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An energy balance perspective on regional CO₂-induced temperature changes in CMIP5 models

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1 **Abstract**

2 An energy balance decomposition of temperature changes is conducted for
3 idealized transient CO₂-only simulations in the fifth phase of the Coupled Model
4 Intercomparison Project (CMIP5). The multimodel global mean warming is
5 dominated by enhanced clear-sky greenhouse effect due to increased CO₂ and
6 water vapour, but other components of the energy balance substantially modify
7 the geographical and seasonal patterns of the change. Changes in the net surface
8 energy flux are important over the oceans, being especially crucial for the muted
9 warming over the northern North Atlantic and for the seasonal cycle of warming
10 over the Arctic Ocean. Changes in atmospheric energy flux convergence tend to
11 smooth the gradients of temperature change and reduce its land-sea contrast, but
12 they also amplify the seasonal cycle of warming in northern North America and
13 Eurasia. The three most important terms for intermodel differences in warming
14 are the changes in the clear-sky greenhouse effect, clouds, and the net surface
15 energy flux, making the largest contribution to the standard deviation of annual
16 mean temperature change in 34%, 29% and 20% of the world, respectively.
17 Changes in atmospheric energy flux convergence mostly damp intermodel
18 variations of temperature change especially over the oceans. However, the
19 opposite is true for example in Greenland and Antarctica, where the warming
20 appears to be substantially controlled by heat transport from the surrounding sea
21 areas.

22

23 **KEYWORDS:** temperature change, energy budget, atmospheric heat
24 convergence, surface energy flux, CMIP5

25

26

27 **1. Introduction**

28 Increases in CO₂ and other greenhouse gases make the atmosphere less
29 transparent in the thermal infrared area, thus reducing the outgoing longwave
30 radiation (OLR). The resulting surplus of energy warms the surface and the lower
31 atmosphere. This warming increases OLR, thereby reducing the energy imbalance
32 (e.g. Houghton 2015). However, the outcome of this process in terms of the
33 resulting near-surface temperature change is affected by several feedbacks that
34 alter the fluxes of energy in the climate system.

35

36 The equilibrium global and annual mean temperature response to increasing CO₂
37 is commonly analysed in terms of the water vapour, lapse rate, cloud and surface
38 albedo feedbacks (Hansen et al. 1984; Flato et al. 2013). Typically the results are
39 expressed in terms of feedback factors that relate the change in the top-of-the-
40 atmosphere (TOA) radiation balance to the near-surface temperature change.
41 However, it is also possible to diagnose the contributions of the direct CO₂ forcing
42 and the feedbacks to the temperature change (Dufresne and Bony 2008; hereafter
43 DB08), although the nonlinearity of the problem makes this decomposition
44 mathematically non-unique (Caldwell et al. 2016). In energy balance analysis of
45 transient climate change, ocean heat uptake must be included in addition to the
46 processes that regulate the equilibrium warming (Gregory and Mitchell 1997;
47 DB08).

48

49 When considering temperature change at regional scales, the effects of
50 atmospheric energy transport also need to be implicitly or explicitly included (e.g.
51 Boer and Yu 2003). Recently, two techniques have been proposed for diagnosing
52 the energetic contributors to regional temperature change: the surface energy
53 budget approach of Izumi et al. (2015; hereafter IBH15) and the climate feedback-
54 response analysis method (CFRAM) introduced by Lu and Cai (2009).

55

56 IBH15 applied their method to ensemble mean temperature changes from six
57 models in the fifth phase of the Coupled Model Intercomparison Project (CMIP5).
58 The warming in simulations with quadrupled CO₂ was found to be strongly
59 dominated by increased clear-sky downward longwave (LW) radiation, which was

60 partly compensated by a widespread increase in latent heat flux and reduced clear-
61 sky downward shortwave (SW) radiation mainly caused by increased water vapor
62 absorption in the atmosphere. Similar findings with signs reversed applied to
63 simulations for the Last Glacial Maximum, but the change in surface albedo
64 contributed much more to the glacial cooling than to the CO₂-induced warming.
65 In both cases, variations in the clear-sky downward LW radiation dominated the
66 geographical variations of temperature change, although several other terms also
67 contributed.

68

69 In CFRAM, the temperature changes associated with each individual process are
70 solved in the atmosphere-surface column, using a one-dimensional energy balance
71 equation that incorporates the local and non-local effects of temperature change
72 on the LW radiation transfer. Taylor et al. (2013) used this method to show that
73 the polar amplification of the simulated CO₂-induced warming in the NCAR
74 CCSM4 model was mostly due to the surface albedo feedback. Sejas et al.
75 (2014a) used the same method to analyse the seasonal cycle of temperature
76 changes in the same model. In particular, they demonstrated the importance of
77 ocean heat storage changes in shifting the maximum of polar warming from
78 summer (when the albedo feedback is greatest) to late autumn and winter.

79

80 CFRAM and the IBH15 surface energy balance approach both have their
81 strengths and limitations. CFRAM is more detailed in terms of the processes
82 considered, but requires a relatively sophisticated calculation of radiative transfer
83 which makes it more challenging to apply to a large ensemble of model
84 simulations. The IBH15 method is more straightforward and only requires a
85 limited number of two-dimensional model fields. On the other hand, as this
86 approach is entirely based on the surface energy budget, the results are
87 disconnected from studies that use the TOA radiation balance for analysis of
88 global mean temperature change. The strong dominance of the clear-sky
89 downward LW radiation in explaining the magnitude and patterns of surface
90 temperature change may also be regarded as a complicating feature. Separation
91 between cause and effect is difficult in this case, because much of the downward
92 LW radiation originates from the lowest atmospheric layers whose temperature is
93 closely correlated with the surface temperature (Zhao et al. 1994).

94
95 Here, we propose an alternative method for studying the energy balance
96 contributions to regional temperature change. The method was introduced in
97 Räisänen and Ylhäisi (2015; hereafter RY15) but is here refined for its treatment
98 of SW radiation. Only two-dimensional surface and TOA model output is needed,
99 which makes the method convenient to apply to large ensembles of model
100 simulations. On the other hand, the diagnostics obtained from this method are
101 easier to compare with the traditional global TOA radiation balance approach than
102 is the case with a surface energy budget method.

