

1 **Discontinuous daily temperatures in the WATCH forcing data sets**

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## Abstract

3  
4 The WATCH forcing data sets have been created to support the use of hydrological and land  
5 surface models for the assessment of the water cycle within climate change studies. They are  
6 based on ECMWF reanalysis products (ERA-40 or ERA-Interim) with temperature (among  
7 other variables) adjusted such that their monthly means match the monthly temperature  
8 data set from the Climatic Research Unit. To this end, daily minimum, maximum and  
9 mean temperatures within one calendar month have been subjected to a correction involv-  
10 ing monthly means of the respective month. As these corrections can be largely different  
11 for adjacent months this procedure is potentially leading to unplausible differences in daily  
12 temperatures across the boundaries of calendar months. We analyze day-to-day temperature  
13 fluctuations within and across months and find that across months differences are signifi-  
14 cantly larger, mostly in the tropics and frigid zones. Average across-months differences in  
15 daily mean temperature are typically between 10% to 40% larger than their correspond-  
16 ing average within-months temperature differences. However, regions with differences up  
17 to 200% can be found in the tropical Africa. Particularly in regions where snow-melt is  
18 a relevant player for hydrology, a few degrees difference can be decisive for triggering this  
19 process. Daily maximum and minimum temperatures are affected in the same regions but  
20 in a less severe way.

## 21 1. Introduction

22 An assessment of the global water cycle requires reliable data sets with global coverage  
23 of the meteorological variables driving the water cycle. The EU WATCH project has created  
24 global data sets meant to meet these needs: e.g., the WATCH Forcing Data 20th Century  
25 (Weedon et al. 2010, 2011, WFD,). With the same methodology the WATCH-Forcing-Data-  
26 ERA-Interim (WFDEI, Weedon et al. 2014) was created. This data set has been frequently  
27 used in the context of hydrological modeling (e.g., Gudmundsson et al. 2011; Koch et al.  
28 2013; Prudhomme et al. 2014).

29 The WFD is based on the ECMWF 40-yr reanalysis (ERA-40, Uppala et al. 2005) with  
30 variables adjusted by observational products, while the WFDEI uses ERA-Interim (ERA-  
31 Interim, Dee et al. 2011) as a basis. Sub-daily temperatures are adjusted such that their  
32 monthly means match the corresponding Climatic Research Unit (CRU) dataset’s monthly  
33 temperatures running from January 1958 to December 2001 (New et al. 1999, 2000; Mitchell  
34 and Jones 2005; Weedon et al. 2010, 2011). This implies potentially very different adjust-  
35 ments for adjacent days belonging to different calendar month. Hence, the difference in daily  
36 temperatures between the first day of month and the last day of the previous month might  
37 be very different from the day-to-day temperature difference within the same month. Ideally  
38 this day-to-day differences at the beginning or end of calendar months are of the typical  
39 size of day-to-day temperature variations and hence should neither be detectable nor pose  
40 serious problems for further application of the WATCH forcing data sets in a hydrological  
41 context. But what if the typical across-months differences are notably larger than typical  
42 within-months differences? Implausible temperature differences between adjacent days oc-

43 cur. To quantify this problem, we compare the distribution of day-to-day differences in daily  
44 temperatures within calendar months to differences across months for both the WFD and  
45 the WFDEI. Specifically, we count events with across-months daily temperature differences  
46 being larger in magnitude than extreme within-months daily temperature differences and  
47 we compare the magnitude of across-months temperature differences to the corresponding  
48 within-months differences in total and on a monthly resolved basis.

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

52 The WATCH forcing data sets (WFD and WFDEI) as well as the methods used to detect  
53 and quantify untypical daily temperature differences are presented in Sec. 2. Section 3 shows  
54 the affected regions and quantifies the resulting discontinuities for the whole datasets and  
55 for transitions from specific month to the subsequent one; conclusions are given in Sec. 4.

## 56 2. Data and Methods

57 We consider mean (tas), minimum (tasmin) and maximum (tasmax) near-surface tem-  
58 perature (2m) from the WFD and WFDEI. The data can be obtained from the International  
59 Institute for Applied Systems Analysis (<ftp://rfdata@ftp.iiasa.ac.at/>).

60 Plotting interquartile ranges (IQR, difference between third and first quartile) of daily  
61 mean temperature across the year for a grid-box from Ethiopia in the WFD data set provides  
62 a first visual impression of the problem (Fig. 1): The larger than usual differences between  
63 daily temperature at the boundaries of months become particularly evident between March

64 and April, May and June, September and October, as well as November and December;  
 65 these are of the size of the inter-quartile range of within-month temperature differences.

