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Energetics of interannual temperature variability

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1 **Abstract**

2 Energetics of interannual temperature variability in the years 1980-2016 is studied
3 using two reanalysis data sets. Monthly temperature anomalies are decomposed to
4 contributions from the net surface energy flux, atmospheric energy convergence
5 minus storage (CONV), and processes that affect the top-of-the-atmosphere
6 radiation balance. The analysis reveals a strong compensation between the net
7 surface heat flux and CONV over the ice-free oceans, with the former driving the
8 temperature variability over the tropical oceans and the latter at higher latitudes.
9 CONV also makes a dominant contribution to temperature anomalies in the winter
10 hemisphere extratropical continents. During the summer half-year and in the tropics,
11 however, variations in cloudiness dominate the temperature variability over land,
12 while the contribution of CONV is modest or even negative. The latter reflects the
13 diffusion-like behaviour of short-term atmospheric variability, which acts to spread
14 out the local, to a large extent cloud-induced temperature anomalies to larger areas.
15 The ERA-Interim and MERRA2 reanalyses largely agree on the general energy
16 budget features of interannual temperature variability, although substantial
17 quantitative differences occur in some of the individual terms.

18

19 **KEYWORDS:** temperature variability, energy budget, reanalysis, ERA-Interim,
20 MERRA2

21

22

23 **1. Introduction**

24 Interannual variations in climate are of great practical importance. In particular,
25 extended periods of anomalously hot or cold weather have large impacts on nature
26 and society. Recent prominent examples include the heat waves in central Europe
27 in 2003 (García-Herrera et al. 2010) and in Russia in 2010 (Barriopedro et al. 2011),
28 and the cold winter in eastern North America in 2013-2014 (Yu and Zhang 2015).
29 Nonetheless, such extremes are just the tip of the iceberg within an omnipresent
30 continuum of temperature variability, the magnitude of which depends on both the
31 season and the location. The largest interannual temperature variability is observed
32 over ice-covered oceans and high-latitude continents in winter, whereas the
33 variability over the low-to-mid-latitude oceans is relatively muted outside of the
34 eastern Tropical Pacific (Holmes et al. 2016; see also Figs. 3a and 4a-b).

35

36 A fraction of interannual temperature variability is driven by external forcing such
37 as major volcanic eruptions (Robock 2000; Paik and Min 2017). However, most of
38 it results from the chaotic internal dynamics of the climate system: the variations in
39 atmospheric and oceanic circulation, and the resulting perturbations in sea and land
40 surface conditions. The influence of the oceans is largest at low latitudes, where the
41 atmospheric circulation and temperatures are strongly controlled by the distribution
42 of sea surface temperature (SST) (Wells 2012; Holton and Hakim 2012). In
43 particular, the El Niño – La Niña variability in the eastern-to-central equatorial
44 Pacific SSTs generates atmospheric teleconnections that profoundly affect the
45 climate all around the tropics but to some extent also in extratropical latitudes (Diaz
46 et al. 2001, Yang and DelSole 2012). However, the relative impact of SST
47 variability decreases and that of internal atmospheric dynamics increases towards
48 higher latitudes (Zwiers and Kharin 1998). The interannual SST variability over the
49 extratropical oceans is strongly regulated by variations in the atmospheric
50 circulation, whereas the ocean’s effect on the extratropical atmosphere is more
51 subtle (Bjerknes 1964, Deser and Blackmon 1993). Nevertheless, there is evidence
52 that the ocean plays a more active role in generating atmospheric variability on
53 decadal than interannual time scales (Kushnir 1994).

54

55 Although ultimately driven by atmospheric and oceanic circulation, variations in
56 near-surface temperature are modulated by feedbacks that affect the atmospheric

57 and surface energy budget. For example, both reduced cloudiness (which increases
58 the absorption of solar radiation) and reduced soil moisture (which decreases the
59 evaporative cooling of the surface) have been identified as important ingredients in
60 European heat waves (Black et al. 2004, Fischer et al. 2007). Consistent with both
61 mechanisms, the correlation between monthly temperature and precipitation is
62 widely negative over midlatitude continents in summer and in tropical land areas
63 (Trenberth and Shea 2005). As another example, Park et al. (2015) used the Climate
64 Feedback – Response Analysis Method (Lu and Cai 2009) to explain the
65 temperature differences between winters with a strong and a weak Siberian high.
66 They found that lower temperatures in central Siberia in winters with a strong
67 Siberian high result from a combination of factors, including cold advection,
68 increased surface cooling due to larger sensible heat flux, and weaker greenhouse
69 effect due to reduced water vapour and cloud water content. Hu et al. (2016) used
70 the same method to energetically explain the different distribution of surface
71 temperature anomalies in Eastern and Central Pacific El Niños. Although the heat
72 flux from the ocean was identified as the main cause of surface temperature
73 anomalies in both cases, the larger warming in the Eastern Pacific during the
74 Eastern Pacific El Niños was attributed to a stronger water vapour feedback in this
75 area.

76
77 Despite the previous work, a systematic view on the energetics of interannual
78 temperature variability still appears to be lacking. Variations in several factors,
79 among others atmospheric energy transport, surface-atmosphere energy exchange,
80 surface albedo, clouds, and the atmospheric clear-sky greenhouse effect might all
81 be important under at least some circumstances. But how important are they in
82 general, in different parts of the world and in different seasons? This study aims to
83 give at least an initial answer to this question, focusing on the interannual variability
84 of monthly mean temperatures. The study is based on data sets from two modern
85 atmospheric reanalyses (Section 2) and an energy balance framework that was
86 earlier used for analysis of model-simulated CO₂-induced temperature changes by
87 Räisänen (2017; hereafter R17) (Section 3). The results are reported in Section 4,
88 and some aspects of their physical interpretation are discussed further in Section 5.
89 The main conclusions are presented in Section 6.

90

91 **2. Data sets**

92 Data from the ERA-Interim (Dee et al. 2011) and MERRA2 (Gelaro et al. 2017)
93 reanalyses for the years 1980-2016 are used. The variables required by the energy
94 balance decomposition include surface air temperature, total cloudiness, surface
95 latent and sensible heat fluxes, and surface and top-of-the-atmosphere (TOA)
96 downward and upward short-wave (SW) and long-wave (LW) radiative fluxes for
97 both all-sky and clear-sky conditions (Table 1 in R17). These variables were
98 downloaded as monthly means in a $2.5^\circ \times 2.5^\circ$ latitude-longitude grid.

99
100 For ERA-Interim, surface pressure and six atmospheric variables (u and v wind,
101 vertical velocity ω , temperature, geopotential and specific humidity) at 37 pressure
102 levels were additionally downloaded at $0.75^\circ \times 0.75^\circ$ horizontal resolution and 6-h
103 time interval. This large (2.8 TB) data set was used for explicit calculation of the
104 atmospheric energy flux convergence term (Sections 3.2 and 4.5 and Appendix A)
105 that was inferred as a residual in the other parts of the analysis.

106
107 The suitability of reanalysis data sets for energy budget analysis might be
108 questioned because reanalyses violate energy conservation (e.g., Trenberth and
109 Fasullo 2013) and show spurious large-scale trends associated with changes in the
110 observing system (Allan et al. 2014). However, because the focus in this study is
111 on interannual climate variability, the energy budget biases only matter to the extent
112 that they vary from year to year. We assessed this issue in two ways, by analyzing
113 the analysis increments in MERRA2 and by studying the mutual agreement and
114 differences between ERA-Interim and MERRA2. The analysis increments were
115 found to be large, but their impact on our main diagnostic results is moderated by
116 their relatively weak correlation with the actual temperature anomalies (Section
117 S1.1 in the Supplementary material). Furthermore, ERA-Interim and MERRA2
118 give a largely consistent view on the energetics of interannual temperature
119 variability, although there are in many cases substantial quantitative differences
120 between these two reanalyses (Section 4.1).

