Discontinuous daily temperatures in the WATCH forcing data sets

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Introduction

Assessment of the global water cycle requires reliable data with global coverage of those variables driving the water cycle. Based on ECMWF Reanalyses (ERA-40 and ERA-Interim Uppala et al., 2005; Dee et al., 2011), the EU WATCH project created global data sets, e.g., WATCH Forcing Data 20th Century (WFD, G. P Weedon et al., 2010; Weedon et al., 2011) and WATCH-Forcing-Data-ERA-Interim (WFDEI, Weedon et al., 2014). Daily temperatures are adjusted such that their monthly means match the CRU monthly temperature data set (New et al., 1999, 2000). Thus, daily minimum, maximum and mean temperatures within one calendar month have been subjected to a correction involving monthly means. As these corrections can be largely different for adjacent months, this procedure is potentially leading to implausible differences in daily temperatures across the boundaries of calendar months, potentially causing problems for subsequent applications.

The problem of discontinuities in adjusted (bias-corrected) reanalyses has been discussed, e.g., in Hempel et al. (2013). Hagemann et al. (2011) and Piani et al. (2010) pointed already to potential jumps between months and suggested a continuous correction.

Motivation from a grid-box from Ethiopia

- inter-quartile ranges of daily mean temperature across the year (Fig. 1, left) exemplifies the problem
- comparing day-to-day temperature fluctuations $\Delta T_i = T_i - T_{i-1}$ within and across months ($\Delta T_{i,\text{in}}$ and $\Delta T_{i,\text{across}}$) in Fig. 1 (right) give a first quantification of the severity of the problem

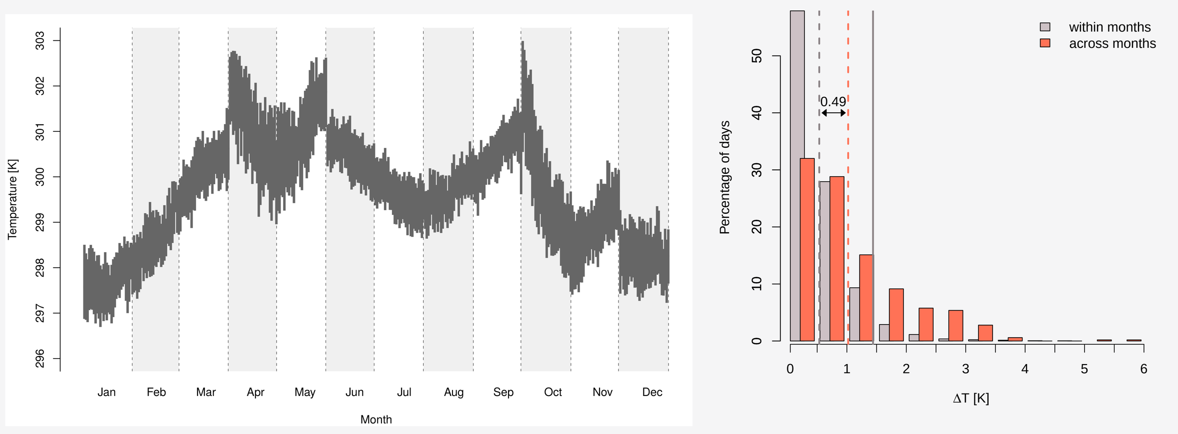

Figure 1: Left: Inter-quartile ranges (IQRs) of daily mean temperature from WFD for a grid-box in Ethiopia (40.75°E, 11.25°N). The dark gray bars mark the IQR of the 45-year temperature series for a given day in the year. Alternating gray and white shadings separate different calendar months. Right: Histogram of absolute daily temperature fluctuations from WFD within-months $|\Delta T_{i,\text{in}}|$ (45 years with 365 − 12 days, gray bars) and across-months $|\Delta T_{i,\text{across}}|$ (45 years with 12 days, orange bars). The dashed vertical lines mark the mean of the corresponding distributions, the solid gray line marks the 0.95 quantile of $|\Delta T_{i,\text{in}}|$.

