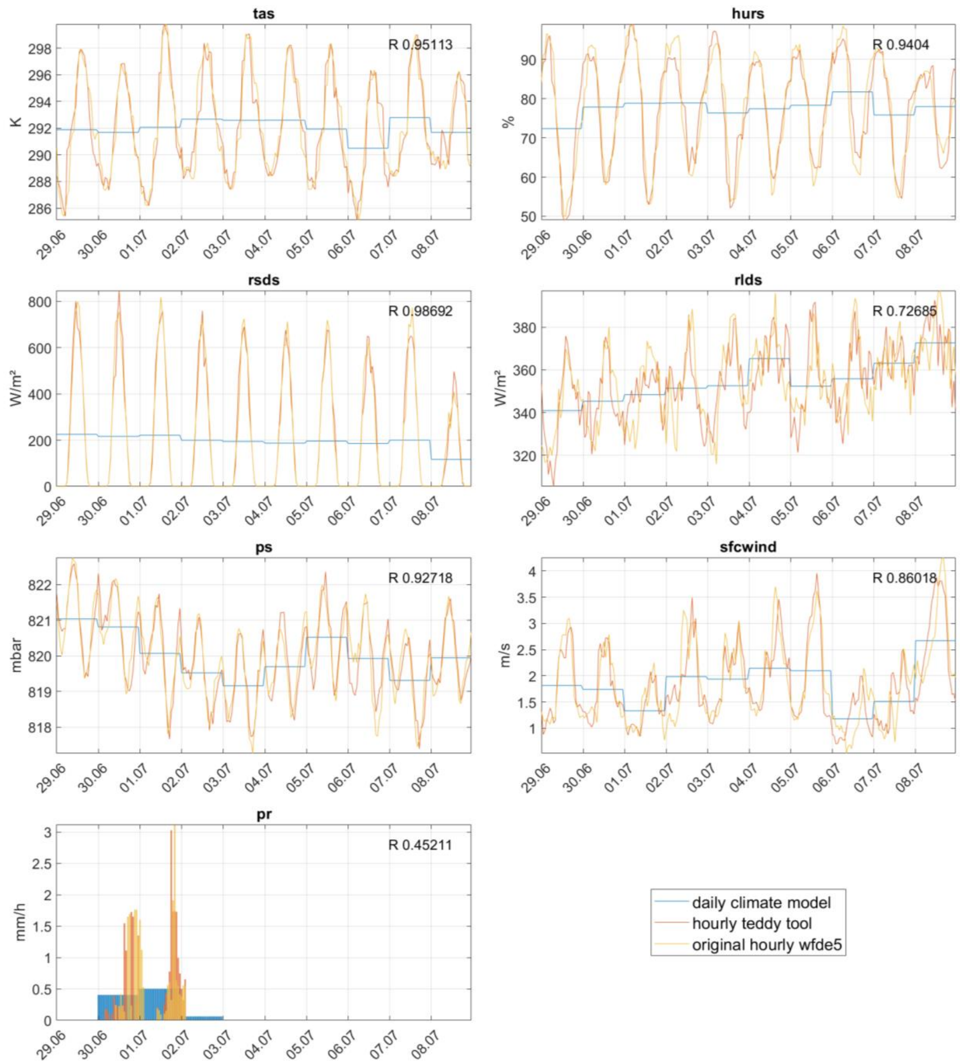

Figure 3: Time-series for all variables comparing daily climate model data, disaggregated hourly results of Teddy from the performed cross-validation and the original hourly WFDE5 data, shown for sample location 16 in Ethiopia with a DOY window size of 7 for the 10-day period 29.06. – 08.07.2010. The Pearson correlation coefficient (R) is displayed for the shown time period for each variable.