121

122 **3. Methods**

123 This section first describes the main features of the R17 energy balance method and
 124 its application to the interannual variability of monthly mean temperatures. After
 125 this, the methods used in the explicit calculation of atmospheric energy flux
 126 convergence in the ERA-Interim reanalysis are summarized. They are described in
 127 more detail in Appendix A.

129 **3.1 Energy balance framework**

131 The R17 method is built around the concept of effective planetary emissivity ε_{eff} ,
 132 which connects the surface air temperature T to the outgoing longwave (LW)
 133 radiation L at the TOA

$$134 \quad L = \varepsilon_{eff} \sigma T^4 \quad (1)$$

135 and is (in broad terms, see Section 4.4) an inverse measure of the atmospheric
 136 greenhouse effect. Thus, warm anomalies in T require either a negative anomaly in
 137 ε_{eff} , a positive anomaly in L , or both. Combining (1) with the atmospheric energy
 138 budget equation gives

$$139 \quad \varepsilon_{eff} \sigma T^4 = S - G + (C - \frac{\partial E}{\partial t}) \quad (2)$$

140 where S is net SW radiation at the TOA, G net downward heat flux to the surface,
 141 C horizontal energy flux convergence in the atmosphere, and E the total energy in
 142 the atmospheric column.

143 Referring to the climatological monthly mean of variable X as X_{CLIM} , the anomaly is
 144 $\Delta X = X - X_{CLIM}$. After also defining $[X] = (X + X_{CLIM})/2$, (2) leads to

$$145 \quad \sigma[\varepsilon_{eff}]\Delta(T^4) = \underbrace{-\sigma\Delta\varepsilon_{eff}[T^4]}_I + \underbrace{\Delta S}_{II} \underbrace{-\Delta G}_{III} + \underbrace{\Delta(C - \frac{\partial E}{\partial t})}_{IV} \quad (3)$$

146 Finally, linearizing the left side of (3) as

$$147 \quad \sigma[\varepsilon_{eff}]\Delta(T^4) \approx 4\sigma[\varepsilon_{eff}][T]^3\Delta T = D\Delta T \quad (4)$$

148 allows one to decompose the temperature anomaly ΔT as

$$\Delta T = \underbrace{LW}_I + \underbrace{SW}_{II} + \underbrace{SURF}_{III} + \underbrace{CONV}_{IV} + ERR \quad (5)$$

where the terms I – IV in (3) have been divided by $D = 4\sigma[\varepsilon_{eff}][T]^3$. These four terms represent the temperature anomalies due to LW and SW radiation, net surface energy flux, and atmospheric energy flux convergence minus storage. On the average, $D \approx 3.3 \text{ Wm}^{-2} \text{ K}^{-1}$, so that a 1 Wm^{-2} energy perturbation is typically equivalent to 0.3 K in temperature.

The linearization in (3) is performed around $(T + T_{CLIM})/2$ rather than T_{CLIM} . This makes the linearization residual ERR very small, with a mean absolute value of less than 10^{-3} K . On the other hand, variations in D allow the means of LW , SW , $SURF$ and $CONV$ to differ from zero when averaged over the whole period. Nevertheless, their mean values are small relative to their interannual variability that is the focus of this paper.

The terms LW and SW are further divided to two and five parts, respectively

$$LW = LW_{CLEAR} + LW_{CRE} \quad (6)$$

$$SW = SW_{IN} + SW_{CLEAR-ATM} + SW_{ALBEDO} + SW_{CLOUD} + SW_{NL} \quad (7)$$

In (6), LW_{CLEAR} is the temperature anomaly attributed to the clear-sky greenhouse effect (anomaly of ε_{eff} under clear-sky conditions) and LW_{CRE} that due to the long-wave cloud radiative effect. The division (7) is based on the approximate partial radiative perturbation (APRP) method (Taylor et al. 2007). The five terms represent the SW radiation anomalies associated with incoming SW radiation (SW_{IN}), SW radiative properties of the clear-sky atmosphere ($SW_{CLEAR-ATM}$), surface albedo (SW_{ALBEDO}), clouds (SW_{CLOUD}), and nonlinear effects (SW_{NL}). Different notations are used for the two cloud terms (LW_{CRE} and SW_{CLOUD}) because of the difference in their way of calculation. LW_{CRE} is based directly on the anomaly in the cloud radiative effect, which may be affected by variations in the clear-sky radiative properties of the atmosphere in addition to those in clouds. By contrast, SW_{CLOUD} attempts to isolate the effect of cloud anomalies on the SW radiation budget by explicit although highly simplified modelling of the radiative transfer. For further details, see R17.

181 The focus in this paper is on interannual variability. To separate this from long-term
 182 climate change, all the anomalies were linearly detrended before the energy budget
 183 decomposition. Conversely, X_{CLIM} as given above Eq. (3) was defined by the least-
 184 square trend line fitted for each calendar month separately.

186 **3.2 Direct calculation of the convergence term**

187
 188 For most parts of the analysis, $CONV$ in (5) was calculated from the difference of
 189 the net surface and TOA energy fluxes. This is straightforward but offers no
 190 information on the mechanisms that contribute to $CONV$. Therefore, we also
 191 estimated $CONV$ directly from ERA-Interim data. In practice, the calculation of
 192 energy flux convergence was replaced by calculation of three-dimensional energy
 193 advection in the interest of numerical accuracy (Appendix A). However, because
 194 the convergence and advection forms are physically equivalent, the word
 195 “convergence” will be used when discussing the results.

196
 197 The resulting direct estimate for $CONV$ is

$$198 \quad CONV_{DIR} = CONV_{MON} + CONV_{SM} + STOR \quad (8)$$

199 Here $CONV_{MON}$ denotes the temperature anomaly attributed to the energy flux
 200 convergence by the monthly mean flow, whereas $CONV_{SM}$ results from sub-
 201 monthly covariation between winds and atmospheric energy content. $STOR$
 202 represents the change in the total atmospheric energy content, being positive when
 203 the energy content anomaly decreases from the beginning to the end of the month
 204 (term IV in (3)).

206 **4. Results**

207 To introduce the method, Fig. 1 depicts time series of January and July mean
 208 temperature anomalies in central Finland (62.5°N, 25°E) and their decomposition
 209 to the main energy budget contributions, separately for the two reanalyses.
 210 Temperature variability at this location is much larger in January than July
 211 (standard deviation ~4°C vs. ~1.5°C), and the energy contributions to the variability
 212 are also partly different. In January, LW_{CLEAR} , $CONV$ and to a slightly smaller extent

213 *CLOUD* are the main drivers of variability, with positive values in most of the mild
 214 Januarys and negative values in most of the cold Januarys. *LW_{CLEAR}* and *CLOUD*
 215 also act to amplify temperature variability in July, but *CLOUD* is more important
 216 than *LW_{CLEAR}* particularly in ERA-Interim. By contrast, *CONV* mostly opposes the
 217 actual temperature anomalies in July. The same applies to *SURF* in both January
 218 and July, since the anomalous net surface energy flux is directed from the
 219 atmosphere to the ground in most anomalously warm months and vice versa in
 220 anomalously cold months.

221

222 *SW_{ALBEDO}* is excluded from Fig. 1 because it is negligible in both January (due to
 223 lack of solar radiation) and July (when the surface is always snow-free). *SW_{CLEAR-ATM}*
 224 *ATM* is also generally small, but is substantially negative in MERRA2 after the Mt.
 225 Pinatubo eruption in July 1992 and 1993 (Fig. 1d). This feature is lacking from
 226 ERA-Interim, which uses prescribed climatological aerosol distributions that vary
 227 seasonally but not from year to year, and thus excludes the Pinatubo eruption (Dee
 228 et al. 2011, Allan et al. 2014). In MERRA2, by contrast, aerosols are simulated
 229 explicitly based on emissions that vary from year to year, and observations of
 230 aerosol optical depth are assimilated into the analysis (Randles et al. 2017).