103
104 We apply our method to idealized transient CO₂ experiments from 16 CMIP5
105 models, analysing both the multimodel mean changes and the contributions of
106 different energy balance processes to the intermodel differences in temperature
107 change. A general finding from our research is that the energetics of temperature
108 change are highly regionally variable. For example, while cloud feedbacks have
109 been identified as the main uncertainty in the global mean temperature change
110 (Flato et al. 2013, Vial et al. 2013), their contribution is not dominant in all
111 seasons and all areas.

112
113 The model output used for the study is detailed in Section 2. The energy balance
114 framework is described in Section 3. The results are covered in Section 4, starting
115 from global and regional annual mean temperature changes and then proceeding
116 to the seasonality of the changes in selected regions. In the end of the section, the
117 role of atmospheric energy transport changes in modulating the temperature
118 changes is discussed in some more depth. The main conclusions are presented in
119 Section 5.

120

121 **2. Data sets and data processing**

122 Monthly data for 16 CMIP5 models were used: ACCESS1-3, BCC-CSM1-1,
123 BCC-CSM1-1-m, CanESM2, CESM1-BGC, GFDL-CM3, INM-CM4, IPSL-
124 CM5A-MR, IPSL-CM5B-LR, MIROC5, MIROC-ESM, MPI-ESM-LR, MPI-
125 ESM-MR, MRI-CGCM3, NorESM1-M and NorESM1-ME, where the acronyms
126 follow Table 9.1 in Flato et al. (2013). This includes all the models for which the

required variables could be retrieved both for the preindustrial control simulation (*piControl*) and the simulation with CO₂ increasing 1 % per year compound (*1pctCO2*) until the quadrupling of CO₂ in 140 years. Only one realization of these two simulations (*rlilp1*) was used for each model. All the model data were interpolated to a common 2.5×2.5 degrees latitude-longitude grid using the Climate Data Operators (<https://code.zmaw.de/projects/cdo>) first-order conservative remapping (*remapcon*).

134

The 15 variables used are listed in Table 1. In the energy balance analysis described in Section 3, their decadal monthly means from the *1pctCO2* and *piControl* simulations were first used to calculate the temperature change and its various components for each decade and month. Then the changes were averaged over the six decades centred at the doubling of CO₂ (years 41-100). Conventionally, the transient climate response is defined using bidecadal means over the years 61-80 (Cubasch et al. 2001). A longer averaging period is preferred here because it helps to reduce internal variability, which would have a large effect on the monthly mean changes in the individual models if bidecadal means were used. However, the multimodel mean results are only modestly affected by this difference in periods. The multimodel global mean warming is 1.78 K for the years 61-80 and 1.82 K for the years 41-100.

147

When calculating statistics for land and sea areas separately, a common land sea mask (from the National Centers for Environmental Prediction – National Center for Atmospheric Research reanalysis) is used. This choice is preferred for simplicity, even though it may induce some “leakage” between land and sea in the individual models.

153 .

154 **3. Energy balance framework**

To relate the changes in surface air temperature with the atmospheric energy budget, a modified version of the method of RY15 was used. As discussed below, this method is rough in its treatment of LW radiation. However, the adoption of the approximate partial radiative perturbation (APRP) method (Taylor et al. 2007) allows a cleaner separation of shortwave (SW) radiative feedbacks than in RY15.

160

161 The rate of change of total energy in an atmospheric column is

$$162 \quad \frac{\partial E}{\partial t} = S - L - G + C \quad (1)$$

163 where S is net SW radiation at the TOA, L outgoing LW radiation at the TOA, G
 164 net downward heat flux to the surface and C horizontal energy flux convergence
 165 in the atmosphere. To relate (1) with the surface air temperature T , we write

$$166 \quad L = \varepsilon_{eff} \sigma T^4 \quad (2)$$

167 where ε_{eff} is an effective planetary emissivity. ε_{eff} is essentially a measure of the
 168 atmospheric greenhouse effect, although it is also to some extent affected by
 169 variations in the surface emissivity, the surface-to-air temperature difference, and
 170 short-term (below decadal monthly means) temperature variations. However, an
 171 inspection of the surface upwelling LW radiation in the CMIP5 models confirmed that
 172 these latter factors are generally unimportant for the changes in ε_{eff} . Substituting
 173 (2) into (1), one obtains

$$174 \quad \varepsilon_{eff} \sigma T^4 = S - G + \left(C - \frac{\partial E}{\partial t}\right) \quad (3)$$

175 Letting now $\Delta X = X_2 - X_1$ denote the change in quantity X between two climates (1 =
 176 baseline CO₂, 2 = increased CO₂) and $[X]$ the mean of these two, (3) gives

$$177 \quad \sigma [\varepsilon_{eff}] \Delta(T^4) = \underbrace{-\sigma \Delta \varepsilon_{eff} [T^4]}_I + \underbrace{\Delta S}_{II} - \underbrace{\Delta G}_{III} + \underbrace{\Delta \left(C - \frac{\partial E}{\partial t}\right)}_{IV} \quad (4)$$

178 Finally, linearizing the left side of (4) as

$$179 \quad \sigma [\varepsilon_{eff}] \Delta(T^4) \approx 4 \sigma [\varepsilon_{eff}] [T]^3 \Delta T = D \Delta T \quad (5)$$

180 allows one to decompose the simulated temperature change as

$$181 \quad \Delta T = \underbrace{LW}_I + \underbrace{SW}_{II} + \underbrace{SURF}_{III} + \underbrace{CONV}_{IV} + ERR \quad (6)$$

182 where the terms I – IV in (4) have been divided by $D = 4 \sigma [\varepsilon_{eff}] [T]^3$. LW
 183 represents the temperature change caused by the change in ε_{eff} and SW that due to
 184 the change in the net TOA SW radiation. $SURF$ is negative when the net
 185 downward heat flux at the surface increases. $CONV$ is evaluated as a residual of

the energy budget. RY15 denoted this term as *CONV – STOR* to emphasize that the changes in both the atmospheric horizontal energy flux convergence and local atmospheric storage are included. However, at least for annual means it is safe to assume that the change in energy flux convergence dominates (RY15). *ERR* results from the linearization in (5) but turns out to be very small (Section 4.1).