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions

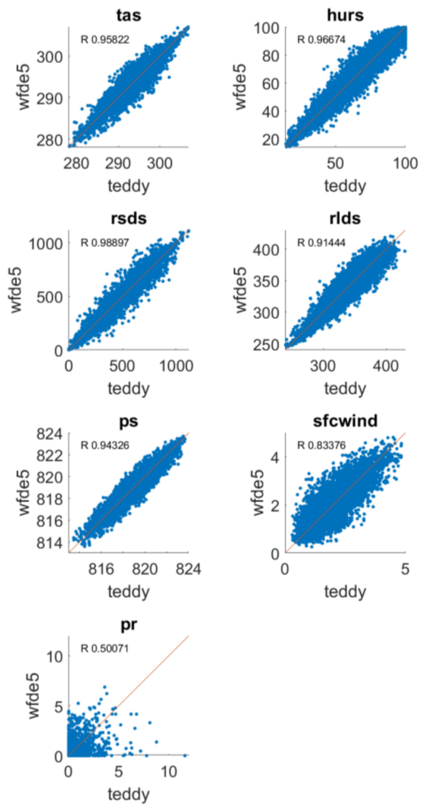

Figure 4: Hourly values for the year 2010 between disaggregated values generated by the Teddy-Tool and the original WFDE5 data used for the cross-validation, exemplarily for sample 16 in Ethiopia with a DOY window size of 7.

2.1 <u>Sensitivity analysis DOY window size</u>

The sensitivity analysis averaged over all 30 samples shows that the Pearson correlation coefficient of hourly values for the year 2010 show high correlations for all variables (r>0.9), except windspeed (r>0.7) and precipitation (r>0.4), which are generally are the most difficult variables for disaggregation (Fig 5). The selected DOY window size has an effect on the quality of the results. While no DOY window (size=0) results in the lowest correlation coefficient across all variables, the DOY window size does not significantly affect the correlation except for precipitation and wind speed (Fig. 5).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

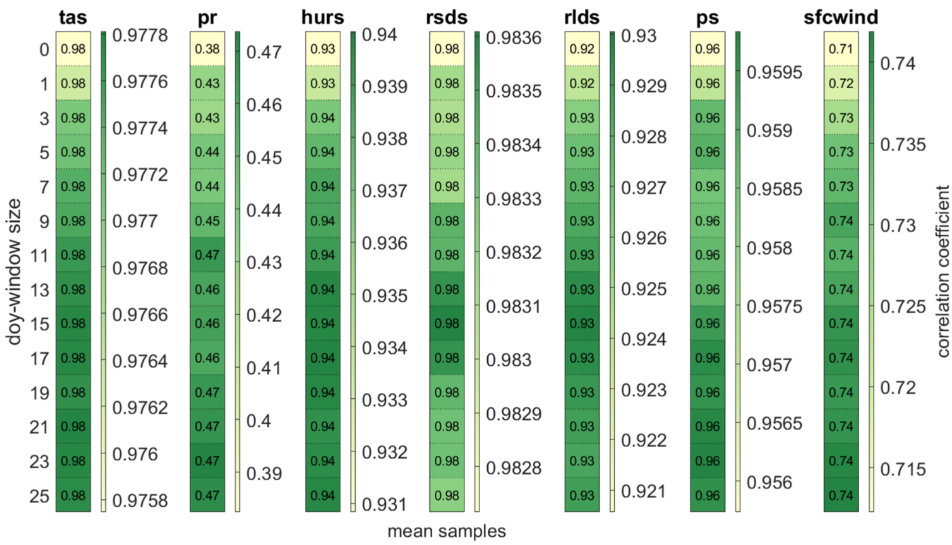

Figure 5: Pearson correlation coefficient for different DOY window sizes averaged over all 30 samples for the year 2010 for all variables being disaggregated to hourly values. The scaling of the colorbar differs between variables.

For precipitation, the impact of the DOY window size on the correlation varies between regions. Larger DOY windows are mainly beneficial for precipitation in tropical and arid regions, while in regions with pronounced seasons, the correlation might decrease with larger DOY window size (Fig. 6). The results also show that the correlation for precipitation is generally larger in tropical regions than in continental regions.

Figure 6: Pearson correlation coefficient for different DOY window sizes averaged over the samples for each Koeppen-Geiger climate zone (A=tropical, B=arid, C=temperate, D=continental).

While hourly precipitation can be best reproduced for winter seasons in continental and arid regions, winter seasons show the lowest correlation for temperate regions. Tropical regions only show relatively low variations over the year, independently from the selected DOY window size (Fig. 7). Especially in arid regions, the length of the DOY window size affects the results differently in different seasons. Here, larger DOY windows decrease the correlation during the rainy season (winter and spring), while correlation is increased during the dry season (summer and autumn).