66 In the following, we compare day-to-day temperature fluctuations between days  $i$  and  
 67  $i - 1$

$$\Delta T_i = T_i - T_{i-1} \tag{1}$$

68 within months ( $\Delta T_{i,\text{in}}$ ) to those across months ( $\Delta T_{i,\text{across}}$ ). Figure 2 shows the histograms  
 69 of absolute temperature differences  $|\Delta T_{i,\text{in}}|$  ( $N_{\text{in}} = 45 \cdot (365 - 12)$ , gray bars) and  $|\Delta T_{i,\text{across}}|$   
 70 ( $N_{\text{across}} = 45 \cdot 12$ , orange bars) as well as the differences in their sample means (dashed  
 71 lines) for the same grid-box in Ethiopia used for Fig. 1. The 0.95-quantile of inner-monthly  
 72 daily fluctuations is marked as a solid vertical line and we classify values below this line  
 73 as *normal* day-to-day variations, which is expected to be exceeded in only 5% of day-to-  
 74 day variations. For the given example grid-box, we find 24.5% of across months day-to-day  
 75 variations exceeding this line and thus more than the expected 5%. To assess whether  
 76 this number of exceedances is significantly different from the expected 5% inner-monthly  
 77 exceedances, we construct the following hypothesis test: under the null hypothesis  $H_0$  we  
 78 assume that  $|\Delta T_{i,\text{across}}|$  are realizations of independent and identically distributed random  
 79 variables (iid) with the same distribution as  $|\Delta T_{i,\text{in}}|$ . We further assume the sample estimate  
 80 of the 0.95-quantile being an adequate estimate of the true quantile and, hence, a probability  
 81 of  $p = 0.05$  for  $|\Delta T_{i,\text{across}}|$  exceeding it. For 45 years with 12 months, we have  $N = 45 \times 12 =$   
 82 540 beginnings of months, i.e.  $N$  trials of a Bernoulli experiment with probability  $p = 0.05$   
 83 for exceeding this quantile. We thus expect 27 exceedances and deduce from the binomial  
 84 distribution that the number of exceedances is smaller than 36 for 95% of all trials. These

85 36 exceedances correspond to about 7% of  $N = 540$  trials and hence 7% marks a critical  
 86 value which we consider as not being consistent with  $H_0$  at a 5%-level of significance.

87 Additionally, we analyze the direction of the discontinuities, that is whether the across-  
 88 month temperature differences are positive or negative on average. These average across-  
 89 month temperature differences  $\overline{\Delta T_{m,\text{across}}}$  are compared separately for every month  $m$  to  
 90 *normal* variations, estimated from the temperature differences before and after the transi-  
 91 tions across months

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

92 with the indices  $(m, f, y)$  and  $(m, f + 1, y)$  denoting the first ( $f$ ) and second ( $f + 1$ ) day  
 93 of calendar month  $m$  in year  $y$ , respectively;  $f - 1$  and  $f - 2$  are thus the last and second  
 94 last day of the previous month. Additionally, we consider the normalized difference in mean  
 95 values of within-months and across-months fluctuations

$$t_m = \frac{\overline{\Delta T_{m,\text{across}}} - \overline{\Delta T_{m,\text{in}}}}{\sqrt{\frac{s_{\Delta T_{m,\text{across}}}^2}{n} + \frac{s_{\Delta T_{m,\text{in}}}^2}{2n}}} \quad (3)$$

96 with  $s^2$  being the associated sample variances for month  $m$  and  $n$  the number of years  
 97 available.

### 98 3. Results

99 For every grid-box in the WFD and WFDEI data set, we obtain fractions of days with  
 100 absolute across-month temperature fluctuations  $\Delta T_{i,\text{across}}$  above the estimated 0.95-quantile  
 101 of absolute within-months daily fluctuations  $\Delta T_{i,\text{in}}$ . These fractions (in percent) are depicted