ε_{eff} in (2) is affected by atmospheric LW opacity and the vertical lapse rate of temperature, but is largely insensitive to vertically uniform temperature changes. Consequently, the coefficient D in (5) is a good approximation of the Planck feedback parameter. It has a multimodel global and annual mean value of $3.3 \text{ Wm}^{-2} \text{ K}^{-1}$, whereas the Planck feedback parameter is close to $3.2 \text{ Wm}^{-2} \text{ K}^{-1}$ in both the CMIP3 and CMIP5 models (Soden and Held 2006; Flato et al. 2013). Thus, in the conversion from (4) to (6), an energy flux perturbation of 1 Wm^{-2} is typically equivalent to a 0.3 K change in temperature, although the precise value varies with month, model and geographic location.

By using the TOA all-sky ($rlut$) and clear-sky ($rlutcs$) LW fluxes, LW is further divided into clear-sky and cloud radiative effect contributions.

$$LW = LW_{CLEAR} + LW_{CRE} \quad (7)$$

In broad terms, LW_{CLEAR} incorporates the LW radiative forcing due to increasing CO_2 together with the water vapour and the lapse rate feedbacks, whereas LW_{CRE} represents the change in the LW cloud radiative effect (CRE). Unfortunately, LW_{CRE} is a negatively biased approximation of the actual LW cloud feedback, because increases in CO_2 and water vapor act to reduce the effect of clouds on the OLR (Section 4.1).

The treatment of SW radiation is based on the APRP method. Using the TOA and surface all-sky and clear-sky SW fluxes and total cloudiness, the change in the TOA net SW radiation is divided to five components, which are further converted to the corresponding temperature changes as

$$SW = SW_{IN} + SW_{CLEAR - ATM} + SW_{ALBEDO} + SW_{CLOUD} + SW_{NL} \quad (8)$$

The first term in (8) accounts for the change in the TOA incoming solar radiation (ΔS in Eq. (6) of Taylor et al. 2007), whereas the next three terms represent the

219 changes in the SW radiative properties of the clear-sky atmosphere, surface
 220 albedo, and clouds (Eqs. (16a-c) of Taylor et al. 2007). Higher-order nonlinear
 221 effects are collected in the last term. Note that SW_{CLOUD} represents, within the
 222 accuracy of the APRP method, the actual SW cloud feedback rather than the
 223 change in SW CRE. In particular, this avoids the aliasing of surface albedo and
 224 cloud change contributions in the SW radiation budget that affects the changes in
 225 SW CRE (Qu and Hall 2006; RY15).

226

227 **4. Results**

228 **4.1 Global and local mean values**

229

230 The magnitude of the various terms in (6)-(8) is explored in Table 2. The first
 231 three columns give their multimodel annual means for the globe and land and sea
 232 areas separately. For the remaining columns, the absolute values of the terms are
 233 averaged over all individual models, months and grid boxes, so to avoid
 234 compensation between positive and negative values. We first note that SW_{IN} , SW_{NL}
 235 and ERR are negligible, with values of $\leq 10^{-3}$ K in all cases. ERR is much smaller
 236 than the linearization residuals in Taylor et al. (2013), Sejas et al. (2014a,b) and
 237 IBH15. This is achieved by conducting the linearization in (5) around the average
 238 of the baseline and perturbed temperatures rather than the baseline mean.

239

240 The multimodel global annual mean warming of 1.82 K is dominated and actually
 241 exceeded by LW_{CLEAR} (2.07 K). Other terms that enhance the warming include
 242 $SW_{CLEAR-ATM}$ (0.21 K), SW_{ALBEDO} (0.19 K) and SW_{CLOUD} (0.13 K). The first of these
 243 reflects stronger absorption of solar near-infrared radiation by increased CO_2 and
 244 water vapour, the second the effects of reduced snow and ice cover, and the third
 245 reduced cloud cover over many low-to-mid-latitude areas. The warming is
 246 counteracted by $SURF$ (-0.39 K), due to ocean heat uptake during transient CO_2
 247 increase, and LW_{CRE} (-0.39 K).

248

249 The global means for $SURF$ and SW_{ALBEDO} are very close to those reported by
 250 DB08 for their sample of 12 CMIP3 models (transient temperature changes for
 251 “Albedo” and “OHU efficiency” in their Table 3). This results from the close

252 similarity between D in (5) and the Planck feedback parameter used to convert the
 253 energy flux perturbations to temperature changes in DB08. However, the sum of
 254 SW_{CLOUD} and LW_{CRE} (hereafter $CLOUD$) gives a net cloud contribution of -0.26 K,
 255 in stark contrast with the mean cloud feedback of 0.4 K found by DB08. Studies
 256 with CMIP5 models also support a predominantly positive net cloud feedback
 257 and, in particular, a positive LW cloud feedback in nearly all models (Tomassini
 258 et al. 2013; Vial et al. 2013; see also Fig. 7.10 of Boucher et al. 2013 and Table
 259 9.5 of Flato et al. 2013). This discrepancy arises because LW_{CRE} is calculated
 260 directly from the change in the LW CRE, instead of a radiative kernel or a partial
 261 radiative perturbation approach that would explicitly isolate the effect of cloud
 262 changes (Soden et al. 2004). Increases in CO_2 and water vapour make the above-
 263 cloud atmosphere less transparent for LW radiation, thus making OLR less
 264 sensitive to the presence of clouds and reducing the LW CRE for unchanged
 265 cloud cover. The excessively negative cloud LW contribution also implies that
 266 LW_{CLEAR} exaggerates the clear-sky LW contribution to the simulated warming.