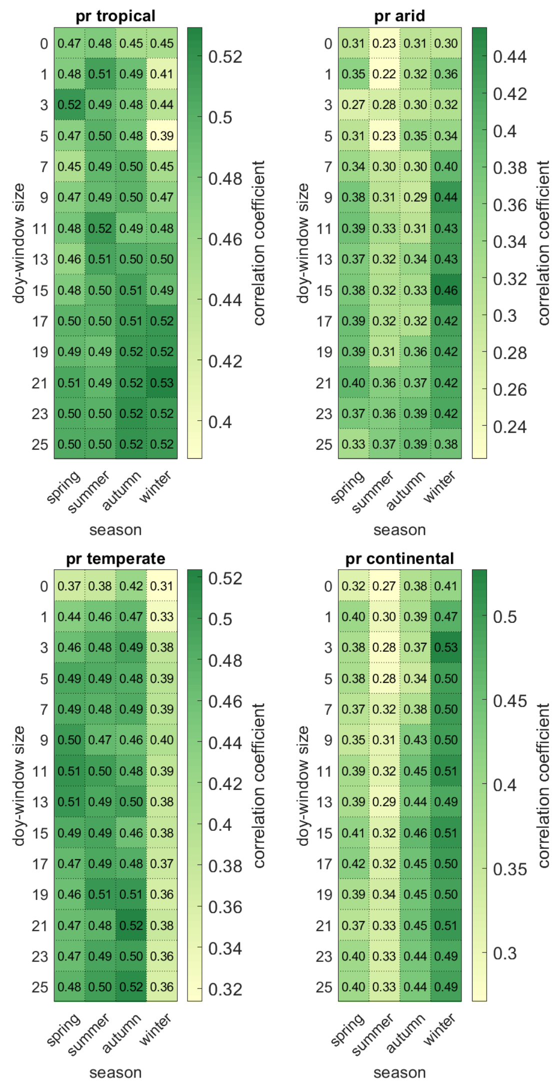

Figure 7: Pearson correlation coefficient for different DOY window sizes averaged over the samples for the four seasons (spring=MAM, summer=JJA, autumn=SON, winter=DJF). The shift of the seasons between Northern and Southern hemisphere is considered. The heatmap is averaged over the samples for each Koeppen-Geiger climate zone (A=tropical, B=arid, C=temperate, D=continental).

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions
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Furthermore, we evaluate the sensitivity of the DOY window size to the reproduction of temporal autocorrelation (Fig. 8). Therefore, the autocorrelation over lag times between one and 24 hours is calculated for precipitation and wind speed. Autocorrelation refers to the similarity of a time series to a lag duration shifted version of the same time series. This allows sub-daily patterns and inter-hour connectivity to be statistically captured and validated in time series of precipitation and wind speed. In addition, we also check the reproduction of wet hours (precipitation above 0.1 mm h^{-1}) in 2010 and the number of hours with low wind speeds (sfcwind < 2.5 m s^{-1}) referring to the typical cut-in wind speed of wind turbines.

Here, we find that short DOY window sizes below 5 days are not beneficial to all statistics. The autocorrelation of precipitation (wind speed) is reproduced more accurately with window sizes of 9 days or longer. The number of wet hours is better recreated with window sizes above 15 days. For hours with low wind speed, a minor improvement is found above 9 days.