231

232 The time series from the two reanalyses agree well on the interannual temperature
 233 variations. Apart from *SW_{CLEAR-ATM}*, the same qualitatively applies to the energy
 234 balance contributors to this variability. However, quantitative differences are
 235 apparent. For example, in some Julys *CLOUD* and *CONV* differ by several °C
 236 between ERA-Interim and MERRA2, but to opposite directions. Recall that *CONV*
 237 is derived from the difference of the surface and TOA net energy fluxes and any
 238 reanalysis-specific errors in these fluxes are therefore directly mirrored in it.

239

240 **4.1 Magnitude of the terms and the agreement between the** 241 **two reanalyses**

242

243 The global importance of the energy balance components is characterized in Fig. 2
 244 with two statistical measures: (i) their interannual standard deviation, and (ii) their
 245 contribution to the interannual standard deviation of temperature. The latter is
 246 calculated as

$$SDC(i) = r(i)SD(i) \quad (9)$$

where $SD(i)$ is the standard deviation of term i and $r(i)$ is the correlation between term i and temperature. Using the definition of correlation, one can show that the $SDCs$ sum up to the interannual standard deviation of temperature:

$$\sum_i SDC(i) = SD(\Delta T) \quad (10)$$

For Fig. 2, both the SDs and $SDCs$ were first calculated for each month and grid box and then averaged over the 12 months and the global area, so to characterize the general behaviour of the terms. SW_{IN} and SW_{NL} are both very small, with $SD < 0.1$ K, and will therefore not be discussed further. Conversely, $SURF$ and $CONV$ are very large, with $SD \approx 5$ K. However, as discussed in Section 4.2, they turn out to have a strong mutual cancellation particularly over the oceans. LW_{CRE} and SW_{CLOUD} are also large, SW_{CLOUD} being the larger. Unsurprisingly, however, there is also some compensation between LW_{CRE} and SW_{CLOUD} . We will therefore mainly study their sum, denoted as $CLOUD$, in the rest of this paper. Although smaller than $SD(SW_{CLOUD})$, $SD(CLOUD)$ is also substantial (9th column of Figs. 2a,b). Of the remaining terms, LW_{CLEAR} is of similar magnitude with the actual monthly mean temperature anomalies, whereas $SW_{CLEAR-ATM}$ and SW_{ALBEDO} are relatively small on the average.

The largest average contributors to the standard deviation of ΔT are, in this order, $CONV$, LW_{CLEAR} and $CLOUD$ (red bars in Fig. 2). The average $SDCs$ of LW_{CRE} and SW_{CLOUD} are both positive in MERRA2 but the former is slightly negative in ERA-Interim. On the other hand, the net surface heat flux ($SURF$) has a strong tendency to reduce interannual temperature variability. This is particularly the case over the extratropical oceans (Section 4.2).

The globally averaged SDs and $SDCs$ are generally similar between the two reanalyses. The largest differences occur in the SD and SDC of $CLOUD$ and its two components, $SDC(SURF)$ and $SDC(CONV)$ (recall that $CONV$ is a residual). In addition, $SD(SW_{CLEAR-ATM})$ is twice as large in MERRA2 than in ERA-Interim. This is consistent with the already mentioned difference in the treatment of aerosols.

279 To further quantify the agreement between ERA-Interim and MERRA2, the
 280 correlation coefficients between the two reanalyses were calculated for (i) the full
 281 space-time interannual variability of ΔT and its energy balance components during
 282 the 37-year period, and the space-time variability in the (ii) SDs and (iii) SDCs over
 283 the global area and the 12 calendar months (Table 1). All three correlations are
 284 strongly positive for ΔT (> 0.9) and most of the major energy balance components,
 285 particularly LW_{CLEAR} , $SURF$ and $CONV$ (≥ 0.85). However, the correlations for
 286 $CLOUD$ are somewhat lower, and the difference in the treatment of aerosols
 287 strongly deteriorates the agreement on $SW_{CLEAR-ATM}$. Maps of the inter-reanalysis
 288 differences in the SDCs are shown in Fig. S2. Typically, the differences on the grid
 289 box scale are about 10% of the two-reanalysis mean for the temperature anomalies,
 290 25% for LW_{CLEAR} , of the order of 40% for $SURF$ and $CONV$, and between 60% and
 291 100% for $SW_{CLEAR-ATM}$, SW_{ALBEDO} and $CLOUD$.

292

293 It seems obvious that MERRA2 provides more realistic estimates of $SW_{CLEAR-ATM}$
 294 than ERA-Interim. For the other terms, the relative performance of the two
 295 reanalyses is more difficult to assess, although some insight might be gained from
 296 comparison with satellite data (e.g., Loeb et al. 2018) and other observational data
 297 sets. In the figures shown in the rest of this paper, we will simply average the
 298 statistics derived from the two reanalyses to emphasize their common features.
 299 Selected maps for ERA-Interim and MERRA2 separately are included in the
 300 Supplementary material (Figs. S3-S4, S6-S7 and S12-S13).

301 **4.2 Geographic variability**

302

303 The first column in Fig. 3 shows the SDs of ΔT and its main energy balance
 304 components, averaged over the 12 months and the two reanalyses. The
 305 corresponding SDCs are displayed in the third column, with the grey shading
 306 indicating areas where their sign is not robust. The SDC is considered robust if it
 307 has the same sign in the two reanalyses, and differs in at least one of them from
 308 zero at the 5% significance level based on a two-sided sign test (Appendix B). The
 309 SDs and SDCs are connected by the correlation between the individual energy
 310 balance terms and temperature, shown in the middle column. Following (9), the
 311 “average” correlation is defined here by dividing the average SDC by the average
 312 SD.

313

314 Interannual temperature variability is generally larger at high than low latitudes and
315 over the continents than over the oceans (Fig. 3a). However, the Arctic Ocean and,
316 relative to its latitude, the tropical East Pacific also stand out with large variability.
317 The SD patterns for the individual energy balance components are variable (left
318 column of Fig. 3). For example, $SD(SW_{ALBEDO})$ is small in most areas, but locally
319 large where interannual variations in sea ice and snow cover are substantial: the
320 margins of the Arctic Ocean, off the coast of Antarctica, and in the Northern
321 Hemisphere extratropical continents, notably the Tibetan Plateau (Fig. 3h). By
322 contrast, $SD(CLOUD)$ is large (1-4 K) nearly everywhere, but smaller over the
323 Arctic Ocean, Greenland, Antarctica, and the deserts extending from Sahara to
324 central Asia (Fig. 3k). An inspection of LW_{CRE} and SW_{CLOUD} separately (Fig. S5)
325 suggests two main explanations for the relatively small magnitude of $SD(CLOUD)$
326 in these areas: lack of optically thick clouds (over deserts and ice sheets), and/or
327 limited sensitivity of the TOA radiation balance to clouds where modest insolation
328 (in polar regions in most of the year) and/or high surface albedo (over ice sheets
329 and sea ice) make it easier for LW_{CRE} to offset SW_{CLOUD} .

330

331 $SD(SURF)$ and $SD(CONV)$ are both very large over the oceans (Figs. 3n,q),
332 exceeding 8 K in many areas mainly in the extratropics. Their patterns are very
333 similar, which results from a strong mutual compensation. This compensation
334 reflects, on one hand, the ability of the ocean to absorb large amounts of heat with
335 only modest changes in the surface temperature, and on the other hand, the tendency
336 of the atmospheric circulation to horizontally spread the effects of local energy
337 input over a larger area (Section 5). $SD(CONV)$ is also large over the continents,
338 generally in the range 1-4 K, with the largest values at mid-to-high latitudes. By
339 contrast, $SD(SURF)$ is < 1 K in most land areas, due to the modest heat capacity of
340 the land surface. The main exception are the northern parts of Eurasia and North
341 America, where variations in the energy consumed by snowmelt amplify the
342 variability in the net surface heat flux in winter and spring.