267

268 The annual multimodel mean warming is on the average 0.89 K larger over land
 269 (2.46 K) than sea (1.57 K). The largest contributor to this difference is $SURF$,
 270 which has little impact over land but cools the oceans by 0.53 K. LW_{CLEAR} ,
 271 SW_{CLOUD} and SW_{ALBEDO} also increase the land-sea contrast (by 0.28, 0.25 and 0.12
 272 K, respectively). On the other hand, $CONV$ moderates this contrast by 0.40 K,
 273 cooling land but warming the oceans. Anomalous heat transport from land to
 274 ocean develops during transient increase of atmospheric CO_2 , thus spreading the
 275 effect of the ocean heat uptake from the oceans to the continents (Lambert et al.
 276 2011).

277

278 The terms LW_{CLEAR} , $SW_{CLEAR-ATM}$ and SW_{ALBEDO} are nearly uniformly positive.
 279 Therefore, their multimodel global annual means also give a good idea of their
 280 typical local and monthly absolute values even for individual models (right half of
 281 Table 2). By contrast, LW_{CRE} , SW_{CLOUD} , $SURF$ and $CONV$ vary commonly in sign.
 282 They thus have much larger values in individual models, months and grid boxes
 283 than the multimodel global annual means would suggest. In particular, the mean
 284 absolute values of both $SURF$ and $CONV$ over ocean exceed 2 K.

285

286 To the extent that LW_{CRE} and SW_{CLOUD} are dominated by changes in cloud
 287 amount, a partial cancellation between them would be expected. Consistent with
 288 this, the sum of LW_{CRE} and SW_{CLOUD} ($CLOUD$) has in all columns of Table 2 a
 289 smaller magnitude than one or both of these terms individually. In the rest of this
 290 paper, we will therefore focus on $CLOUD$ rather than its two parts. $SURF$ and
 291 $CONV$ also tend to oppose each other, particularly over the oceans, where $SURF$
 292 is much larger than over land. Combining (1), (4) and (6) gives

$$293 \quad \Delta(S - L) = \Delta G - \Delta \left(C - \frac{\partial E}{\partial t} \right) = -D(SURF + CONV) \quad (9)$$

294 The compensation between $SURF$ and $CONV$ thus implies $|\Delta(S - L)| < |\Delta G|$
 295 which means that the net TOA radiation balance changes typically less than the
 296 net surface energy flux.

297

298 **4.2 Annual mean temperature change**

299

300 The decomposition of the annual mean temperature change to its main
 301 components is depicted on maps in Fig. 1. Along with the multimodel mean (first
 302 column), two measures are used to characterize the intermodel relationship
 303 between the components and the total change ΔT : correlation (second column)
 304 and the contribution to standard deviation (right column). The latter is defined as

$$305 \quad SDC_i = \frac{\overline{\Delta T_i' \Delta T'}}{\sqrt{(\Delta T')^2}} = r_i \sqrt{(\Delta T_i')^2} \quad (10)$$

306 where the overbars indicate multimodel averages and the primes deviations from
 307 them. The last expression shows that SDC_i is affected by both the correlation of
 308 the component i with the total temperature change (r_i) and the intermodel standard
 309 deviation of this component. The SDC_i s are additive and sum up to the standard
 310 deviation of ΔT .

311

312 LW_{CLEAR} widely dominates the multimodel mean warming (Fig. 1d). Its
 313 intermodel variations tend to be strongly correlated with ΔT (Fig. 1e), and the
 314 highest correlations (> 0.9) mostly occur in those mid-to-high-latitude areas where
 315 the intermodel differences in ΔT are large (Fig. 1c). These positive correlations

316 reflect, presumably to a large extent, the water vapour feedback that enhances the
317 greenhouse effect most strongly in the models with the largest warming. Still, the
318 SDC of LW_{CLEAR} (Fig. 1f) falls clearly short of the standard deviation of ΔT (Fig.
319 1c), particularly at extratropical latitudes. Thus, LW_{CLEAR} substantially amplifies
320 intermodel differences in temperature change but may not generally be the
321 ultimate driver of these differences. The spatial distribution of the multimodel
322 mean warming is also not properly explained by LW_{CLEAR} alone.

323
324 $SW_{CLEAR-ATM}$ is small in the multimodel mean (Fig. 1g) and makes a minute
325 contribution to intermodel variations in temperature change (Fig. 1i). However, it
326 correlates positively with ΔT particularly over the oceans (Fig. 1h), presumably
327 because water vapor increases more in models with larger warming.

328
329 SW_{ALBEDO} enhances the multimodel mean warming where snow and ice are
330 reduced. Although modest when globally averaged, its contribution locally
331 exceeds 2 K over (e.g.) the Barents Sea, the Hudson Bay and the Tibetan plateau
332 (Fig. 1j). There is a strong positive intermodel correlation between SW_{ALBEDO} and
333 ΔT over the Arctic and Antarctic oceans and parts of the northern hemisphere
334 extratropical continents (Fig. 1k), where this term also substantially amplifies the
335 intermodel standard deviation (Fig. 1l).

336
337 $CLOUD$ reduces the multimodel mean warming by over 1 K over the Southern
338 Ocean and the northern North Atlantic (Fig. 1m), in both cases mainly due to a
339 negative SW contribution associated with increased cloud cover. The largest
340 positive values over the eastern tropical Pacific and the Arctic Ocean reflect an
341 increase in the LW CRE, and are also connected to increased cloudiness. $CLOUD$
342 is positively correlated with the simulated warming in most parts of the world
343 (Fig. 1n), and its contribution to the intermodel standard deviation of ΔT
344 approaches that of LW_{CLEAR} (Fig. 1o).

345
346 $SURF$ plays a large role over the oceans. Although its contribution is negative in
347 most areas, the geographical variation is huge, ranging from a multimodel mean
348 cooling of up to 10 K to the south of Greenland to a warming of 5 K in the Barents
349 Sea (Fig. 1p). $SURF$ and ΔT are strongly correlated near the sea ice edge in both

350 hemispheres, as well as in the northwestern North Atlantic (Fig. 1q). In these
351 regions, intermodel differences in temperature change are substantially amplified
352 by changes in the net surface flux, or ultimately by sea ice and ocean circulation
353 changes that regulate the net air-sea heat exchange (Fig. 1r).