102 in Fig. 3 for minimum (tasmin), mean (tas) and maximum (tasmax) daily temperature. For  
 103 both data sets, regions with very pronounced differences in the mean temperature (tas,  
 104 Fig. 3, middle row), i.e. fractions of 20% or larger, are the horn of Africa, the south of the  
 105 Arabian Peninsula and Angola. Large parts of Africa, South America, Greenland, Siberia,  
 106 India and South-East Asia are also affected but in a less severe way. Minimum (tasmin,  
 107 Fig. 3, top row) and maximum (tasmax, Fig. 3, bottom row) daily temperature show the  
 108 same regional patterns but in a less pronounced way. Additionally, Fig. 4 gives ratios of  
 109 mean absolute values  $\overline{|\Delta T_{\text{across}}|}/\overline{|\Delta T_{\text{in}}|}$  for the daily minimum, mean and maximum temper-  
 110 atures. The above mentioned regions show ratios of 2 and more, indicating that the average  
 111 across-months fluctuation is of twice the magnitude than the average within-months fluctu-  
 112 ation. Corresponding results for minimum (tasmin, Fig. 4, top row) and maximum (tasmax,  
 113 Fig. 4, bottom row) daily temperatures again show basically the same spatial patterns. The  
 114 differences in magnitude between across-months and within-months is, however, not as pro-  
 115 nounced as for daily mean temperatures. Day-to-day fluctuations of extreme temperatures  
 116 are in general larger (more variable) than mean temperatures and thus the adjustment does  
 117 not lead to outstanding across-months fluctuations that easily. Regions which are little or  
 118 not affected (i.e. a fraction of less than 7%) roughly correspond to areas where the CRU  
 119 temperature data set profits from a particularly good coverage of observational data, see  
 120 Mitchell and Jones (2005).

121 To resolve seasonal effects, Fig. 5 shows normalized differences (Eq. (3)) of across-month  
 122 and surrounding within-month temperature fluctuations for every transition from one to the  
 123 subsequent month for WFD. The color bar is chosen such that color starts for  $|t_m| > 2$   
 124 which roughly corresponds to a two-sided  $t$ -test on a 95% level of significance (Welsh's  $t$ -test

125 with modified degrees of freedom, von Storch and Zwiers 1999). A positive (negative)  $t_m$   
126 indicates a positive (negative) deviation of the climatological annual cycle caused by the  
127 adjustment scheme. The affected regions are identical to those mentioned before. How-  
128 ever, implausible positive and negative across-month fluctuations are distributed differently  
129 across the year for different regions. For a given region, there are typically transitions with  
130 both, large positive and large negative fluctuations. This is an indication that the seasonal  
131 cycle of the underlying reanalyses do not match the cycle of the CRU temperature series.  
132 Discontinuities are most severe in the transition seasons for the tropical regions, as well as  
133 the Northern Hemisphere sub-polar to polar latitudes. While the direction of discontinuities  
134 is predominantly downward in spring and upward in summer to autumn over Greenland,  
135 Siberia exhibits an opposite behavior. The Arabian Peninsula shows downward (upward)  
136 jumps from late winter through early summer (late summer and autumn). Northern and  
137 Southern Africa exhibit similar signals, equatorial Africa an opposite behavior. These pat-  
138 terns extend more or less zonally with India and Southeast Asia behaving like equatorial  
139 Africa and opposite signs for South America and Northern Australia. In order to allow a  
140 first assessment whether these statistically significant implausible across-months fluctuations  
141 are relevant for further analyses to be build upon, Fig. 6 shows non-normalized differences  
142  $\overline{\Delta T_{m,\text{across}}} - \overline{\Delta T_{m,\text{in}}}$  for mean temperature which are probably more intuitive than Fig. 5.  
143 Discontinuities in the tropical regions which were found to be statistically highly significant  
144 in Fig. 5, are comparably small in absolute numbers. They hardly exceed a magnitude of  
145  $\pm 2\text{K}$  and, hence, might be neglectable in terms of potential impacts for applications such  
146 as hydrological modelling. However, results for the extra-tropics are completely different,  
147 magnitudes of across-months fluctuations are much larger here. Especially those in (boreal)



148 autumn, winter, and spring are striking, representing widespread sudden jumps of mean  
149 temperature in the order of  $\pm 5\text{K}$  and beyond. In North America, Greenland and the frigid  
150 parts of Asia discontinuities of a few degrees exists (e.g., up to  $7\text{K}$  in Greenland for De-  
151 cember to January). A few degrees difference in these regions are responsible for triggering  
152 snow-melt and are thus important for hydrological modeling. The corresponding figure for  
153 WFDEI (not shown) depicts very similar spatial structures and values but differs in detail.