343

344 How much a given energy term amplifies or attenuates temperature variability is
345 affected by both its standard deviation and its correlation with temperature
346 anomalies (Eq. (9)). A case in point is LW_{CLEAR} , which has a strong positive

correlation (> 0.7) with ΔT in most extratropical areas, but a weaker or locally negative correlation with ΔT in much of the tropics (Fig. 3c). This makes $SDC(LW_{CLEAR})$ less positive in most of the tropics than at higher latitudes (Fig. 3d), although $SD(LW_{CLEAR})$ is also large in the tropics (Fig. 3b). An exception with large $SDC(LW_{CLEAR})$ is the equatorial East Pacific, where LW_{CLEAR} is both highly variable and highly correlated with temperature. The interpretation of LW_{CLEAR} is discussed in more detail in Section 4.4.

$SW_{CLEAR-ATM}$ is positively correlated with ΔT in most regions, particularly at mid-to-high latitudes (Fig. 3f). This indicates a positive SW water vapor feedback due to a positive correlation between temperature and atmospheric water vapor, which leads to larger water vapor absorption of SW radiation in months with positive temperature anomalies. However, since $SD(SW_{CLEAR-ATM})$ is relatively small, this term makes a fairly modest contribution to interannual temperature variability (Figs. 3e,g).

Where $SD(SW_{ALBEDO})$ is substantial, this term is positively correlated with ΔT , because warm anomalies typically coincide with negative anomalies in snow and ice cover (Figs. 3h,i). However, there are also areas where this correlation is negative. In particular, the negative correlation over Antarctica reflects a positive correlation between temperature and snowfall: higher snowfall during anomalously warm summer months counteracts the ageing of snow, thereby slightly increasing the surface albedo (Picard et al. 2012). This feature is more pronounced in ERA-Interim than in MERRA2 (Figs. S3-S4).

$CLOUD$ is also positively correlated with ΔT in most areas, and therefore generally acts to amplify temperature variability (Figs. 3l,m). Exceptions with a slightly negative correlation include, among others, eastern tropical Pacific and parts of the Southern Ocean. The physical interpretation of $CLOUD$ is discussed in some more detail in Section 4.3.

$SURF$ and $CONV$ strongly oppose each other over the oceans. In the tropics, particularly over the equatorial East Pacific, $SURF$ is large in magnitude and positively correlated with ΔT , and is thus strongly driving anomalies in surface air

381 temperature (Figs. 3o,p). However, in the same areas, *CONV* strongly damps the
 382 temperature variability, effectively diffusing out the impact of the local surface heat
 383 flux anomalies (Figs. 3r,s). Over most of the mid-to-high-latitude oceans, the roles
 384 of *SURF* and *CONV* are reversed, with the atmospheric heat convergence strongly
 385 driving but the net surface heat flux strongly attenuating the temperature variability.
 386 This picture of mainly ocean-driven temperature variability over the tropical and
 387 atmosphere-driven variability over the extratropical oceans is consistent with a
 388 large number of earlier studies (e.g., Bjerknes 1964, Deser and Blackmon 1993, Wu
 389 and Kirtman 2007).

390

391 Over nearly all land areas, the variation in the net surface heat flux acts to reduce
 392 the interannual temperature variability (Figs. 3o,p). This effect is modest but not
 393 negligible: as averaged over the 12 months and all land, $SDC(SURF) = -0.44$ K, or
 394 30% of the corresponding mean of $SD(\Delta T) = 1.47$ K. Conversely, $SDC(CONV)$ is
 395 positive over most land areas (Fig. 3s). The correlation between *CONV* and ΔT is
 396 mostly not very strong (Fig. 3r), but exceeds 0.7 over large parts of the Greenland
 397 and Antarctic ice sheets and 0.9 over East Antarctica. The high correlations in
 398 Greenland and Antarctica seem to be linked to the relatively modest interannual
 399 variability in the other energy balance terms over these ice sheets (left column of
 400 Fig. 3). On the other hand, *CONV* attenuates interannual temperature variability in
 401 northern South America and some other low-to-midlatitude land areas. The physical
 402 interpretation of *CONV* is explored in more depth in Section 4.5.

403

404 **4.3 Seasonality**

405

406 We next discuss the seasonality of the six main energy terms included in Fig. 3,
 407 focussing on their SDCs. Comparison between extended Northern Hemisphere
 408 winter (November-to-March, NDJFM) and summer (May-to-September, MJJAS)
 409 seasons reveals several differences (Fig. 4).

410

- 411 1. Temperature variability in extratropical latitudes is larger in the local winter
 412 than the summer season (Figs. 4a,b). The same applies to $SDC(LW_{CLEAR})$
 413 (Figs. 4c,d).

2. $SDC(SW_{CLEAR-ATM})$ is largest over the summer hemisphere ice sheets, in Greenland in NDJFM and in Antarctica in MJJAS (Figs. 4e,f).
3. The seasonality of SW_{ALBEDO} reflects the seasonalities of snow and ice cover and incoming solar radiation. Accordingly, in the Northern Hemisphere continents, SW_{ALBEDO} is mainly important in midlatitudes in winter but in the Arctic in summer (Figs. 4g,h). Near the sea ice edge, SW_{ALBEDO} is mainly important during the local summer.
4. $SDC(CLOUD)$ is typically more positive during the local summer than winter (Figs. 4i,j), particularly in the midlatitudes. This is due to SW_{CLOUD} , which strongly amplifies the temperature variability in the midlatitudes in summer, when solar radiation is abundant and reduced cloudiness therefore tends to increase temperature (Fig. S8). In winter, the paucity of solar radiation makes SW_{CLOUD} much less important. However, LW_{CRE} also plays a role, attenuating temperature variability when and where temperature is negatively correlated with (particularly high-top) cloudiness, but amplifying the variability when the correlation is positive. The latter is typical at mid-to-high latitudes in winter, as well as in the tropical East Pacific (Fig. S8). In the tropical East Pacific, SW_{CLOUD} and LW_{CRE} nearly cancel out (see also Fig. S10d), but in high latitudes in winter, LW_{CRE} dominates. Over the Arctic Ocean, the high-latitude Southern Ocean, and the Greenland and Antarctic ice sheets, the net effect represented by $SDC(CLOUD)$ in Figs. 4i,j is therefore more positive in winter than in summer.
5. Reflecting the more vigorous extratropical atmospheric circulation and the stronger climatological temperature gradients in the winter hemisphere, $SDC(CONV)$ is more positive and $SDC(SURF)$ more negative over the mid-latitude oceans in winter than in summer (Figs. 4k,n). The seasonality of $SDC(CONV)$ is even more striking over the northern halves of Eurasia and North America, where the atmospheric heat flux convergence strongly amplifies temperature variability in winter but slightly attenuates it in summer. The interpretation of $CONV$ is explored further in Section 4.5.

As an example that illustrates the seasonal variation in more detail, the monthly contributions of the main energy balance terms to temperature variability in central Finland (cf. Fig. 1) are shown in Fig. 5. At this location, there is a gradual shift from

large *CONV*- and *LW_{CLEAR}*-dominated variability in October-March to smaller *CLOUD*-dominated and *CONV*-suppressed variability in May-August. *SW_{ALBEDO}* only plays a significant role during the snowmelt season in March-April.

To explore the seasonal variation in another way, Fig. 6 identifies for every grid box and every second month of the year the term that provides the largest positive contribution to the standard deviation of temperature in this month. The broad picture over the oceans is seasonally uniform to the extent that *SURF* tends to make the largest contribution to interannual variability in the tropics and *CONV* at higher latitudes. However, the border between the *CONV*- and *SURF*-dominated zones is further poleward in summer than in winter, particularly in the Northern Hemisphere. *LW_{CLEAR}* and *CLOUD* are also important, overriding all the other terms in some months in some ocean regions. *CLOUD* is more frequently the foremost term in summer than in winter; in particular it dominates the variability over large parts of the extratropical North Pacific and North Atlantic in summer. In addition to the larger insolation, this reflects the weaker midlatitude baroclinicity in summer, which reduces the importance of *CONV* relative to the winter season. To provide some more detail, diagrams similar to Fig. 5 are shown for six ocean grid boxes (in the Arctic Ocean, extratropical North Atlantic and North Pacific, eastern and western tropical Pacific, and high-latitude Southern Ocean) in Fig. S10.