354

355 Over land, *SURF* is much smaller than over the oceans, with compensating
356 positive and negative values in different months (see Fig. 4 for examples). Yet it
357 does not fully average out in the annual mean. This is mainly due to changes in
358 snowfall (which imply changes in the energy consumed by snow melt) and,
359 primarily over Greenland and Antarctica, increased melting of glacier ice.

360

361 As already seen from Table 2, *CONV* tends to oppose *SURF* over the oceans
362 (Figs. 1s and 1p). For example, in the northern North Atlantic where the
363 atmosphere loses heat to the surface, this is primarily compensated by increased
364 heat flux convergence and the effect on the local temperature change is thus
365 dampened. Therefore, *CONV* generally reduces the spatial gradients in warming
366 over the oceans (compare Figs. 1s and 1a). In most areas, it also reduces the
367 intermodel differences (Fig. 1u).

368

369 *CONV* slightly reduces the multimodel mean warming in most land areas (Fig.
370 1s). Exceptions include, among others, Greenland and eastern Antarctica. The
371 Greenland and Antarctic ice sheets also stand out as areas with a substantial
372 positive intermodel correlation between *CONV* and ΔT (Fig. 1t). Thus, unlike in
373 most parts of the world, changes in heat flux convergence act to amplify
374 intermodel differences in temperature change over Greenland and Antarctica (Fig.
375 1u).

376 **4.3 Seasonality of temperature changes**

377

378 The effect of the individual energy balance terms on the seasonality of the
379 multimodel mean temperature change is studied in Fig. 2. The seasonality is
380 measured here by the intermonthly standard deviation of ΔT (Fig. 2a). The largest
381 values in the Arctic and over the high-latitude Southern Ocean result from greater
382 warming in late fall and winter than in summer, while the warming in summer

383 slightly exceeds that in winter in many lower-latitude regions (Christensen et al.
384 2007).

385

386 Figures 2c-h show the contributions of the main energy balance components to the
387 intermonthly standard deviation of the temperature change, using the analogy of
388 (10) but with intermodel variations replaced by intermonthly variations. LW_{CLEAR}
389 and $CLOUD$ make major contributions to the change in seasonality in large parts
390 of the world. $SURF$ is also important in many areas, particularly over the Arctic
391 Ocean and the high-latitude Southern Ocean, where sea ice is reduced.
392 Conversely, SW_{ALBEDO} reduces the seasonality of temperature changes in the
393 Arctic and over the high-latitude Southern Ocean. $CONV$ is important in many
394 regions but its contribution varies in sign. Notably, $CONV$ strongly damps the
395 seasonality of temperature changes over the Arctic Ocean but amplifies it
396 immediately to the south in northern North America and Eurasia.

397

398 To exemplify the factors that regulate the seasonality of temperature change and
399 its intermodel differences, four oceanic and four continental regions are chosen
400 for a closer study. See Fig. 2b for a map of the regions and Table 3 for their
401 boundary coordinates. For each region, the left-hand-side panels in Figs. 3-4 show
402 the contributions of the various energy balance terms to the multimodel mean
403 temperature change, whereas the right-hand-side shows their contributions to the
404 intermodel standard deviation. The latter are first calculated for each grid box
405 separately and then averaged over the domain considered. This order of
406 calculation avoids the systematic effect of the domain size (smaller standard
407 deviations for larger domains) that would occur if calculating the area means
408 before the standard deviations. Both the mean change and the standard deviation
409 contributions vary within the regions, but the main area-averaged results were
410 found to be robust to small changes in the delineation of the areas. Note, however,
411 that the scales in Figs. 3-4 differ from region to region due to the widely varying
412 magnitude of the mean warming and the intermodel differences.

413 4.3.1 Examples for oceans

414

415 The multimodel mean warming over the **Arctic Ocean (AO)** (Fig. 3a) is strongly
416 seasonal, ranging from 1 K in June and July to 9 K in November. This seasonality
417 is driven primarily by *SURF*, which amplifies the warming in autumn and winter
418 but strongly damps it in summer. Reduced ice cover allows the ocean to absorb
419 more SW radiation during the summer, and this heat is released back to the
420 atmosphere in autumn and winter when thinner and less extensive ice cover
421 enhances the heat flux from the relatively warm ocean to the cold atmosphere
422 (Sejas et al. 2014a). *LW_{CLEAR}* and to some extent *CLOUD* also enhance the
423 seasonality of the warming. *SW_{ALBEDO}* in isolation would induce a summer
424 maximum of warming, but the resulting heat gain is stored by the ocean. *CONV*
425 also damps the seasonality with a positive contribution in summer (when the
426 Arctic Ocean warms less than the surrounding land areas) and a negative
427 contribution from October to December (when the warming is greatest over the
428 Arctic Ocean). In the annual multimodel area mean, both *SURF* and *CONV* nearly
429 average out.

430

431 In most cases, those energy balance terms that increase the multimodel mean
432 warming also tend to increase the intermodel differences over the Arctic Ocean
433 and vice versa (Fig. 3b). The main exceptions are *SURF*, which acts to increase
434 the intermodel differences in all months except from May to July, and *CONV*,
435 which reduces these differences throughout the year but most strongly in autumn
436 and winter.

437

438 The ensemble mean warming in the **Northern North Atlantic (NNA)** is small
439 throughout the year, but with a minimum in late spring and a maximum in autumn
440 and winter (Fig. 3c). It mainly represents a balance between large cooling due to
441 *SURF* and warming by *CONV*, but *LW_{CLEAR}* and *CLOUD* also make non-
442 negligible contributions. Both *LW_{CRE}* and *SW_{CLOUD}* are negative, but the latter
443 dominates in spring and summer (not shown). In these seasons, cloud cover
444 increases, presumably due to increased lower-tropospheric stability over a local
445 minimum in the surface warming. Intermodel differences of temperature change
446 in the northern North Atlantic are dominated by differences in *SURF* for most of
447 the year, but in summer *CLOUD* makes the largest contribution (Fig. 3d). Again,
448 *CONV* systematically reduces the intermodel differences.