Are Distributions of Across and Within-Months Differences Different?

Hypothesis Test

- H_0: $|\Delta T_{i,\text{across}}|$ are IID with distribution identical to $|\Delta T_{i,\text{in}}|$, assume that the 0.95-quantile can be adequately estimated, hence a probability of $p = 0.05$ for $|\Delta T_{i,\text{across}}|$ exceeding it
- 45 years with 12 months $\rightarrow N = 45 \times 12 = 540$ trials of a Bernoulli experiment with $p = 0.05$ and thus expect 27 exceedances
- binomial distribution $\rightarrow$ number of exceedances < 36 for 95% of all trials, this corresponds to 7% of $N = 540$, thus 7% marks critical value (not being consistent with H_0 at a 5%-level of significance).

The colours in Fig. 2 are chosen such that non-significant results ($\leq 7\%$) are shown in white.

Direction of Jumps

Average across-months temperature differences $\overline{\Delta T_{m,\text{across}}}$ are compared to *normal* variations

$$\overline{\Delta T_{m,\text{in}}} = \frac{1}{2n} \sum_{y=1}^{n} \left(T_{m,f-1,y} - T_{m,f-2,y} + T_{m,f+1,y} - T_{m,f,y} \right) \qquad (1)$$

with (m, f, y) and $(m, f+1, y)$ denoting the first (f) and second ($f+1$) day of calendar month m in year y, respectively; $f-1$ and $f-2$ are the last and second last day of the previous month. The normalised difference is

$$t_m = \frac{\overline{\Delta T_{m,\text{across}}} - \overline{\Delta T_{m,\text{in}}}}{\sqrt{\frac{s^2_{\Delta T_{m,\text{across}}}}{n} + \frac{s^2_{\Delta T_{m,\text{in}}}}{2n}}} \qquad (2)$$

with $s^2_\cdot$ being the associated sample variances for month m and n the number of years available. $|t_m| > 2$ roughly corresponds to a two-sided t-test on a 95% level of significance; colours in Fig. 4 are chosen accordingly.

Results

Where are significant differences?

Significantly more extreme across-months temperature differences than expected can be detected in many regions of the world; most prominently in regions with low availability of observational data.