## 154 4. Conclusion

155 The availability of consistent and homogeneous sets of global forcing data is of great  
156 importance for hydrological modeling and climate research. Particularly, hydrological impact  
157 studies need a set of reference data with consistent temperature and precipitation. The WFD  
158 and WFDEI have been designed to meet these demands for the global land areas. However,  
159 in certain regions implausible day-to-day differences in temperature across the boundaries  
160 of calendar months arise. These result most likely from a combination of the adjustment  
161 scheme used in combination with a mismatch of the seasonal cycle of the two data sets  
162 under consideration: The adjustment scheme involves CRU-TS monthly mean values and  
163 thus adjustments change abruptly at the boundaries of calendar months if the seasonal cycles  
164 of CRU-TS and the ERA reanalyses differ in phase or amplitude. Hence, the introduction of  
165 discontinuities it is not an effect of the adjustment scheme alone, nor of the CRU temperature  
166 data set; problems occur when the seasonal cycles in the reanalysis and reference data sets  
167 differ in amplitude or phase. While this spurious effect of the adjustment scheme may not  
168 become evident in seasons and locations where "normal" inner-monthly daily temperature

169 fluctuation are comparably large, we found noticeable and potentially problematic differences  
170 in the tropics and frigid regions.

171 Daily mean temperature exhibits fluctuations between two consecutive months of about  
172 150% or more of the size of the "normal" inner-monthly daily temperature fluctuations for  
173 regions in South America and central Africa; for the Arabian peninsula and Ethiopia twice  
174 the size is found. As extreme temperatures (tasmin, tasmax) exhibit larger day-to-day tem-  
175 perature fluctuations than daily mean temperatures (tas), the tolerance for inhomogeneous  
176 adjustments is larger for minimum and maximum daily temperatures. The few degrees dis-  
177 continuities in the frigid regions can be decisive for triggering snow-melt and are thus relevant  
178 for hydrological modeling.

179 According to Weedon et al. (2011, Tab. 1), the adjustment scheme based on monthly  
180 values was applied to 2-m temperature, downward shortwave radiation, rainfall rate, snowfall  
181 rate. Hence these variables are potentially affected by discontinuities in the same way if  
182 similar mismatches between their seasonal cycles in the ERA reanalyses and the reference  
183 data set exist. However, for variables as precipitation potential discontinuities are more  
184 difficult to detect as the day-to-day variability is a larger than for temperature.

185 Analysis of the individual months' transitions reveals most severe discontinuities in the  
186 transition seasons, organized in approximately zonally symmetric patterns. Africa and the  
187 Arabian Peninsula exhibit the largest magnitudes of these discontinuities with downward  
188 jumps in boreal late winter to early summer and upward jumps in autumn.

189 A detailed assessment of related impacts on hydrological applications is beyond the scope  
190 of this study. However, we assume that such impacts exist and do imply significant conse-  
191 quences for hydrological applications. This is particularly reasonable when temperatures are

192 close to 0°C and triggering of snow-melt come into play. In conclusion, any application of  
193 the WFD or WFDEI in the mentioned regions should be aware of implausible temperature  
194 fluctuations across boundaries of calendar months.

195 *Acknowledgments.*

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197 set and the EU FP7 EMBRACE project for supporting the development of the WFDEI data  
198 set.

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## 244 List of Figures

- 245 1 Interquartile ranges (IQRs) of daily mean temperature from WDF for a grid-  
246 box in Ethiopia (40.75°E,11.25°N. The dark gray bars mark the IQR of the  
247 45-year temperature sample of a given day in the year. Alternating gray and  
248 white shadings separate different calendar months. 16
- 249 2 Histogram of absolute daily temperature fluctuations from WDF within-months  
250  $|\Delta T_{i,\text{in}}|$  (45 years with 365-12 days, gray bars) and across-months  $|\Delta T_{i,\text{across}}|$   
251 (45 years with 12 days, orange bars). The dashed vertical lines mark the mean  
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261 column). Relative differences larger than 2 exists but are not depicted in  
262 separate color. 19

- 263 5 Normalized mean differences between across-months and surrounding within  
264 months daily mean temperature fluctuations (Eq. (3)) for WFD, e.g. mean  
265 difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec. and 1  
266 Jan./2 Jan. (top left). 20
- 267 6 Non-normalized mean differences between across-months and surrounding within  
268 months daily mean temperature fluctuations (numerator of Eq. (3)) for WFD,  
269 e.g. mean difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec.  
270 and 1 Jan./2 Jan. (top left). 21