Over most of the winter hemisphere continents, either *CONV* or *LW_{CLEAR}* is the largest contributor to temperature variability. In summer, however, *CLOUD* is widely dominant in the extratropical continents. *CLOUD* is also commonly the largest term in tropical land areas, although this varies with month and region. Seasonal cycles of the individual energy terms in six land grid boxes (in Greenland, Siberia, Central Europe, the Tibetan Plateau, Amazonia and East Antarctica) are shown in Fig. S11.

The variations of snow and sea ice conditions make either *SW_{ALBEDO}* or *SURF* the largest contributor to temperature variability in some months and locations. *SW_{ALBEDO}* has this position in midwinter in parts of the United States and south-central Asia. During the spring, such areas shift northward. In May, in particular, *SW_{ALBEDO}* is the largest term over much of northern Siberia and northernmost North

America, as well as the Tibetan Plateau (see also Figs. S11b,d). Due to variations in the ice edge position, SW_{ALBEDO} is also locally dominant over the Arctic and Antarctic Oceans in the local spring and summer (see also Figs. S10a,f). Variations in ice conditions also dramatically affect the atmosphere-ocean heat exchange during the cold season (Deser et al. 2010, Petrie et al. 2015). This locally makes $SURF$ the largest contributor to temperature variability near the sea ice edge in late fall and winter, both over the Arctic Ocean and the high-latitude Southern Ocean (see also Figs. S10a,f).

Averaging over all 12 months and the global area, $CONV$ is the largest contributor to variability in 47% of cases, followed by $CLOUD$ (21%), LW_{CLEAR} (16%), $SURF$ (14%), and SW_{ALBEDO} (2%). $SW_{CLEAR-ATM}$ only has this position in limited parts of the Antarctic continent in the local summer (0.1%).

To complement the overview provided this far, we next focus on the physical interpretation of two of the major energy terms: LW_{CLEAR} (Section 4.4) and $CONV$ (Section 4.5). In both cases, there are several factors involved and a more detailed analysis is therefore useful.

4.4 Factors affecting LW_{CLEAR}

Using the method detailed in Appendix C, the term LW_{CLEAR} was further decomposed as

$$LW_{CLEAR} = LW_{CLEAR-S} + LW_{CLEAR-WW} + LW_{CLEAR-LR} + \varepsilon \quad (11)$$

Here $LW_{CLEAR-S}$ represents variations in an effective surface emissivity calculated from the monthly means of surface air temperature and surface upward LW radiation (Eq. (C2)). In practice, this term mainly reflects variations in the surface minus surface air temperature difference. The next two terms represent the main factors expected to affect the atmospheric clear-sky greenhouse effect (Webb et al. 1993), i.e. the atmospheric water vapor content (WW) and the lapse rate between the surface and the midtroposphere (LR). These terms were estimated using linear regression. ε is the residual from this regression.

515 The factors that contribute to $SDC(LW_{CLEAR})$ based on (11) are analysed in Fig. 7.
516 Variations in the effective surface emissivity (term $LW_{CLEAR-S}$) are unimportant
517 over most land areas (Fig. 7a). However, they are more important over the mid-to-
518 high latitude oceans, particularly the northern North Atlantic, where relatively large
519 differences between the surface and surface air temperatures occur. Elsewhere,
520 $SDC(LW_{CLEAR})$ is dominated by variations in the atmospheric clear-sky greenhouse
521 effect.

522
523 Both the water vapour and the lapse rate variations are found to amplify temperature
524 variability in most areas (Figs. 7b,c). The lapse rate contribution (Fig. 7c) is largest
525 in areas where temperature anomalies typically have a bottom-heavy structure, so
526 that anomalies of surface temperature are not accompanied by equally large
527 anomalies aloft. This is generally the case in high latitudes (especially in winter,
528 Figs. S16-S17), but also over dry land areas such as Australia. The lapse rate
529 contribution is also substantial in the easternmost tropical Pacific, where local SST
530 variations mainly affect air temperature in the boundary layer below a
531 climatological subsidence inversion (Andrews and Webb 2018). The water vapour
532 contribution is widely dominant at lower latitudes, being particularly large over the
533 central and eastern Pacific Ocean (Fig. 7b), but is still not positive everywhere. One
534 of the exceptions is the western tropical Pacific, where the highest surface air
535 temperatures coincide with remotely forced anomalous subsidence that warms the
536 surface by reducing cloud cover but also simultaneously reduces the atmospheric
537 water vapour (Trenberth and Shea 2005).

539 **4.5 Interpretation of *CONV***

540
541 For the maps and diagrams shown this far, *CONV* was calculated as a residual. Here
542 we report the results obtained from the direct calculation of the term using ERA-
543 Interim data (Section 3.2 and Appendix A).

544
545 It is first necessary to note that $CONV_{DIR}$ (8) and the residual *CONV* are far from
546 identical. $CONV_{DIR}$ exhibits larger interannual variability than *CONV* (Figs.
547 S18a,d), and the interannual standard deviation of their mutual difference exceeds
548 4 K in many parts of the world (Fig. S18g). Given the earlier experience of

numerical difficulties in the calculation of atmospheric energy flux convergence (e.g., Chiodo and Haimberger 2010; Mayer and Haimberger 2012; Liu et al. 2017), these differences are not unexpected. Nevertheless, the time series of $CONV_{DIR}$ and $CONV$ are positively correlated nearly everywhere, and over most of the oceans the correlation exceeds 0.7 (Figure S19). $CONV_{DIR}$ and $CONV$ also share broadly the same statistical relationship with temperature anomalies, particularly over the oceans (Figs. S18b,c,e,f). Still, the SDC of the residual estimate tends to be somewhat more positive than that of the direct estimate over the midlatitude continents, and less positive over the midlatitude oceans (Fig. S18i). This systematic feature might reflect a mismatch between the interannual variations of the atmospheric energy flux convergence and the TOA and surface energy fluxes in ERA-Interim, rather than just numerical errors in $CONV_{DIR}$.

Following (8), $CONV_{DIR}$ was divided into three terms that represent the energy flux convergence by the monthly mean atmospheric flow and sub-monthly variations in the flow, and changes in the atmospheric energy content during a month (“storage”) (Fig. 8). This division reveals a strong tendency of cancellation between the monthly mean and sub-monthly energy flux convergence components at extratropical latitudes (Figs. 8d-i). In midlatitudes, the monthly mean energy flux convergence component amplifies temperature variability (Figs. 8e-f), whereas the sub-monthly component acts to reduce the variability (Figs. 8h-i) but is typically slightly smaller in magnitude. Outside of midlatitudes, the situation is less clear-cut. For example, over parts of Antarctica, sub-monthly energy flux convergence appears to amplify, but monthly mean convergence to attenuate temperature anomalies. In the tropics, the monthly mean component generally dominates over the sub-monthly component. Finally, Fig. 8j shows that within-month changes in atmospheric energy storage are a non-negligible part of $CONV$ in individual months. However, these changes neither systematically amplify nor reduce the temperature variability (Fig. 8l). The atmospheric energy content tends to be broadly in phase with surface air temperature, and hence its change from the beginning to the end of the month is nearly uncorrelated with the monthly mean temperature anomaly (Fig. 8k).

582 The tendency of sub-monthly energy flux convergence to reduce interannual
 583 temperature variability in midlatitudes is consistent with earlier research. In
 584 particular, Lau and Nath (1991) found a negative correlation between anomalies of
 585 monthly mean temperature at the 850 hPa level and the temperature tendencies
 586 induced by synoptic-scale eddy heat fluxes (their Fig. 13). This diffusion-like
 587 behavior of eddies also applies to the time mean flow, with the eddy heat fluxes
 588 acting to reduce both the meridional and zonal gradients of temperature (Lau and
 589 Holopainen 1984). One may therefore assume that, at least in the midlatitudes, the
 590 anomalies in the sub-monthly energy flux convergence are more a consequence
 591 than a cause of the monthly mean energy content (or temperature) anomalies.