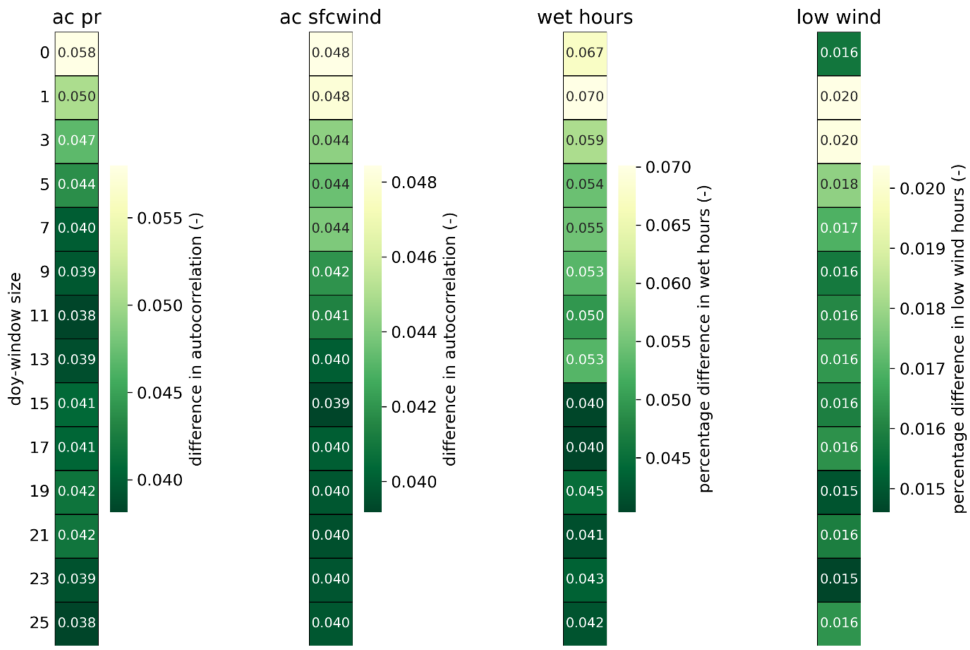

Figure 8: Extended validation statistics for the sensitivity analysis of the DOY window size for the year 2010. The difference in autocorrelation refers to the average over all 30 stations and lag durations between one and 24 hours. Wet hours are defined as precipitation intensities above 0.1 mm h-1 and low wind speeds refer to hours with sfcwind < 2.5 m s-1.

As the ISIMIP data base is used for future impact modelling and historical attribution science (Mengel et al., 2021), extremes are of major interest for the community. The ability of global climate models to simulate sub-daily extremes is limited and depends on the variable of interest and the spatio-temporal conditions of the extreme and the respective model setup (Wehner et al., 2021; Kumar et al., 2015; Wang and Clow, 2020). However, in this validation, we need to evaluate how the Teddy-Tool is able to preserve the statistics of sub-daily extreme values. Therefore, we select precipitation as variable of interest. Figure 9 shows the reproduction of sub-daily precipitation extremes for 1980 – 2019 for

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions
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EGU

sample location 29 in southern Germany, where Teddy is run with a DOY window size of 11 days. The 40 annual maxima are extracted from the original and the disaggregated data. Additionally, the Generalized Extreme Value (GEV) distribution is fitted to these empirical data. Thereby, 95% confidence intervals are generated applying a bootstrap procedure with 1000 iterations to account for extreme value statistical uncertainties. We find that the Teddy-Tool leads to an overestimation of annual maximum precipitation. For the hourly duration, the differences are large with the confidence intervals of the GEV hardly overlapping. For the longer durations, Teddy values approach the original data, with noticeable differences only for the rare events with return periods above 5 years.

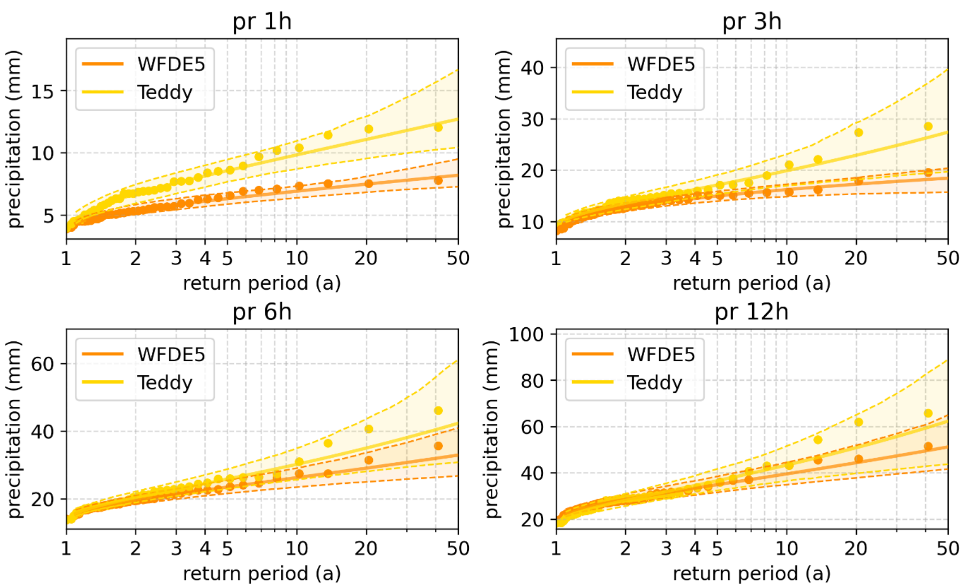

Figure 9: Extreme value statistical evaluation of sub-daily precipitation. The annual maxima of the WFDE5 and Teddy are shown as dots. Additionally, GEV fits (lines) with 95% confidence intervals (transparent areas and dashed lines) account for uncertainties. The Teddy-Tool is run with a DOY window size of 11 days.