449

450 In the **Tropical East Pacific (TEP)**, the multimodel mean warming is about 40%
451 smaller than the contribution of LW_{CLEAR} alone (Fig. 3e). At the annual mean
452 level, this is mostly due to $CONV$, i.e. increased atmospheric energy transport out
453 of the region. However, although the simulated warming is nearly seasonally
454 invariant, the contributions of the individual energy balance terms vary. During
455 the northern winter and spring, LW_{CLEAR} is mainly moderated by $CONV$, but in
456 summer and autumn, $SURF$ overtakes its role. $CLOUD$ slightly enhances the
457 multimodel mean warming in most of the year, but is also the main contributor to
458 intermodel differences in temperature change (Fig. 3f). As in the previous regions,
459 $CONV$ strongly attenuates the intermodel differences in warming.

460

461 The ensemble mean warming over the **Southern Ocean (SO)** is relatively small
462 overall, but has its maximum during the local winter (Fig. 3g). As in the northern
463 North Atlantic, $SURF$ attenuates the warming but is counteracted by $CONV$,
464 although both of these are smaller in magnitude. Similar to the northern North
465 Atlantic, $CLOUD$ also reduces the warming, particularly in the southern summer
466 when increased cloud cover makes SW_{CLOUD} strongly negative (not shown).
467 $CLOUD$ together with LW_{CLEAR} seemingly explains the seasonal cycle of the
468 warming, but the interpretation is complicated because several physically
469 intermingled terms are important in the balance. The same applies to the
470 intermodel differences in warming (Fig. 3h). In particular, although SW_{ALBEDO} acts
471 to amplify these differences in spring and early summer, its influence is
472 moderated by the simultaneous negative contribution from $SURF$. In those models
473 and grid boxes in which the surface albedo decreases due to sea ice melting, the
474 heat gain is stored in the ocean and has limited impact on the local surface
475 temperature. This closely resembles the situation in the Arctic Ocean in the
476 summer.

477 4.3.2 Examples for land areas

478

479 The ensemble mean warming in **Siberia (SIB)** is largest in early winter and
480 smallest in summer (Fig. 4a). This seasonality is largely driven by $CONV$, which
481 enhances the warming in the winter half-year but strongly reduces it from May to

482 August. The patterns in Fig. 2h suggest that this primarily reflects heat exchange
483 with the Arctic Ocean, where the warming is larger than in Siberia in late autumn
484 and winter but smaller in summer. Due to earlier snow melt, SW_{ALBEDO}
485 substantially contributes to the warming in spring and early summer, but the
486 resulting heat gain is counteracted by increased atmospheric energy divergence
487 out of the area. $SURF$ is also negative in April and May but positive in summer.
488 Snowmelt occurs earlier in a warmer climate (e.g., Räisänen 2008), and the
489 associated energy sink is thus enhanced (reduced) early (late) in the melting
490 season.

491

492 SW_{ALBEDO} makes a large contribution to intermodel differences in temperature
493 change in Siberia in spring and early summer (Fig. 4b), but this is largely
494 compensated by a negative contribution from $CONV$ in the same season. By
495 contrast, $CONV$ slightly amplifies the intermodel differences in late autumn and
496 winter. In summer, $CLOUD$ also increases the intermodel differences in
497 temperature change.

498

499 In **Central Europe (CEU)**, $CONV$ reduces the ensemble mean warming, keeping
500 it below the contribution of LW_{CLEAR} in most of the year (Fig. 4c). The exception
501 is late summer (July-September), when a positive $CLOUD$ contribution due to
502 reduced cloudiness amplifies the simulated warming, thus explaining its annual
503 maximum in this season. More strikingly, $CLOUD$ strongly amplifies the
504 intermodel differences in warming in the summer half-year, although being
505 counteracted by $CONV$ (Fig. 4d). In winter, $CONV$ slightly enhances the
506 intermodel differences in warming.

507

508 In a surprising contrast with the seasonal cycle of LW_{CLEAR} , the multimodel mean
509 warming in **Amazonia (AMZ)** is slightly larger in the southern hemisphere winter
510 and spring than in summer and autumn (Fig. 4e). This is largely due to $CONV$,
511 which reduces the warming less in winter than in summer. Intermodel differences
512 in warming in Amazonia are mainly attributed to LW_{CLEAR} , $CONV$ and $CLOUD$.
513 They are largest during the southern winter and spring, when the contribution of
514 $CONV$ has its maximum.

515

516 The warming over **Antarctica (ANT)** is nearly seasonally uniform (Fig. 4g). This
 517 results from a compensation between the seasonalities of *CLOUD*, *SURF*, *CONV*
 518 and *SW_{CLEAR-ATM}*. Interestingly, *SW_{CLEAR-ATM}* enhances the warming by up to 0.6°C
 519 during the Antarctic summer when solar radiation is abundant. Intermodel
 520 differences in temperature change over Antarctica are amplified by *CONV*
 521 throughout the year, although most strongly in the autumn and winter (Fig. 4h).
 522 Other major contributors to these differences include *LW_{CLEAR}* and *CLOUD*.

523

524 **4.4 Discussion**

525

526 As shown above, different energy balance terms dominate the intermodel spread
 527 of temperature change in different seasons and areas. For a simple overview, Fig.
 528 5 identifies the terms that make the largest local contributions to the standard
 529 deviation of the annual mean temperature change based on the values shown in
 530 the third column of Fig. 1. *LW_{CLEAR}* and *CLOUD* are the most prominent terms,
 531 making the largest contributions in 34% and 29% of the global area. *CLOUD* is
 532 important particularly over lower-latitude oceans, but is rarely the largest
 533 uncertainty over land. The third most important term in terms of the area of
 534 domination is *SURF*, being largest in 20% of the global area and 27% of the
 535 oceans. *CONV* dominates the uncertainty in 10% of the world, including parts of
 536 the Greenland and Antarctic ice sheets. *SW_{ALBEDO}* has a share of 8%, ranking as
 537 first e.g. in eastern Siberia, Tibet and parts of the Southern Ocean. A broadly
 538 similar picture arises if the dominance is counted on a monthly rather than annual
 539 basis, although *CONV* tends to grow more important in this case (not shown).

