

# *Time-varying global energy budget since 1880 from a new reconstruction of ocean warming*

Article

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# 1 Time-varying global energy budget since 1880 2 from a new reconstruction of ocean warming

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9 The global energy budget is fundamental for understanding climate change. It states that  
10 the top-of-atmosphere imbalance between radiative forcing (which drives climate change)  
11 and radiative response (which resists the forcing) equals energy storage in Earth's heat  
12 reservoirs (i.e. the ocean, atmosphere, land and cryosphere). About 90% of Earth's energy  
13 imbalance is stored as heat content in the ocean interior, which is poorly sampled before  
14 1960. Here, we reconstruct Earth's energy imbalance since 1880 by inferring subsurface  
15 ocean warming from surface observations via a Green's function approach. Our estimate of  
16 Earth's energy imbalance is consistent with the current best estimates of radiative forcing and  
17 radiative response during 1880–2020. The consistency is improved in this study compared to  
18 previous ones. We find two distinct phases in the global energy budget. In 1880–1980, Earth's  
19 energy imbalance closely followed the radiative forcing. After 1980, however, Earth's energy  
20 imbalance increased at a slower rate than the forcing; in 2000–2020, the imbalance amounted  
21 to less than 50% of the forcing. In simulations of historical climate change, the model-mean  
22 energy imbalance is consistent with observations within uncertainties, but individual models  
23 with a "weak" response to anthropogenic aerosol agree better with observations than those  
24 with a "strong" response. Because the global energy budget before and after 1980 imply very  
25 different global warming in the future, further studies are required to better understand the  
26 cause of this historical variation.

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28 global energy budget | ocean heat uptake | radiative forcing | radiative response | climate model

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31 The global energy budget is a fundamental aspect of Earth's climate system.  
32 Human-induced changes in the atmospheric composition have resulted in a  
33 positive radiative forcing  $F$  at the top of the atmosphere (TOA) since 1750, which  
34 warms the Earth's surface (1, 2). A warmer Earth tends to radiate more energy to  
35 space, counteracting the effect of  $F$ ; this is referred to as Earth's radiative response  
36  $R$  (3). The imbalance between  $F$  and  $R$  determines the net TOA radiative flux,  
37 which must be equal to  $N$ , the change in Earth's heat storage (4), as required by  
38 energy conservation, i.e.  $N = F + R$ . Reproducing the historical global energy  
39 budget is a basic test for climate models. The energy budget itself provides a useful  
40 constraint on the Earth's equilibrium temperature response to CO<sub>2</sub> forcing (3, 5, 6).

41 The global energy budget has been analysed using observation-based data (2, 7–  
42 9). Earth's energy imbalance  $N$  can be derived from observed changes in Earth's  
43 heat reservoirs. During 1971–2020, observations suggest that about 90% of  $N$  is  
44 stored in the ocean, followed by 6% in the ground, 4% in the cryosphere and 1% in  
45 the atmosphere (4, 10). From 2000 onwards, satellite radiometers have provided  
46 a direct estimate of  $N$ , which agrees well with the  $N$  inferred from Earth's heat  
47 storage (11). In contrast, the radiative forcing  $F$  and the radiative response  $R$  are  
48 not observable directly.  $F$  can be derived from radiative transfer models forced  
49 with observed changes in the atmospheric composition.  $R$  can be calculated as  
50 the product of the observed global surface warming  $T$  and the climate feedback  
51 parameter  $\alpha$ , with the caveat that  $\alpha$  exhibits a large uncertainty in the literature  
52 (2). The fifth assessment report of the Intergovernmental Panel on Climate Change  
53 (IPCC) demonstrated that the global energy budget is closed within uncertainties  
54 during 1971–2010 (8). The IPCC sixth assessment report extended this analysis to  
55 2018 with improved consistency (2).