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

Geoscientific Model Development
Discussions
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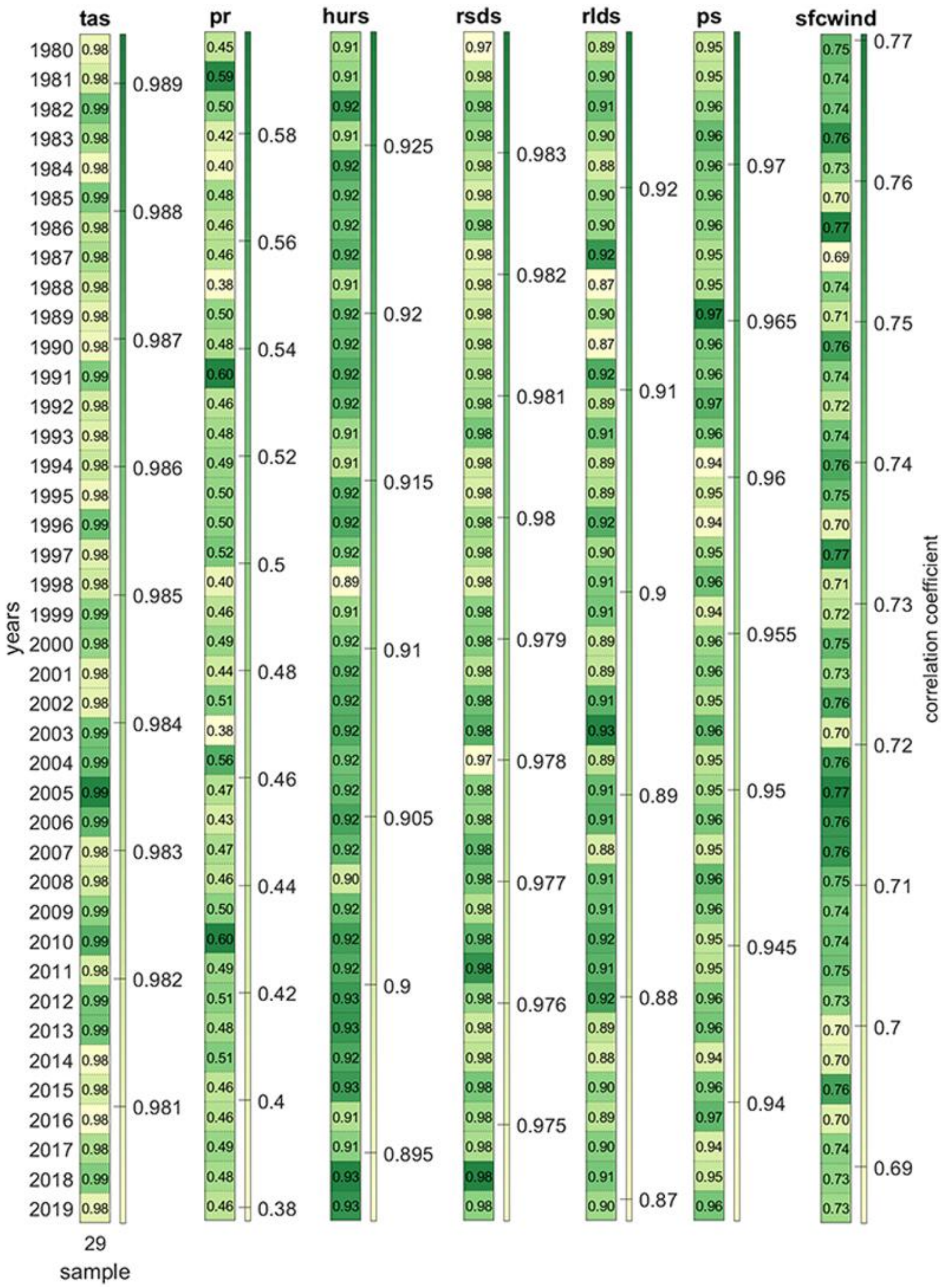

Figure 10: Pearson correlation coefficient for each year for sample location 29 and a DOY window size of 11 days. The scaling of the colorbar differs between variables.