592
 593 Monthly mean energy flux convergence tends to amplify and its sub-monthly
 594 counterpart to attenuate the midlatitude temperature variability in both the NDJFM
 595 and MJJAS seasons (Fig. S20). Interestingly, however, the sub-monthly energy flux
 596 convergence makes a more negative SDC contribution in the northern parts of
 597 Eurasia and North America in summer than in winter. The tendency of *CONV* to
 598 amplify temperature variability in winter but to rather reduce it in summer in these
 599 areas (Figs. 4m,n) thus reflects a delicate balance between the contributions of the
 600 monthly mean and sub-monthly energy flux convergence.

601 **5. Discussion**

602
 603 The results of diagnostic techniques tend to become more difficult to interpret when
 604 the quantity of interest (here the temperature anomaly) is a small residual of large
 605 but compensating right-hand-side terms. The tendency of compensation between
 606 the monthly mean and sub-monthly energy flux convergences was already
 607 discussed in Section 4.5. Another equally important case is the compensation
 608 between *CONV* and *SURF* over the ice-free oceans.

609
 610 As shown in R17,

$$611 \quad \Delta(S - L) = \Delta G - \Delta\left(C - \frac{\partial E}{\partial t}\right) = -D(SURF + CONV) \quad (12)$$

612 The compensation between *SURF* and *CONV* therefore indicates that, over the ice-
 613 free oceans, the anomalies in the net TOA radiation flux $S-L$ are smaller than those
 614 in the net surface energy flux G . In fact, the average interannual standard deviation

615 of G as calculated over the 12 months and all ocean grid boxes exceeds the standard
 616 deviation of $S-L$ by more than a factor of three (not shown). This difference is
 617 qualitatively explicable by the fact that the TOA radiation balance is much less
 618 sensitive to variations in air temperature than the net surface energy flux is to the
 619 air-sea temperature difference. Everything else being the same, a 1 K anomaly in T
 620 only increases L , and hence reduces $S-L$, by $D\Delta T \approx 3.3 \text{ Wm}^{-2} \text{ K}^{-1}$ (Eqs. (1) and (4)).
 621 On the other hand, bulk parameterizations of turbulent energy fluxes (e.g., Kara et
 622 al. 2000) indicate a change of up to several tens of Wm^{-2} in the net surface energy
 623 flux per each 1 K change in the air-sea temperature difference. Over the ice-free
 624 oceans, where a substantial net surface flux can be sustained by the heat capacity
 625 of the ocean mixed layer, ΔG can thus easily exceed $\Delta(S-L)$ even when the anomaly
 626 in the air-sea temperature difference is relatively small.

627

628 One may argue that the multiplier $D^{-1} \approx 0.3 \text{ K W}^{-1} \text{ m}^2$ used in (5) exaggerates the
 629 actual sensitivity of surface air temperature to variations in local energy input. This
 630 is particularly the case over the ice-free ocean, due to the ability of the net surface
 631 flux to consume a large fraction of any anomalous energy input into the air column.
 632 However, the diffusive behavior of the sub-monthly atmospheric energy flux
 633 convergence (Section 4.5) implies that the same also applies in other areas.
 634 Anomalies in the energy input into an air column, regardless of whether they
 635 originate from the net surface energy flux, cloudiness or, for example, surface
 636 albedo, are only partly balanced by local temperature-mediated changes in the TOA
 637 radiation balance. A large fraction of the energy input anomaly rather tends to be
 638 exported away by the atmospheric circulation.

639

640 To alleviate the systematic compensations, an energy budget framework should
 641 ideally take into account the effects of surface air temperature anomalies on $SURF$
 642 and $CONV$, rather than treating all of $SURF$ and $CONV$ as independent right-hand-
 643 side terms. However, this would require a substantial extension of the method. First,
 644 the energy budgets of the upper ocean and ground should be explicitly included, in
 645 addition to that of the atmosphere (Hedemann et al. 2017; Liu et al. 2017). Second,
 646 the effect of temperature anomalies on atmospheric horizontal energy flux
 647 convergence should be parameterized as a diffusion process. The second
 648 requirement is particularly difficult to achieve in a single-column framework,

649 because the energy flux convergence is regulated by the gradients rather than the
650 absolute local values of temperature and atmospheric energy content.

651

652 A local and instantaneous energy budget framework cannot identify processes that
653 are non-local in space or time. For example, during an El Niño, atmospheric energy
654 flux divergence over central and eastern tropical Pacific acts to cool the air locally,
655 thereby balancing a large fraction of the anomalous net surface energy flux.
656 However, energy flux divergence in one area requires convergence elsewhere. Due
657 to the stationary Rossby waves excited by diabatic heating anomalies (Simmons
658 1982, Ji et al. 2016), this energy redistribution process is more complicated than
659 just horizontal diffusion. As another example, an anomaly in atmospheric
660 circulation in the preceding months might help to build a warm or cold anomaly in
661 the upper ocean temperature in some area, which would then feed back to the
662 atmosphere by inducing an anomalous net surface energy flux. Thus, although
663 energy budget analysis is useful for diagnosing the origin of temperature anomalies,
664 it alone will not reveal the full cause-effect chain of events.

665

666 **6. Conclusions**

667

668 This study has investigated the energetics of interannual temperature variability in
669 the ERA-Interim and MERRA2 reanalyses. Using the method introduced in R17,
670 the anomalies in monthly mean surface air temperature were decomposed to six
671 main components, representing the variations in (i) the atmospheric clear-sky
672 greenhouse effect, (ii) clear-sky SW radiative properties of the atmosphere, (iii)
673 surface albedo, (iv) clouds, (v) the net surface energy flux, and (vi) atmospheric
674 energy flux convergence minus storage. Based on their covariation with the actual
675 temperature anomalies, the effects of these individual components on temperature
676 variability were then statistically diagnosed. A rich variety in the energetics of
677 temperature variability in different areas and times of the year was found,
678 depending on the surface conditions, availability of solar radiation and the local
679 meteorological characteristics. Nevertheless, the main findings are the following:

680

- 681 1. Over the ice-free oceans, anomalies in surface air temperature are typically
682 a small residual of opposite contributions from the net surface heat flux and

683 atmospheric energy flux convergence. In the tropics, particularly in the
684 eastern Pacific, the net ocean-to-atmosphere heat flux provides the main
685 energy source for temperature variability, but most of this energy input is
686 transported away by the atmospheric circulation. This pattern is reversed at
687 higher latitudes, where variations in atmospheric energy flux convergence
688 are large but are mainly consumed by heating or cooling the water mass,
689 rather than changing the surface air temperature.

690 2. The net surface heat flux also tends to attenuate temperature variability on
691 land but is mostly a secondary term in the energy budget. Major energetic
692 drivers of temperature variability over land include, depending on season
693 and location, variations in the atmospheric energy flux convergence, clouds,
694 the clear-sky greenhouse effect, and surface albedo. Nonetheless,
695 atmospheric energy flux convergence reduces rather than amplifies
696 temperature variability over large parts of Eurasia and North America in
697 summer, partly compensating a strongly positive cloud contribution to
698 temperature variability. The same happens in some tropical land areas,
699 especially northern South America.

700 3. Care is needed in the interpretation of atmospheric energy flux convergence,
701 which is affected by variations in both the atmospheric circulation and the
702 atmospheric energy content and hence temperature. Thinking of anomalies
703 of energy flux convergence simply as a cause of temperature anomalies is
704 therefore not justified. In midlatitudes, in particular, our results reveal a
705 duality between time scales, with anomalies in the monthly mean flow
706 amplifying, but the sub-monthly variations attenuating temperature
707 variability via their effect on the energy flux convergence. The net of these
708 two very large components leaves a much smaller residual, particularly over
709 land. The counter-intuitive situation in which the net effect of the energy
710 flux convergence is to reduce temperature variability may arise when other
711 components in the energy balance strongly act to amplify the variability.
712 This is the case, for example, with cloud anomalies in much of Eurasia and
713 North America in summer. Thus, although this has not been directly
714 addressed herein, many summer heatwaves with reduced cloudiness may
715 actually coincide with anomalous energy transport out of the air column.
716

717 The two reanalyses agree well on these general features, but some quantitative
718 differences are evident. The ERA-Interim minus MERRA2 differences in the
719 individual terms typically range from about 25% to 100% of the two-reanalysis
720 mean on the grid box scale. Perhaps unsurprisingly, the effect of clouds is one of
721 the most uncertain terms in the decomposition.