56 Global ocean heat content (OHC) change (unit: J) is an important measure of  
57 Earth's energy imbalance  $N$  (unit: W m<sup>-2</sup>) stored in the ocean, i.e. dOHC/dt ≈  
58 90% ×  $N$  ×  $A$ , where  $A$  is the Earth's surface area. Conventionally, OHC estimates  
59 are derived from mapping in-situ temperature data to a global ocean grid ("in-situ"  
60 means that data is collected at the point where the instrument is located). The  
61 historical temperature data are sparse in space and time and suffer from systematic  
62 instrument biases, especially during early periods (12, 13). This has prevented an

## 71 Significance Statement

72 The global energy budget is essential for understanding human-induced climate change. It states  
73 that energy storage in Earth's heat reservoirs is determined by the top-of-atmosphere imbalance between  
74 radiative forcing (which drives climate change) and radiative response (which resists the forcing).  
75 Here, we infer Earth's energy imbalance from a new reconstruction of ocean warming. This improves  
76 the closure of the global energy budget for 1880–2020 compared to previous studies. We find two  
77 distinct phases in the global energy budget. Earth's energy imbalance closely followed the forcing in 1880–  
78 1980, but was less than half of the forcing in 2000–2020. That is: the fraction of forcing that went into  
79 heating the Earth has been smaller in recent decades than in earlier periods.

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125 Q.W. and J.M.G. designed research; Q.W. performed research; L.Z. and S.K. contributed new analytic tools;  
126 Q.W., J.M.G., L.Z. and S.K. wrote the paper.

127 The authors declare no competing interests.

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125 estimate of global OHC change before 1960, which leaves a  
126 gap in the global energy budget record. Since 2006, Argo  
127 autonomous floats have provided high-quality temperature  
128 measurements with unprecedented spatial coverage of the  
129 global ocean, greatly improving the accuracy of the OHC  
130 estimate (14).

131 Recently, methods have been developed for reconstructing  
132 OHC before 1960 (15, 16). In particular, Zanna et al. (16)  
133 estimated OHC change starting from 1870 by propagating  
134 observed sea surface temperatures (SSTs) into the ocean  
135 interior using a Green's function (GF) approach (17–19).

136 In this study, we derive Earth's energy imbalance  $N$  since  
137 1880 from an OHC reconstruction based on an improved GF  
138 approach. Our estimate of Earth's energy imbalance  $N$  agrees  
139 with the sum of radiative forcing  $F$  and radiative response  $R$   
140 derived from independent sources. This allows us to present  
141 a continuous record of the global energy budget starting from  
142 1880 using observation-based data.

#### 143 **Green's Function Method in a Nutshell**

144 In this section, we explain the procedure of computing OHC  
145 change and associated uncertainties using the GF method.  
146 The GF method is detailed in Materials and Methods (MM)  
147 **A** and contrasted with the in-situ method in Table 1.

148 Ocean heat uptake (OHU) is caused by surplus heat being  
149 added to the ocean surface via air-sea fluxes and then carried  
150 to depth by ocean transport (advection and mixing). The  
151 GF method exploits this fact and attempts to reconstruct  
152 ocean warming at depth from its surface signature. For a  
153 given interior location, the GF estimate of ocean warming  
154 can be written as

$$155 \Theta_e(t) = \sum_{\mathbf{r}_s} \sum_{t_s < t} G(\mathbf{r}_s, t - t_s) \Theta_e^s(\mathbf{r}_s, t_s), \quad [1]$$

156 where  $\Theta_e$  and  $\Theta_e^s$  are the interior and surface ocean temperature  
157 change relative to a pre-industrial state, respectively,  $t$   
158 and  $t_s$  their corresponding time variables, and  $\mathbf{r}_s$  (longitude  
159 and latitude) the location vector of  $\Theta_e^s$ . Basically,  $\Theta_e(t)$   
160 is reconstructed as the weighted sum of the  $\Theta_e^s$  values  
161 everywhere at the ocean surface and any time prior to  $t$ ,  
162 with the GF kernel  $G$  providing the weightings. Physically,  
163 the GF kernel partitions a water parcel at a given location  
164 according to the time and place of its last surface contact; i.e.  
165 the joint water-mass and transit-time distribution (17, 19).  
166 Importantly, the GF method does not rely on subsurface  
167 temperature measurements, in contrast to the in-situ method  
168 (Table 1).