https://doi.org/10.5194/gmd-2023-36
Preprint. Discussion started: 15 March 2023

3. Discussion

The Teddy-Tool allows for temporal disaggregation of daily climate model data. The disaggregation is based on location and time specific empirical relationships between variables. The approach is well suitable for all tested variables and results in high correlations (>0.9), except for precipitation (>0.5) and wind speed (>0.75). Compared to other approaches, the advantage of the Teddy-Tool is that no other input data is required rather than the daily climate model data. The Teddy-Tool is relatively simple to apply, considers specific regional and seasonal features of the diurnal course of different climate variables. Mass and energy are conserved and mean daily values of the climate model are reproduced any time.

The spatial and temporal resolution of the results is determined by the provided temporal and spatial resolution of the chosen reference data (WFDE5 used here). Longer available reanalysis time periods extend the basic population for identifying the most similar weather conditions in the past and thus could improve the results. Generally, also other reference data could be used, that provides higher temporal or spatial resolution for a specific region.

The time window to find the most similar historical weather situations can be chosen in different sizes. For most of the variables, we found small effects of time window adjustments, except for precipitation and wind speed. The evaluation of different DOY window sizes reveals that a DOY window size of 11 can generally be recommended across all variables. Larger DOY windows should be avoided mainly in arid regions, while shorter DOY windows generally lead to poorer representations of autocorrelation and extreme events.

One limitation of the Teddy-Tool is the representation of extreme events, mainly for precipitation, which is generally the most difficult variable for temporal disaggregation. We found that hourly precipitation extremes are not always reproduced. For heavy daily precipitation events, Teddy distributes the 24h-sums either correctly, too evenly or on too few hours. When distributing on too few hours, extreme hourly intensities evolve, which may have never occurred or may even be physically implausible. For temporal disaggregation of extreme precipitation, we recommend dynamical downscaling via high-resolution climate models (Poschlod, 2021; Poschlod et al., 2021; Zabel et al., 2012; Zabel and Mauser, 2013).

For the disaggregation of future climate projections using of the Teddy-Tool, we have the following remarks: As the Teddy-Tool derives the relationships between sub-daily and daily values empirically based on reanalysis data, future diurnal profiles, which are outside the historical range of diurnal profiles, might possibly be not fully reproduced. However, this limitation is common for statistical approaches, which are to be calibrated on historical data (Papalexiou et al., 2018). Nevertheless, due to energy and mass conservation, climate trends in the daily climate signal are fully preserved. Hence, applying Teddy for temporal disaggregation under climate change holds under the assumption that we select the most similar day of the historical data and that this diurnal profile is representative for future climatic conditions. However, this assumption might apply to a different degree for different variables. We expect non-stationarity for the diurnal profiles due to changing weather patterns, shifts in rainfall generating processes, and shifts in the seasonality, mainly for precipitation and wind. The daily course of other variables, such as solar radiation and temperature might generally be less affected by a warmer climate. Furthermore, global climate models at coarse resolutions generally do not represent all processes to fully reproduce intraday variability. Teddy applies the diurnal profiles and intraday variability from the WFDE5 data, which are bias-adjusted ERA5 reanalysis data that implicitly consider finer scale effects than coarse-resolution global climate models (Cucchi et al., 2020). Thus, the disaggregation process in Teddy is consistent with the bias adjustment in ISIMIP3.

Further possible developments include an improved inter-day connectivity. Despite the consideration of precipitation classes, still abrupt changes over day changes are possible. A future introduction of temperature classes and surface pressure classes in addition to the precipitation classes could help to reduce this effect. Depending on the location of interest, also including climate modes or weather patterns for the choice of the most similar day could improve the performance. Other optional future developments could include the separation of direct and diffuse radiation, which is also a required information for some impact models which is currently not provided by ISIMIP.

Code availability

The source code of the Teddy-Tool (v1.0) including preprocessed data, results of the cross-validation and exemplary results for SSP 585 (2015 – 2100) and the UKESM1-0-L climate model for 30 samples are provided via Zenodo (https://doi.org/10.5281/zenodo.7679149).

Author contribution

FZ: Conceptualization, Software, Methodology, Validation, Formal analysis, Resources, Data curation, Writing - original draft, Visualization

BP: Methodology, Validation, Formal analysis, Writing - original draft, Visualization

Competing interests

The contact author has declared that none of the authors has any competing interests.

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