722

723 By analyzing the energetic contributions to the standard deviation of monthly mean
724 temperature, this study has emphasized the typical energy budget features
725 associated with temperature anomalies. Nevertheless, the correlation between the
726 individual energy budget components and temperature anomalies is far from perfect
727 (middle column of Fig. 3). Thus, a similar temperature anomaly may result from
728 different combinations of energetic contributions. Examples of this variation are
729 also readily visible in the time series of Fig. 1. For instance, although the net surface
730 heat flux typically attenuates temperature variability, it amplified the cold
731 anomalies in Januarys 2003 and 2010 (Figs 2a,b). In both cases, the cold January
732 was preceded in Finland by a very cold second half of December, which served to
733 reduce the ground-to-air heat flux by cooling the ground. Apart from this case-to-
734 case variability, it would be worthwhile to study to which extent the relationship
735 between energetics and temperature anomalies is (or is not) nonlinear. For example,
736 do summer months with extreme warm anomalies differ from those with moderate
737 anomalies in the relative importance of the energy balance components that
738 contribute to these anomalies?

739

740 To give a globally consistent overview, the analysis in this paper has covered the
741 whole world. More remains to be learned from more in-depth studies of temperature
742 variability on regional scales. Moreover, keeping in mind the issues discussed in
743 the previous section, a diagnostic energy budget approach should ideally be
744 complemented by carefully designed model experiments. Such experiments could
745 help to elucidate, for example, the remote effects of SST variability on the
746 atmospheric energy transport and hence temperature.

747

748 Energetics of interannual temperature variability is also important in the context of
749 climate modelling. The magnitude of interannual variability differs considerably
750 between different global and regional climate models (Räisänen 2002, de Elía et al.

751 2013). Linking this variation to its energetic contributors could potentially help the
752 improvement of climate models. The energetics point of view might also facilitate
753 a better understanding of model-simulated future changes in temperature
754 variability. Together with the evaluation of the present-day energetics of variability
755 in the models, this could help distinguishing between more and less likely
756 projections for the future.
757

758 **Appendix A: Atmospheric energy flux convergence**

759 The total energy in a hydrostatic air column is

$$760 \quad E = \int_0^{p_s} (c_p T + Lq + k) \frac{dp}{g} + p_s h_s \quad (\text{A1})$$

761 where T is temperature, q specific humidity, k kinetic energy per unit mass, c_p
 762 specific heat of air at constant pressure, L the latent heat of vaporization, g the
 763 acceleration of gravity, p_s surface pressure and h_s the local surface height. We treat
 764 $c_p = 1004 \text{ J kg}^{-1} \text{ K}^{-1}$, $L = 2.5 \times 10^6 \text{ J kg}^{-1}$ and $g = 9.81 \text{ m s}^{-1}$ as constants and neglect
 765 the effects of cloud water and ice. For a more precise formulation, see Mayer et al.
 766 (2017).

767

768 Differentiating (A1) with respect to time gives

$$769 \quad \frac{\partial E}{\partial T} = \int_0^{p_s} \frac{\partial e}{\partial T} \frac{dp}{g} + \left(\frac{e(p_s)}{g} + h_s \right) \frac{\partial p_s}{\partial t} \quad (\text{A2})$$

770 where $e = c_p T + Lq + k$. The latter term represents changes in atmospheric mass
 771 rather than in the energy content of air. It can be non-zero even with no net
 772 advection or diabatic source of energy within the air column, and is therefore
 773 neglected in our analysis (cf. Liang et al. 2017). An expression for $\partial e / \partial t$ is
 774 obtained from the thermodynamic, momentum and specific humidity equations:

$$775 \quad \frac{\partial e}{\partial t} = -\vec{U} \cdot \nabla_3 (e + \Phi) + LS_q + Q - d \quad (\text{A3})$$

776 Here $\vec{U}$ is three-dimensional wind, ∇_3 is three-dimensional gradient operator, Φ
 777 is geopotential, S_q is net water vapour source per unit mass, Q is diabatic heating
 778 and d is dissipation of kinetic energy (d also contributes to Q and its net effect is
 779 therefore zero). Vertical integration of (A3) gives

$$780 \quad \int_0^{p_s} \frac{\partial e}{\partial T} \frac{dp}{g} = - \int_0^{p_s} \vec{U} \cdot \nabla_3 (e + \Phi) \frac{dp}{g} + R_a + H + LE \quad (\text{A4})$$

781 where the mass-integrated water vapour source is assumed to equal the difference
 782 between surface evaporation (E) and precipitation. R_a is the atmospheric radiation
 783 balance and H the sensible heat flux from the surface. Note that $R_a + H + LE =$
 784 $S - L - G$ (Eqs. (1)-(2)).

785

786 The first right-hand-side term in (A4) represents the atmospheric energy flux
 787 convergence C , written in advection form. This term is usually converted to flux
 788 convergence form using the identity $\vec{U} \cdot \nabla_3 (e + \Phi) = \nabla_3 \cdot (\vec{U}(e + \Phi))$, where we

789 have used the continuity equation $\nabla_3 \cdot \vec{U} = \nabla_p \cdot \vec{V} + \frac{\partial \omega}{\partial p} = 0$. An advantage of this
790 is that vertical flux convergence integrates to zero if vertical velocity at the surface
791 can be neglected. Furthermore, globally averaged horizontal convergence is zero,
792 as required by energy conservation. On the other hand, the calculation of the energy
793 flux convergence is numerically delicate. The main issue are errors in mass flux
794 convergence, the effects of which can be reduced but not fully eliminated by
795 adjusting the net mass flux to the air column (e.g., Hantel and Haase 1983; Chiodo
796 and Haimberger 2010; Mayer and Haimberger 2012; Liu et al. 2017). After testing
797 both the flux convergence and the advection form, we chose the latter since this
798 yielded a better match between $CONV$ and $CONV_{DIR}$ in our implementation.

799

800 To study how atmospheric phenomena on different time scales contribute to the
801 energy flux convergence, the monthly means of the advection term in (A4) were
802 further divided to two parts by writing

$$803 \quad -\overline{\vec{U} \cdot \nabla_3 (e + \Phi)} = -\underbrace{\overline{\vec{U} \cdot \nabla_3 (\bar{e} + \bar{\Phi})}}_{MON} - \underbrace{\overline{\vec{U}' \cdot \nabla_3 (e' + \Phi')}}_{SM} \quad (A5)$$

804 where the overbar denotes the monthly mean and the prime a deviation from it.
805 When integrated vertically and divided by D , these two components give $CONV_{MON}$
806 and $CONV_{SM}$ in (8). Similarly, dividing the left-hand-side term in (A4) by D gives
807 $STOR$ in (8).

808

809 The energy flux convergence and the change in atmospheric energy content were
810 evaluated using ERA-Interim data at 6-h time resolution, 0.75° horizontal
811 resolution and 37 pressure levels. The results were then aggregated to the 2.5° grid
812 used in the other parts of the analysis.

813

814

815 **Appendix B: Significance testing**

816 The sign test is based on the count of positive and negative values of a variable. If
817 both signs are equiprobable and autocorrelation is neglected, there is a 95.3%
818 probability that the number of positive (or negative) values in a 37-year time series
819 is within 13-24. Therefore, in a two-sided test, the same sign is required in at least
820 25 of the 37 years for statistical significance at 5% level.