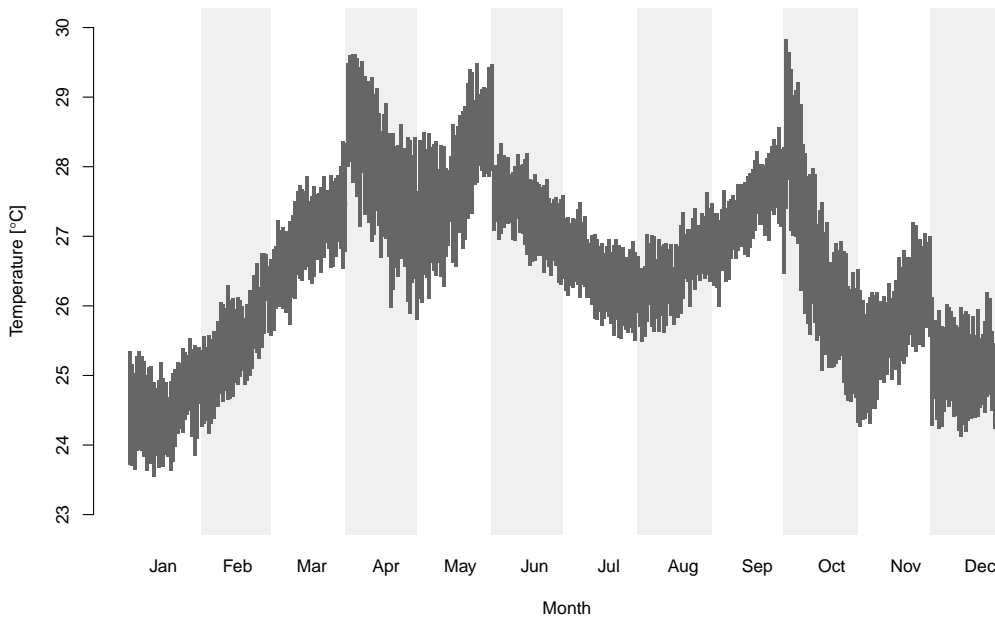


FIG. 1. Interquartile ranges (IQRs) of daily mean temperature from WDF for a grid-box in Ethiopia ( $40.75^{\circ}\text{E}, 11.25^{\circ}\text{N}$ ). The dark gray bars mark the IQR of the 45-year temperature sample of a given day in the year. Alternating gray and white shadings separate different calendar months.

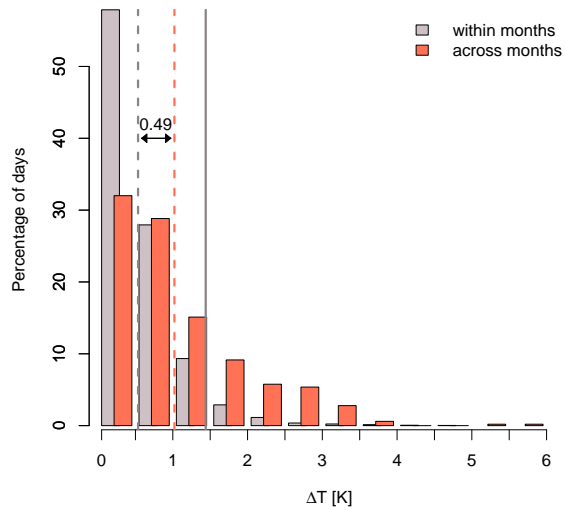


FIG. 2. Histogram of absolute daily temperature fluctuations from WDF within-months  $|\Delta T_{i,\text{in}}|$  (45 years with 365-12 days, gray bars) and across-months  $|\Delta T_{i,\text{across}}|$  (45 years with 12 days, orange bars). The dashed vertical lines mark the mean of the corresponding distributions, the solid gray line marks the 0.95 quantile of  $|\Delta T_{i,\text{in}}|$ .