540

541 Another aspect deserving discussion is the behaviour and physical interpretation
 542 of *CONV*. The first hypothesis that one can make is that *CONV* acts as diffusion-
 543 like process, smoothing out the spatial gradients in temperature change (Boer and
 544 Yu 2003). This could happen under unchanged atmospheric circulation as eddies
 545 spread out regional differences in temperature change, but the circulation might
 546 also adjust to transport more energy from areas of larger warming to areas of
 547 smaller warming. Alternatively, circulation changes not directly related to the
 548 distribution of the near-surface warming could play a more active role in shaping
 549 the temperature response.

550

551 While not precluding the second alternative, our results give much more evidence
552 for the first. First, Figs. 1a and 1s reveal that *CONV* frequently moderates the
553 local extremes and gradients of ΔT . Examples of this include the maximum in
554 warming over the Barents Sea and the minima over the northern North Atlantic
555 and the Southern Ocean, as well as the land-sea contrast of warming across
556 several coastlines. As expected for a diffusion-like process, this tendency for
557 compensation is stronger at small than large spatial scales. The global spatial
558 correlation between ΔT and *CONV* is only slightly negative (-0.22). However, it
559 becomes more negative (-0.43) when large-scale features are filtered out from
560 both fields by using a radius of 2000 km in the smoothing algorithm of Räisänen
561 and Ylhäisi (2011) and retaining the small-scale component.

562

563 Second, also consistent with the diffusion hypothesis, *CONV* more commonly
564 reduces than amplifies the intermodel differences of temperature change (Figs. 1t-
565 u). It is the only term in our decomposition that does this in a globally averaged
566 sense. However, this tendency is not globally uniform. The correlation between
567 *CONV* and ΔT is less regularly negative over land than oceans, and some land
568 areas (most notably Greenland and Antarctica) stand out with a substantial
569 positive correlation (Fig. 1t).

570

571 There are two probable reasons for the stronger anticorrelation between *CONV*
572 and ΔT over the oceans. First, the homogeneity of the ocean surface suggests a
573 tighter coupling between the surface and free tropospheric temperature changes
574 than is the case over more heterogeneous land areas. Large local gradients in the
575 surface air temperature change over the oceans would thus imply large gradients
576 in the change of tropospheric temperatures, which would be dynamically
577 unsustainable (Joshi et al. 2008). Second and perhaps more importantly, the sum
578 of the other temperature change components ($\Delta T_{REST} = \Delta T - CONV$) is much more
579 variable over ocean than land areas (Fig. 6a), essentially due to the larger surface
580 heat flux changes. Thus, there is a larger need for *CONV* to damp this variability
581 over the oceans.

582

583 A very strong anticorrelation prevails between *CONV* and ΔT_{REST} over most of the
584 oceans and also over some land areas (e.g. the Tibetan Plateau) where the
585 intermodel standard deviation of ΔT_{REST} is large (Fig. 6b). Conversely, areas with
586 a local minimum in the intermodel variation of ΔT_{REST} are commonly associated
587 with a weak or even positive correlation between *CONV* and ΔT_{REST} . Examples
588 include the Sahara – Arabian desert, Australia, and most notably Greenland and
589 Antarctica. For both Greenland and Antarctica, a striking contrast between modest
590 local intermodel variations in ΔT_{REST} and much larger variations over the
591 surrounding oceans suggests a remote control of *CONV*. A closer analysis reveals
592 a negative intermodel correlation of *CONV* between the Antarctic continent and
593 the Southern Ocean south of 60°S, and between Greenland and the northern North
594 Atlantic, particularly the Labrador Sea (not shown). This suggests that the local
595 warming over Antarctica and Greenland is substantially modulated by heat
596 transport from the surrounding oceans.

597

598 **5. Conclusions**

599 An energy balance decomposition was conducted for regional temperature
600 changes resulting from a gradual doubling of atmospheric CO₂ concentration in
601 16 CMIP5 models. A simple method was applied that links the surface air
602 temperature with the OLR by using an effective emissivity as a measure of the
603 atmospheric greenhouse effect. The method is rough in its treatment of LW
604 radiation, and can therefore not separate the effects of the direct CO₂ forcing and
605 the water vapour and lapse rate feedbacks from each other. SW radiative
606 processes are treated in more detail using the APRP method (Taylor et al. 2007).
607 Additionally, temperature changes due to the net surface flux and atmospheric
608 energy flux convergence changes are calculated. The method only requires two-
609 dimensional model output for the surface and the TOA, and is therefore easy to
610 apply to large ensembles of climate model simulations.

611

612 As expected, the bulk of the simulated warming was found to be due to an
613 enhanced clear-sky greenhouse effect. However, other components of the energy
614 balance substantially modify the temperature change, particularly its geographical,
615 seasonal and intermodel variations.

616

617 In particular, we found that changes in horizontal atmospheric energy flux
618 convergence mostly act as a diffusion-like process, thus reducing horizontal
619 gradients and intermodel differences in temperature change. This is the case
620 especially over the oceans, but energy convergence changes also typically
621 moderate the intermodel differences over those land areas where the net effect of
622 the other terms would result in a large intermodel variation of warming. However,
623 Greenland and Antarctica are important counter-examples. Intermodel variability
624 in the other energy balance terms is relatively modest over both Greenland and
625 Antarctica, but changes in the net surface energy flux and surface albedo make it
626 much larger over the surrounding sea areas. Changes in energy flux converge act
627 to spread the effects of this larger variability over Greenland and Antarctica, thus
628 amplifying intermodel differences in temperature change over these ice sheets.

629

630 Changes in the net surface heat flux reduce the multimodel global mean warming
631 by 0.4 K, in close agreement with the value found by DB08 for the CMIP3
632 models. Regionally, however, this contribution varies from a cooling of up to 10
633 K over the northern North Atlantic to a warming of 5 K over the Barents Sea. As
634 found earlier by Sejas et al. (2014a) by using the CFRAM method, changes in the
635 net surface energy flux are also crucially important for the seasonal cycle of the
636 warming over the Arctic Ocean.