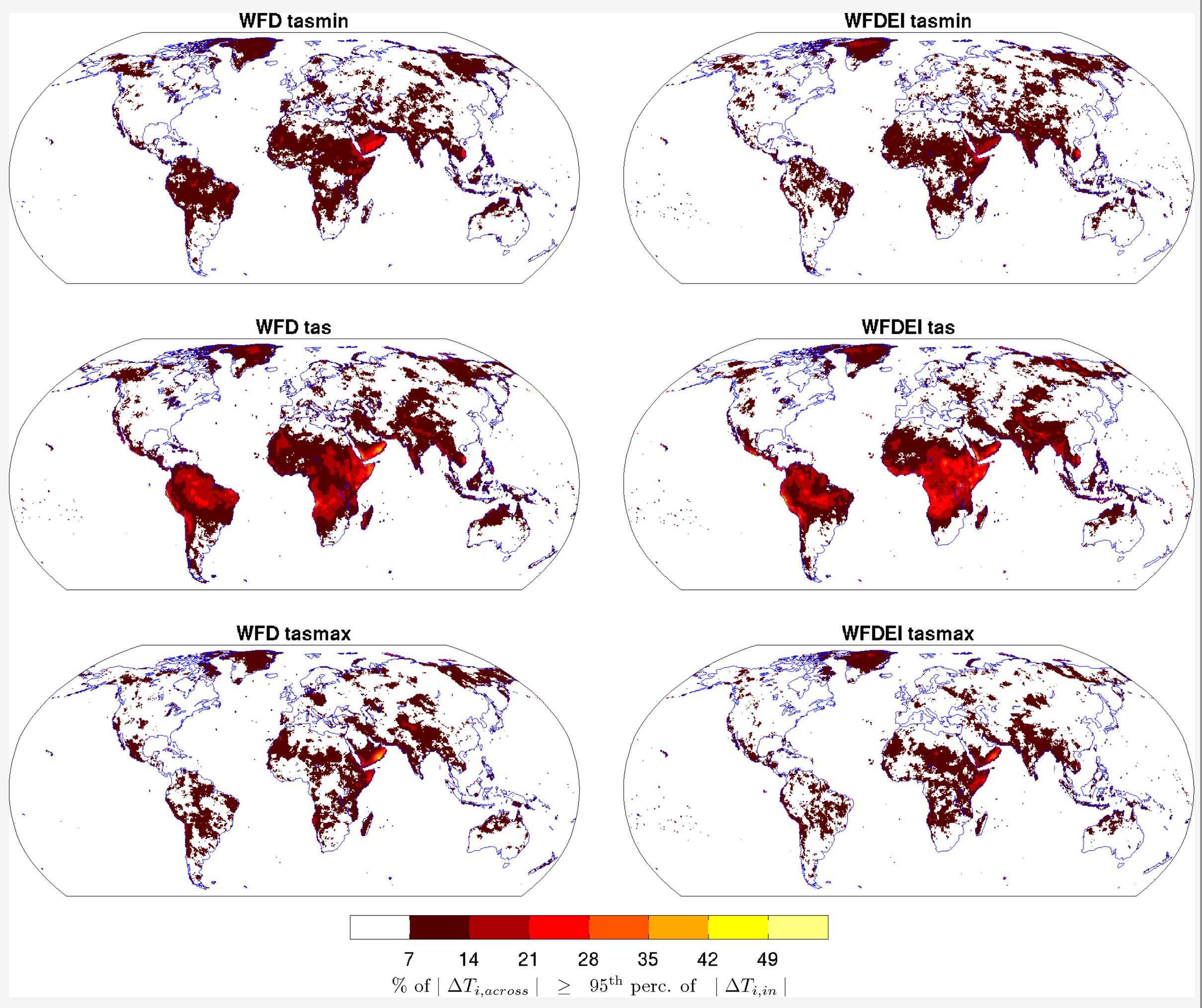

Figure 2: Fraction of days with absolute across-months temperature fluctuations greater than the 0.95-quantile of absolute within months fluctuations for minimum daily temperature at surface (tasmin, top row), mean (tas, middle row), max (tasmax, bottom row) for WFD (left column) and WFDEI (right column).

What size are they on average?

In many regions with significantly more extreme across-months temperature differences, their average fluctuations are only 10% to 30% larger than the within-months fluctuations. However, some regions show twice as large average across-months fluctuations.