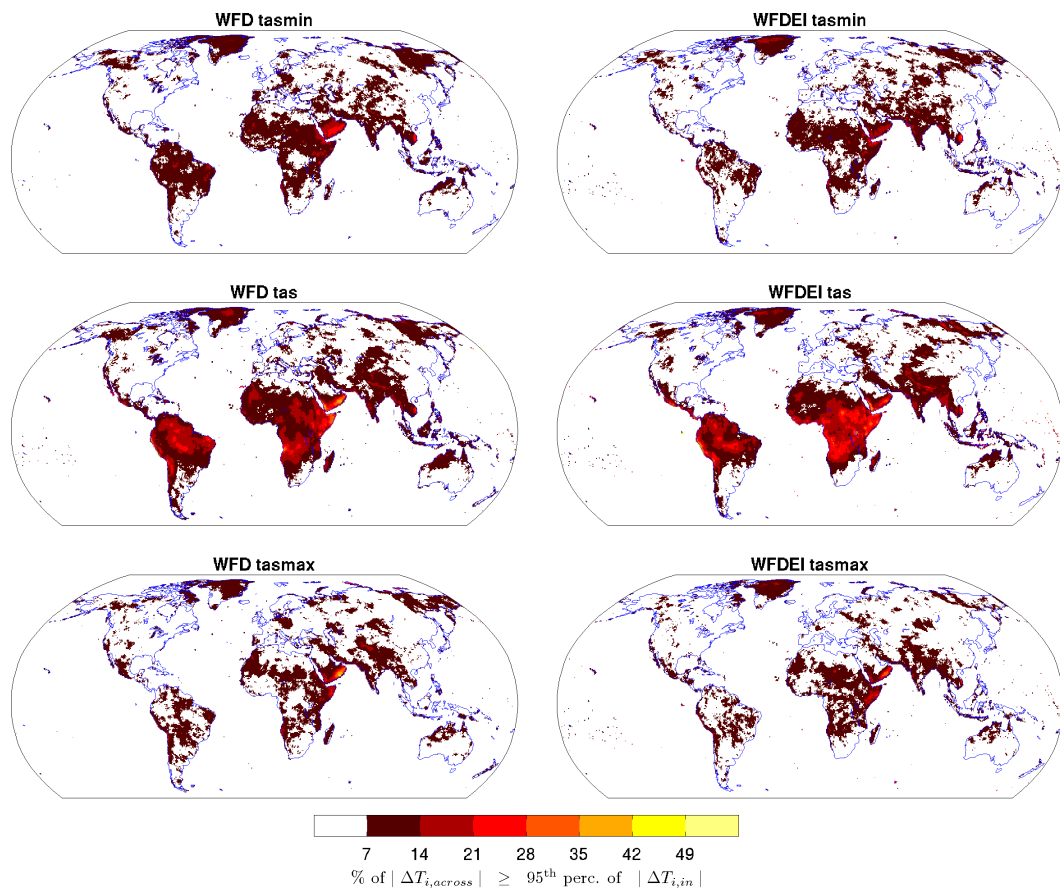


FIG. 3. Fraction of days with absolute across-months temperature fluctuations greater than the 0.95-quantile of absolute within months fluctuations for minimum daily temperature at surface (tasmin, top row), mean (tas, middle row), max (tasmax, bottom row) for WFD (left column) and WFDEI (right column).