821

822 When applying the sign test to SDCs, the obvious choice is to count the number of
823 years in which the temperature anomaly associated with a given energy term agrees
824 in sign with the actual temperature anomaly. However, averaging over calendar
825 months requires normalization. From (9), the mean of $SDC(i)$ over several calendar
826 months is

$$827 \quad [SDC(i)] = [r(i)SD(i)] = \left[\frac{cov(\Delta T(i), \Delta T)}{SD(\Delta T)} \right] \quad (B1)$$

828 where $[]$ denotes averaging over months and $SD(\Delta T)$ and $SD(i)$ are the standard
829 deviations of temperature and its i :th energy balance component. Expanding the
830 definition of covariance,

$$831 \quad [SDC(i)] = \sum_{j=1}^N \left[\frac{\Delta T(i)_j \Delta T_j}{SD(\Delta T)} \right] \equiv \sum_{j=1}^N f(i)_j \quad (B2)$$

832 where $N = 37$ is the number of years. Thus, in the sign test, the positive and negative
833 values of $f(i)_j$ are counted.

834

835

836 **Appendix C: Decomposition of LW_{CLEAR}**

837 The term LW_{CLEAR} represents variations in the clear-sky effective planetary
838 emissivity defined as

$$839 \quad \varepsilon_{eff-CLEAR} = \frac{L_{CLEAR}}{\sigma T^4} \quad (C1)$$

840 where L_{CLEAR} is the monthly mean clear-sky outgoing LW radiation and T is the
841 monthly mean surface air temperature. $\varepsilon_{eff-CLEAR}$ can be further factored as

$$842 \quad \varepsilon_{eff-CLEAR} = \frac{L_{CLEAR}}{L_{S\uparrow}} \cdot \frac{L_{S\uparrow}}{\sigma T^4} \equiv \varepsilon_A \varepsilon_S \quad (C2)$$

843 where $L_{S\uparrow}$ is the upward LW flux at the surface. ε_A is an inverse measure of the
844 clear-sky atmospheric greenhouse effect, whereas ε_S is an effective surface
845 emissivity, which is affected by the actual surface emissivity, differences between
846 the surface and surface air temperatures, and sub-monthly variations of
847 temperature. The corresponding temperature anomalies are

$$848 \quad LW_{CLEAR} = LW_{CLEAR-S} + LW_{CLEAR-A} \quad (C3)$$

849 where

$$850 \quad LW_{CLEAR-S} = -D^{-1} \Delta \varepsilon_S [\varepsilon_A] \sigma [T^4] \quad (C4)$$

851 is the contribution from variations in effective surface emissivity and

$$852 \quad LW_{CLEAR-A} = -D^{-1} \Delta \varepsilon_A [\varepsilon_S] \sigma [T^4] \quad (C5)$$

853 represents the variations in the atmospheric clear-sky greenhouse effect.

854

855 $LW_{CLEAR-A}$ was further decomposed using the linear regression model

$$856 \quad LW_{CLEAR-A} = \underbrace{a \Delta \sqrt{WWP}}_{LW_{CLEAR-WW}} + \underbrace{b \Delta (T_s - T_{300-700})}_{LW_{CLEAR-LR}} + \varepsilon \quad (C6)$$

857 where WWP is the vertically integrated water vapour path, T_s is surface temperature
858 and $T_{300-700}$ is the mean temperature at 300-700 hPa, broadly representing the layers
859 from which most of the longwave radiation escapes to space under typical
860 atmospheric conditions. The coefficients a and b were estimated from 37-year time
861 series of monthly mean data for each of ERA-Interim and MERRA2, using the same
862 values of a and b for all 12 months to avoid overfitting. $\sqrt{WWP}$ was preferred over
863 WWP since it explained a larger fraction of the variance in $LW_{CLEAR-A}$ when used
864 as the only predictor. This two-predictor model explains 83% (84%) of the globally
865 averaged variance in $LW_{CLEAR-A}$ in ERA-Interim (MERRA2), with

866 $\sqrt{WWP}$ alone explaining 61% (65%); see Fig. S14 for the geographical distribution
867 of the explained variance. As expected, the coefficients a and b in (C6) are positive
868 virtually everywhere (Fig. S15).

869

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875

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 995

996 **Tables**

997

998 **Table 1.** *Correlation of ΔT and its main energy balance components between the ERA-*
 999 *Interim and MERRA2 reanalyses*

1000

	IAV	SD	SDC
ΔT	0.92	0.98	0.98
LW_{CLEAR}	0.91	0.90	0.86
$SW_{CLEAR-ATM}$	0.24	0.29	0.43
SW_{ALBEDO}	0.72	0.86	0.72
$CLOUD$	0.57	0.70	0.56
$SURF$	0.85	0.96	0.90
$CONV$	0.88	0.97	0.92

1001 *IAV = spatiotemporal correlation of interannual variability (37 years $\times$ 12 months $\times$*
 1002 *global area); SD and SDC: the correlation of the SDs and SDCs (12 months $\times$ global area)*

1003

1004

Figure captions

Fig. 1. Linearly detrended temperature anomalies in central Finland (62.5°N, 25°E) in January and July 1980-2016 (solid lines) and the contributions of individual energy balance terms to them (bars, legend at the bottom). For reference, the mean and the 36-year linear trend of temperature are given in the top-right corner of the figure panels

Fig. 2. Typical magnitudes of the terms in Eqs. (5)-(7) in the ERA-Interim and MERRA2 reanalyses. The first column shows the interannual standard deviation (SD) of monthly temperature anomalies (ΔT) averaged over the 12 months and the global area. The remaining columns show the corresponding SDs of the energy balance terms (blue) and

1016 their contribution to the standard deviation of ΔT (SDC, red). The numeric values at the
 1017 bottom give the SDs (upper) and SDCs (lower) in units of 0.01 K
 SD (K)

1018
 1019 **Fig. 3.** Left: interannual standard deviation of monthly mean temperature anomalies (ΔT)
 1020 and their main energy balance components. Middle: correlation between the individual
 1021 energy balance components and ΔT . Right: Contributions of the individual energy
 1022 balance components to the standard deviation of ΔT . All statistics are averaged between
 1023 ERA-Interim and MERRA2. In the third column, grey colour indicates areas where the sign
 1024 of the standard deviation contribution is not robust (see Section 4.2 for definition)
 1025

1027 **Fig. 4.** *Interannual standard deviation of monthly mean temperature anomalies in (a)*
1028 *November-March and (b) May-September, and (c-n) the contributions of the main energy*
1029 *balance components to it. All statistics are averaged between ERA-Interim and MERRA2.*
1030 *Grey colour indicates areas where the sign of the standard definition contribution is not*
1031 *robust (see Section 4.2 for definition)*

1032

1033 **Fig. 5.** Interannual standard deviation of temperature in central Finland (the same grid
 1034 box as in Fig. 1) (solid line) and the contributions of the six main energy balance terms to
 1035 it (bars, legend at bottom; contributions that are not robust in the sense defined in Section
 1036 4.2 are indicated with a grey core)

1037

1038 **Fig. 6.** Largest contributors to interannual temperature variability in 6 calendar months,

1039 based on the mean of the ERA-Interim and MERRA2 results

1040

1041 **Fig. 7.** Division of $SDC(LW_{CLEAR})$ (e) to contributions from the four terms in Eq. (11) (a-
 1042 d). All values are averaged over the 12 months and between ERA-Interim and MERRA2.
 1043 The global area means are given in the headings. Note that the colour scale differs from
 1044 Figs. 3-4

1045
 1046 **Fig. 8.** Term CONV as calculated directly from energy flux convergence and storage using
 1047 ERA-Interim data (a-c), and its decomposition to the contributions of (d-f) the monthly
 1048 mean flow, (g-i) sub-monthly flow variations and (j-l) atmospheric energy storage. The
 1049 three columns are the same as in Fig. 3. Grey colour indicates areas where the sign of the
 1050 standard definition contribution is not significant at 5% level based on a sign test
 1051