169 The GF method requires two inputs: the GF kernel  $G$  and  
170 the boundary condition  $\Theta_e^s$ . These are derived as follows.

171 The GF kernel  $G$  is derived from observations of ocean  
172 transient tracers CFC-11 and CFC-12 via an inverse approach,  
173 using simulations of  $G$  as an initial guess (18, 20) (MM **B**).  
174 This method exploits the fact that the GF is an intrinsic  
175 property of ocean circulation (advection and mixing) and  
176 thus applies to any conservative tracer in the ocean.

177 The GF derived here has two caveats. First, CFC  
178 observations only constrain  $G$  for lead times less than  $\sim 50$   
179 years because CFC emissions started in the 1950s. We expect  
180 this caveat has little impact on our result because we focus on  
181 historical climate change, which is dominated by responses on  
182 multi-decadal timescales (21). While tracers such as argon-39

183 can further constrain  $G$  on centennial timescales, very few  
184 measurements are available (22). Second, we assume  $G$  is  
185 stationary in time because observations are insufficient to  
186 constrain its time evolution. That is, we ignore potential  
187 changes in ocean circulation under global warming, which may  
188 lead to a roughly 10% overestimate of global OHC increase  
189 between 2008 and 1980 (16, 23).

190 Technically, the boundary condition  $\Theta_e^s$  should be surface  
191 excess temperature (23). By that we mean the part of  
192 SST change that originates at the surface, excluding SST  
193 redistribution due to changes in ocean circulation. Because  $\Theta_e^s$   
194 is not observable, we construct it by combining observations  
195 and model simulations (MM **C**). We separate  $\Theta_e^s$  into the  
196 global mean and regional anomalies. The former is derived  
197 from the global-mean SST change in observations, while  
198 the latter are diagnosed from climate model simulations.  
199 Deriving the global-mean  $\Theta_e^s$  from the global-mean SST  
200 change introduces a cold bias because the latter contains  
201 a weak cooling signal from SST redistribution (MM **C**). This  
202 leads to an underestimate of global OHC increase, which  
203 partly compensates the overestimate due to  $G$  discussed  
204 earlier.

205 We differ from Zanna et al. (16) in that we impose  
206 observational constraints on the GF kernel and we use  
207 a different construction of boundary conditions (Table 1).  
208 These changes bring the GF OHC estimate closer to the  
209 in-situ estimate during the Argo period (shown later).

210 We quantify the uncertainty of the GF OHC estimate  
211 using sets of alternative estimates of the GF kernel  $G$  and the  
212 boundary condition  $\Theta_e^s$ . We derive twelve  $G$  estimates from  
213 three first-guess solutions and four realisations of ocean tracer  
214 observations (MM **B**). We also derive six  $\Theta_e^s$  estimates from  
215 three observational SST datasets and two excess temperature  
216 simulations (MM **C**). In total, our sensitivity test produces  
217  $12 \times 6 = 72$  members of the GF OHC estimate. Results are  
218 reported as the ensemble mean  $\pm 2 \times$  standard deviation  
219 ( $\sigma$ ). Uncertainties from other studies are converted to the  
220  $2\sigma$ -range when discussed here, assuming a Gaussian error  
221 distribution.

222 SST datasets have two potential biases in early periods:  
223 a cold excursion in 1900–1920 and the World War 2 warm  
224 anomaly in 1939–1945 (24–28). To examine how these biases  
225 affect the GF OHC estimate qualitatively, we apply the  
226 following simple corrections. We remove the 1900–1920 cold  
227 excursion by setting SST anomaly in that period to its 1880–  
228 1900 time mean, and remove the 1939–1945 warm anomaly  
229 by scaling down SST anomaly in that period by 50% (i.e. a  
230 reduction of 0.15 K). In both case, the anomaly is relative  
231 to the 1870–1880 time mean. The bias corrections and the  
232 resulting differences in our OHC estimate are shown in Fig.  
233 S5. In what follows, we focus on the results with the bias  
234 corrections and discuss the differences that arise without  
235 them when relevant.