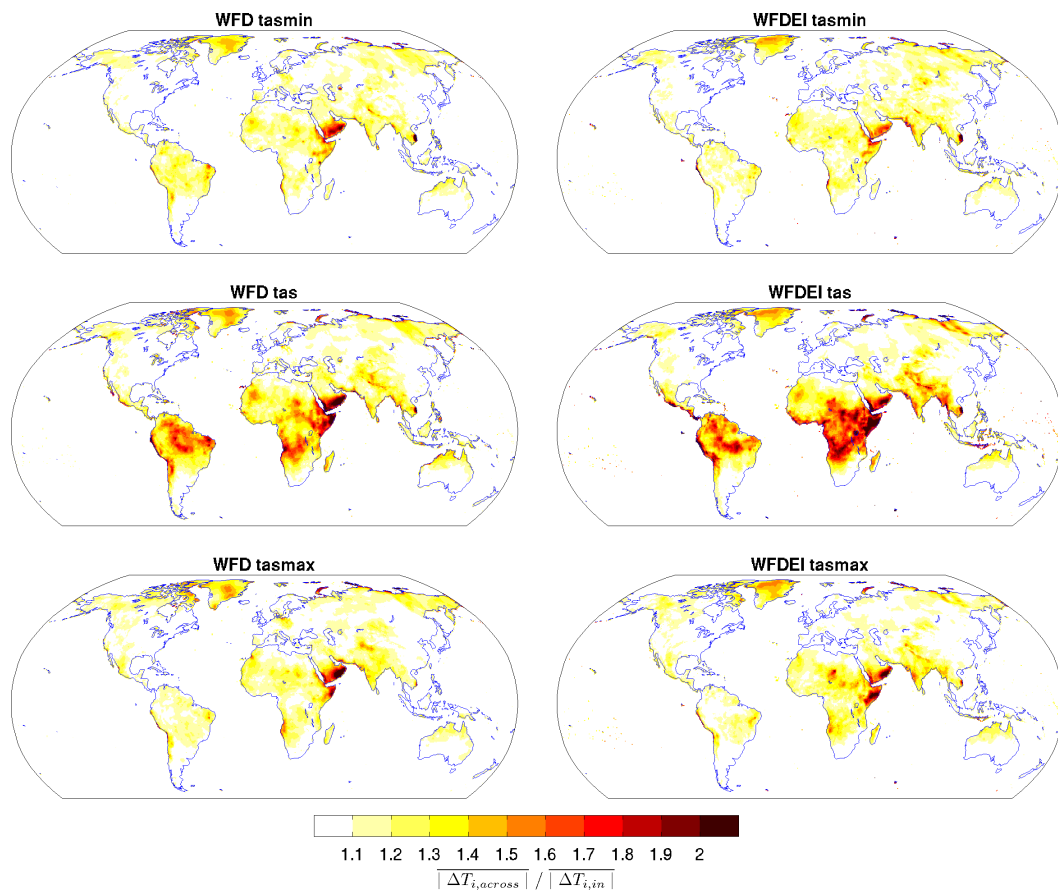


FIG. 4. Ratio of absolute across-months and within months temperature fluctuation for minimum daily temperature at surface (tasmin, top row), mean (tas, middle row), max (tasmx, bottom row) for WFD (left column) and WFDEI (right column). Relative differences larger than 2 exists but are not depicted in separate color.

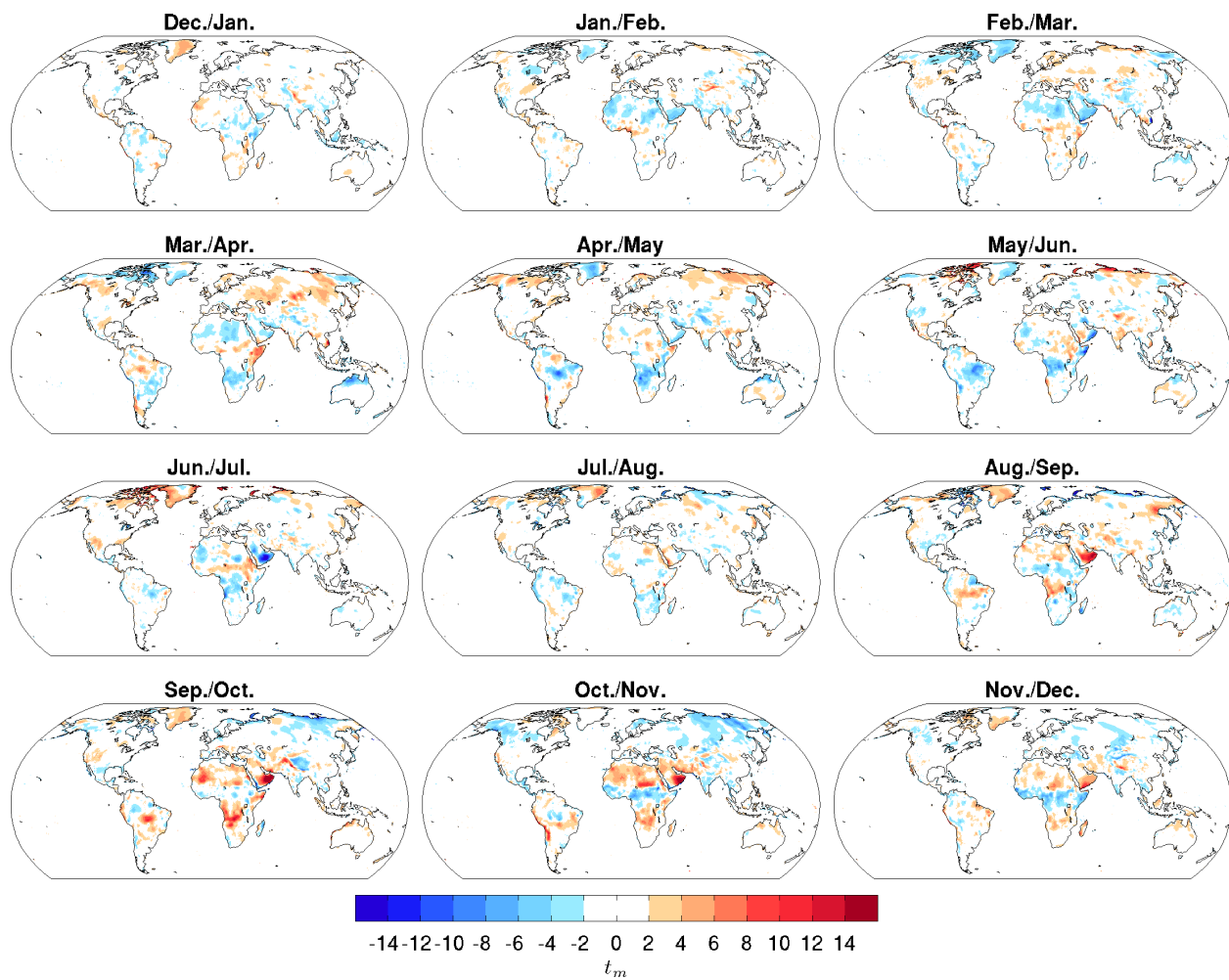


FIG. 5. Normalized mean differences between across-months and surrounding within months daily mean temperature fluctuations (Eq. (3)) for WFD, e.g. mean difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec. and 1 Jan./2 Jan. (top left).