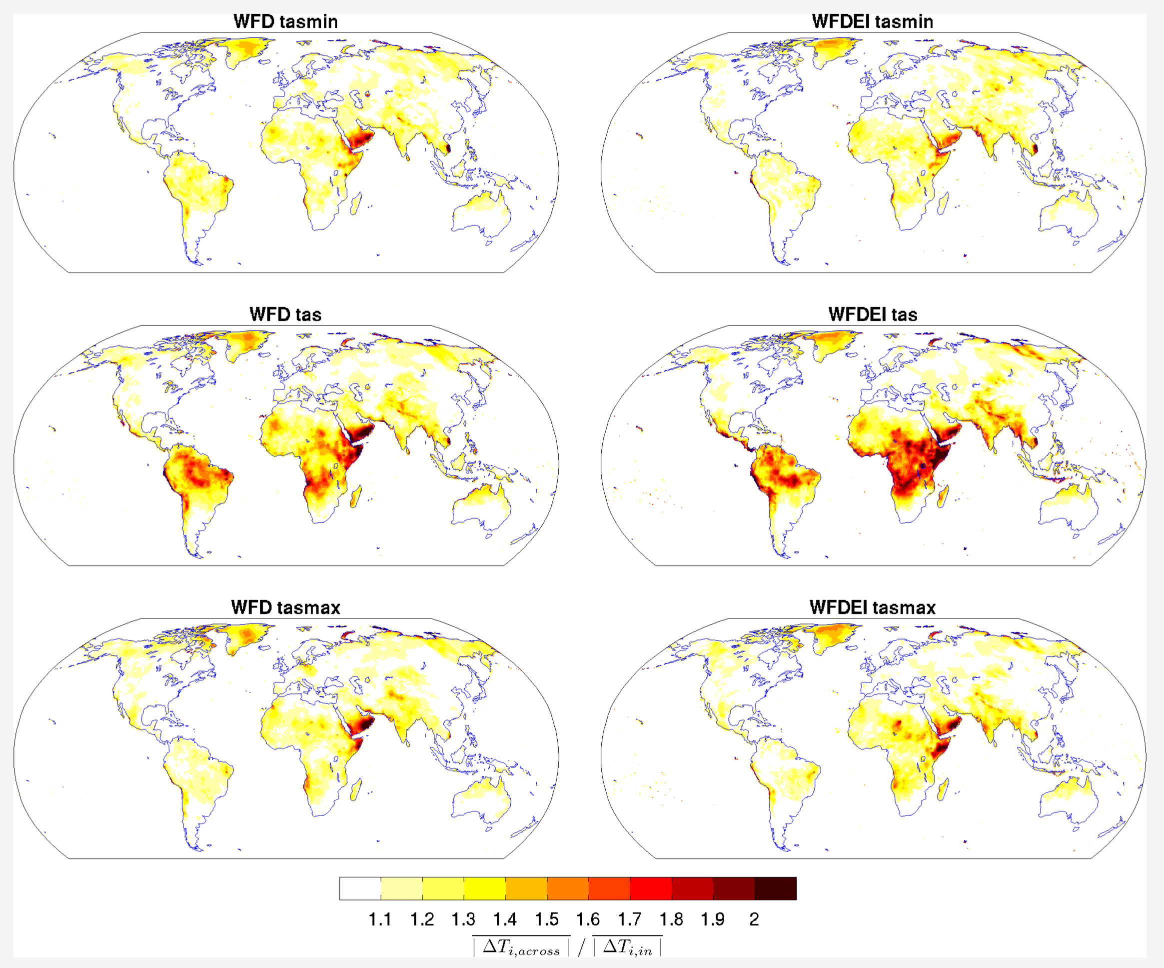

Figure 3: Ratio of absolute across-months and within months temperature fluctuation for minimum daily temperature at surface (tasmin, top row), mean (tas, middle row), max (tasmax, bottom row) for WFD (left column) and WFDEI (right column). Relative differences larger than 2 exists but are not depicted in separate colour.

Seasonally Resolved Directions of Jumps

The direction of jumps depends on the season, Fig. 4. A positive (negative) t_m indicates a positive (negative) deviation of the climatological annual cycle caused by the adjustment scheme. The seasonal cycle of the underlying reanalyses do not match the cycle of the CRU temperature series.