637

638 Several studies have identified cloud feedbacks as the largest uncertainty in global
639 mean temperature change (Flato et al. 2013, Vial et al. 2013). Our analysis
640 extends this finding by indicating that clouds commonly make the largest
641 contribution to intermodel spread of regional temperature change over lower-
642 latitude oceans. However, changes in the clear-sky greenhouse effect (mainly over
643 land) and the net surface energy flux (mainly over extratropical oceans) also
644 dominate the intermodel spread in wide areas.

645

646 Our energy balance approach provides an alternative to the CFRAM method (Lu
647 and Cai 2009) and the surface energy budget method of IBH15. All these methods
648 give different perspectives on the energetic causes of regional temperature
649 change, but a direct comparison is difficult because of differences in the set of

processes that are explicitly included. The main advantages of the present method are (i) its relative simplicity and modest data needs, which are comparable with the IBH15 approach, and (ii) a partial although not perfect comparability with TOA radiation balance based studies of global mean temperature change, such as DB08. The most obvious weakness is the crude treatment of LW processes. This could be improved by an explicit modelling of LW radiative transfer, but at the cost of increasing the data needs and the complexity of the method.

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751

752 **Tables**

753

754 **Table 1.** *List of the variables used*

755

CMIP5 Acronym	Long name
tas	near-surface air (2-meter) temperature
rsdt	TOA incident SW radiation
rsut	TOA outgoing SW radiation
rlut	TOA outgoing LW radiation
rsds	surface downwelling SW radiation
rsus	surface upwelling SW radiation
rlds	surface downwelling LW radiation
rlus	surface upwelling LW radiation
hfls	surface upward latent heat flux
hfss	surface upward sensible heat flux
rsutcs	TOA outgoing clear-sky SW radiation
rlutcs	TOA outgoing clear-sky LW radiation
rsdscs	surface downwelling clear-sky SW radiation
rsuscs	surface upwelling clear-sky SW radiation
clt	total cloud fraction

756 *TOA = top of the atmosphere; SW = shortwave; LW = longwave*

757

758

759 **Table 2.** Mean values (columns 1-3) and mean absolute values (columns 4-6) of the terms
 760 in Eqs. (6)-(8) (unit: K)

761

	Global annual multimodel mean			Absolute value of local monthly means in individual models		
	All	Land	Sea	All	Land	Sea
ΔT	1.82	2.46	1.57	1.83	2.46	1.57
LW_{CLEAR}	2.07	2.27	1.99	2.07	2.27	1.99
LW_{CRE}	-0.39	-0.36	-0.41	0.69	0.64	0.72
SW_{IN}	-2×10^{-4}	-2×10^{-4}	-2×10^{-4}	7×10^{-4}	9×10^{-4}	7×10^{-4}
$SW_{CLEAR-ATM}$	0.21	0.26	0.19	0.22	0.27	0.21
SW_{ALBEDO}	0.19	0.28	0.16	0.22	0.34	0.17
SW_{CLOUD}	0.13	0.31	0.06	0.88	0.79	0.92
SW_{NL}	-2×10^{-4}	-4×10^{-5}	-3×10^{-4}	6×10^{-4}	5×10^{-4}	7×10^{-4}
$SURF$	-0.39	-0.03	-0.53	1.62	0.38	2.12
$CONV$	0.01	-0.28	0.12	1.74	0.97	2.05
ERR	-3×10^{-4}	-3×10^{-4}	-4×10^{-4}	8×10^{-4}	8×10^{-4}	9×10^{-4}
$CLOUD^*$	-0.26	-0.04	-0.35	0.75	0.60	0.81
$SURF + CONV$	-0.38	-0.30	-0.41	0.90	0.88	0.90

762 $*CLOUD = LW_{CRE} + SW_{CLOUD}$

763

764 **Table 3.** *The areas used in Figs. 3-4*

765

Area (acronym in Fig. 2b)	Definition
Arctic Ocean (AO)	Sea (75°-90°N)
Northern North Atlantic (NNA)	Sea (50°-60°N, 10°-50°W)
Tropical East Pacific (TEP)	Sea (5°S-5°N, 80°-180°W)
Southern Ocean (SO)	Sea (50°-65°S)
Siberia (SIB)	Land (50°-75°N, 80°-180°E)
Central Europe (CEU)	Land (45°-55°N, 0°-30°E)
Amazonia (AMZ)	Land (20°S-5°N, 80°-40°W)
Antarctica (ANT)	Land (65°-90°S)

766

767

768

Figures

769

770 **Fig. 1** Simulated annual mean temperature change ΔT (row 1) and its decomposition
 771 (rows 2-7). Left: multimodel means. Middle: intermodel correlation between the
 772 individual components and ΔT . Right: the standard deviation of ΔT and the contributions
 773 of the individual components to it. The global area means are given in the top-right
 774 corner of the panels

775

776 **Fig. 2** Intermonthly standard deviation of the multimodel mean temperature change (a)
 777 and the contributions of the six main temperature change components to it (c-h). Panel
 778 (b) shows the areas studied in Figs. 3-4, using the acronyms listed in Table 3

779

780 **Fig. 3.** Left: contributions of the six main temperature change components to multimodel
 781 mean monthly temperature changes in four oceanic regions (see the legend at the bottom;
 782 the total change is shown by the solid line). The last bar gives the annual mean values.
 783 Right: the corresponding contributions to intermodel standard deviation of temperature
 784 change, first evaluated at the grid box scale and then spatially averaged. See Fig. 2b and
 785 Table 3 for the definition of the areas

Fig. 4. As Fig. 3 but for four land areas

790

791

792 **Fig. 5.** The largest energy balance contributors to the standard deviation of annual mean
793 temperature change

794

795

796 **Fig. 6.** (a) Intermodel standard deviation of annual mean ΔT_{REST} . (b) Intermodel
797 correlation between CONV and ΔT_{REST} .