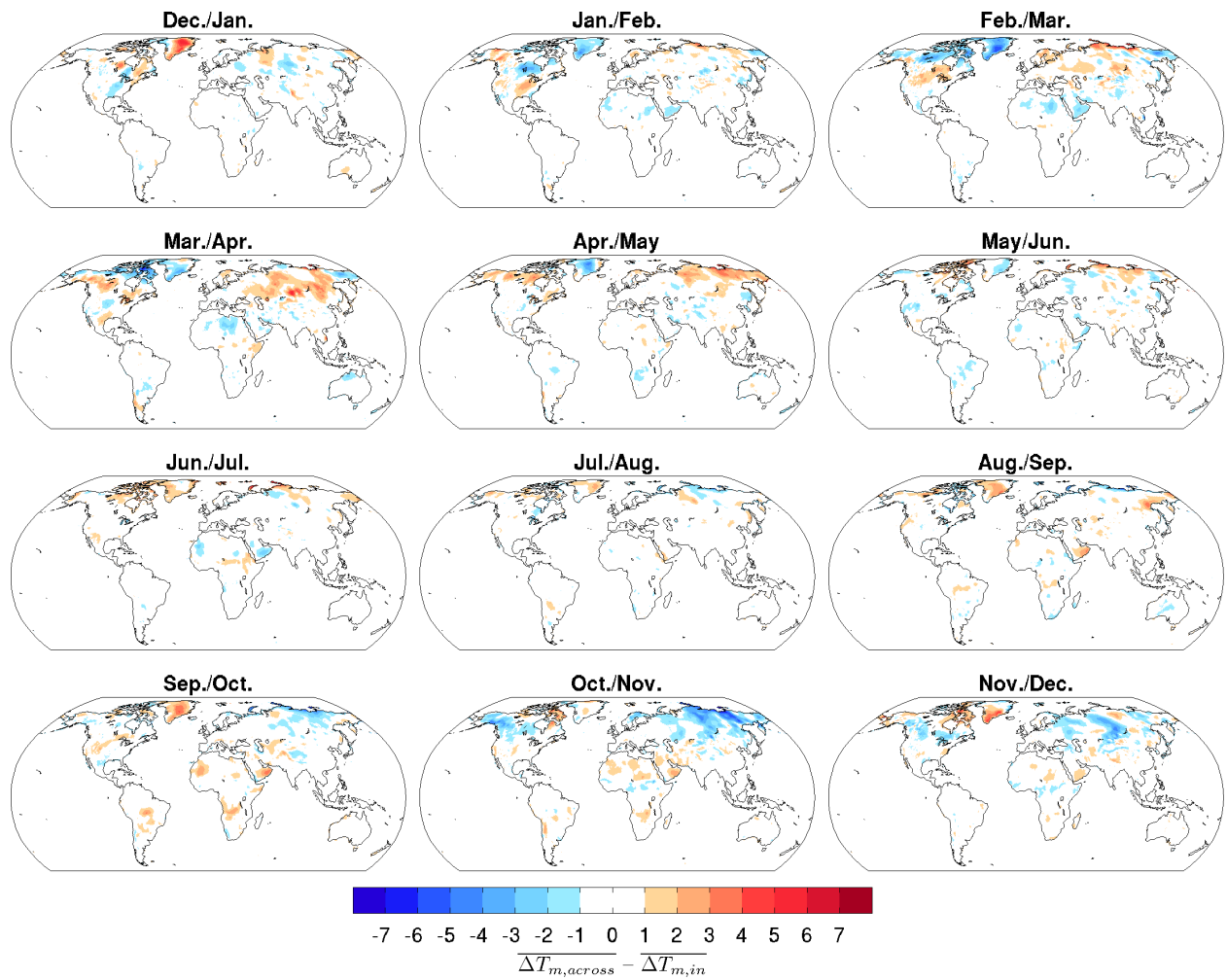


FIG. 6. Non-normalized mean differences between across-months and surrounding within months daily mean temperature fluctuations (numerator of Eq. (3)) for WFD, e.g. mean difference 31 Dec./1 Jan. related to mean difference 30 Dec./31 Dec. and 1 Jan./2 Jan. (top left).