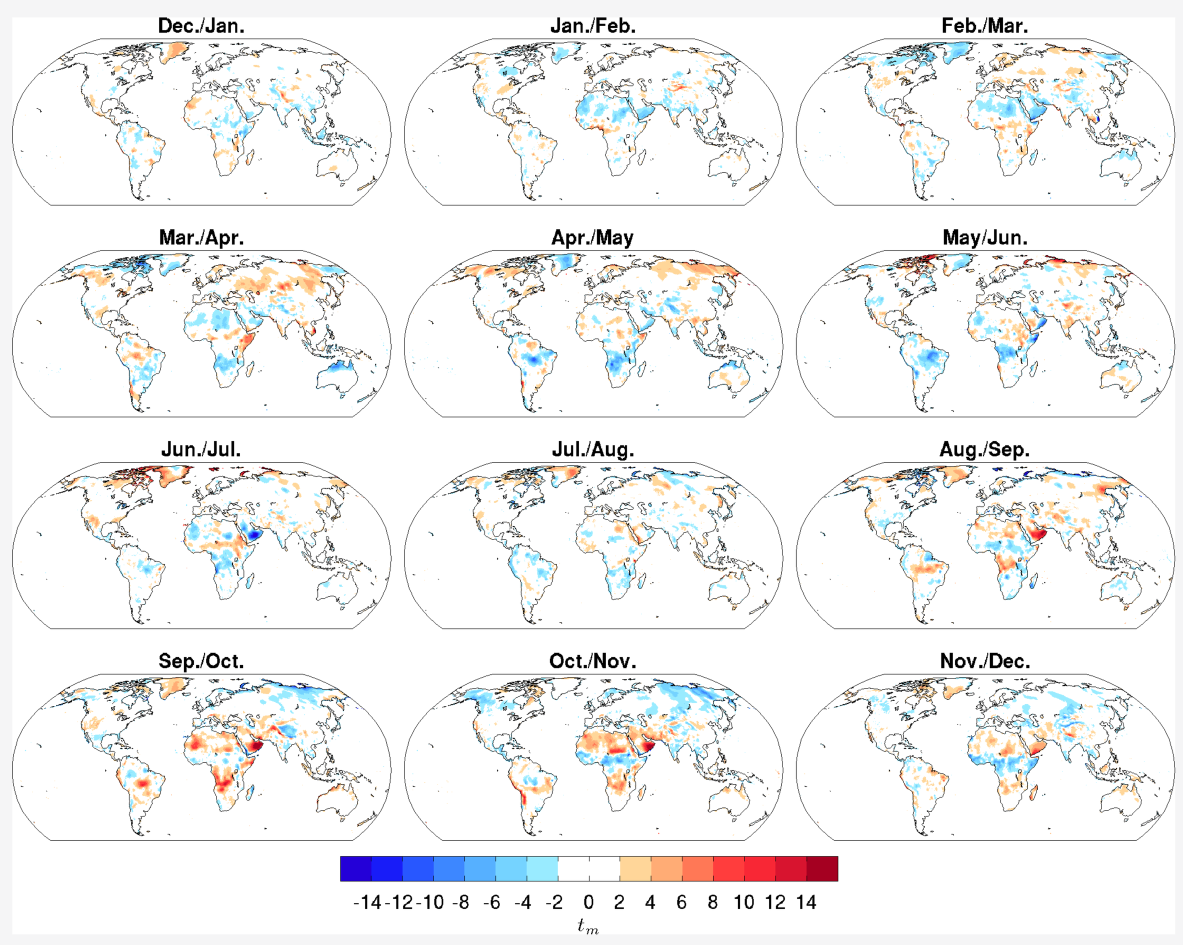

Figure 4: Normalised mean differences between across-months and surrounding within months daily mean temperature fluctuations (Eq. (2)) for WFD (e.g., top left shows mean difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec. and 1 Jan./2 Jan).

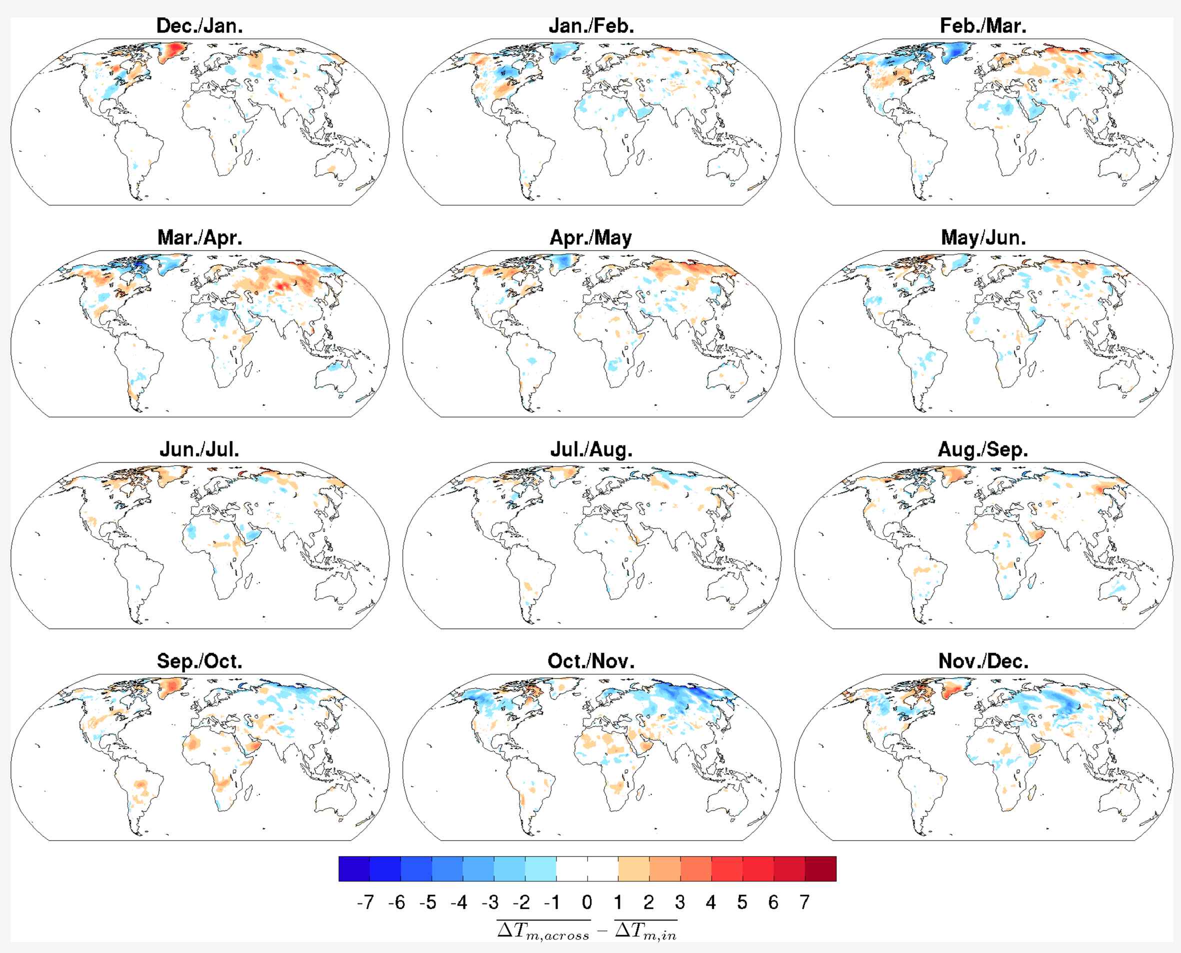

Figure 5: Non-normalized mean differences between across-months and surrounding within months daily mean temperature fluctuations (numerator of Eq. (2)) for WFD (e.g., top left shows the mean difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec. and 1 Jan./2 Jan).

Summary and Conclusions

We find that

- across and within-months fluctuations are significantly different in distribution, mostly in the tropics and frigid zones;
- average across-months fluctuations in daily mean temperature are between 10% to 40% larger than their corresponding within-months fluctuation, regions with differences up to 200% can be found in tropical Africa;
- most severe discontinuities show up in spring and autumn
- effect is apparently caused by different seasonal cycles in the CRU temperature data set and the reanalyses;
- daily maximum and minimum temperatures are affected in the same regions but in a less severe way.

The WATCH data sets are valuable data sets for driving hydrological applications. However, for certain regions and applications, the daily data set has to be used with care. Particularly in regions where snow-melt is a relevant player for hydrology, a few degrees difference can be decisive for triggering this process.

More details can be found in
H. W. Rust, T. Kruschke, A. Dobler, M. Fischer, U. Ulbrich, 2015:
Discontinuous daily temperatures in the WATCH forcing data sets. *J. Hydrometeor.*, **16**, 465-472.

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