#### 236 **Global Ocean Heat Uptake**

237 In this section, we compare the GF OHC estimate of this  
238 study against (i) the in-situ OHC estimates of Cheng (31),  
239 Levitus (32), Ishii (33) and Bagnell (34) and (ii) the GF  
240 OHC estimates of Zanna (16) and Gebbie (15). The results  
241 of Cheng, Levitus, Ishii are shown in Fig. 1, while those of  
242 Gebbie and Zanna are shown in Fig. S5. The GF OHC  
243 estimate is  $0.10 \pm 0.02$  W m<sup>-2</sup> (Table 1), which is  
244 consistent with the in-situ estimates. The GF OHC estimate  
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249 **Table 1. A comparison of different methods for estimating ocean heat uptake**

250 Method	251 Green's function $G$	252 boundary condition $\Theta_e^s$	253 subsurface temperature	254 measurements
255 This study	256 observation-based, constrained by CFC-11 257 and CFC-12 in the ocean, initial guesses are 258 derived from ocean models	259 SST anomaly relative to 1870–1880 + corrections 260 for a) excess temperature, b) the 1900– 261 1920 cold excursion, and c) the World War 2 262 warm anomaly	263 not used	264
265 Zanna (16)	266 derived from an ocean state estimate (29)	267 SST anomaly relative to 1870–1880	268 not used	269
270 Gebbie (15)	271 observation-based, inferred from climatology 272 of ocean tracers (30)	273 SST anomaly relative to 0015	274 not used	275
276 In situ	277 N/A	278 N/A	279 XBT, CTD, Argo, etc.	280

281 Bagnell and Gebbie are shown separately in Fig. S6 for clarity.  
282 All of them are integrated over the upper 2000 m.

283 **Ocean Heat Content Change.** The GF OHC estimate of this  
284 study exhibits an upward trajectory during the historical  
285 period (Fig. 1a). The global OHC change between 2006–2015  
286 and 1956–1965 is  $265 \pm 142$  ZJ from our estimate (black dot,  
287 Fig. 1b, leftmost column),  $230 \pm 38$  ZJ from Levitus (blue dot)  
288 and  $258 \pm 54$  ZJ from Cheng (green dot), for instance; other  
289 OHC estimates are consistent with those numbers within  
290 uncertainties (Figs. 1b and S6b). 1956–1965 is a common  
291 starting period for the in-situ datasets.

292 Different choices of SST dataset and excess temperature  
293 estimate (MM C) result in  $\pm 110$  ZJ ( $\pm 2\sigma$ ) spread in the  
294 GF OHC change between 2006–2015 and 1956–1965 (Fig. 1b,  
295 rightmost column), while the corresponding spread due to  
296 uncertainties in the GF kernel is  $\pm 85$  ZJ (Fig. 1b, middle  
297 column). The latter arises because existing observations are  
298 insufficient to fully constrain the GF kernel.

299 **Ocean Heat Uptake Rate.** We evaluate the rate of OHU (i.e.  
300 its time-derivative) using linear trends derived from a 20-  
301 year moving window, and express the result per unit area  
302 of Earth surface. The choice of 20 years for the window is  
303 a compromise between filtering out the unforced variability  
304 and resolving the time evolution. Altering the window span  
305 from 20 years to 10, 15 or 30 years does not affect the time  
306 evolution of the OHU rate in Fig. 1 very much, although  
307 a longer window does give a smoother timeseries (Fig. S7).  
308 The uncertainty of the in-situ OHU rate has been assessed  
309 in the literature using different methods, as summarised in  
310 Meyssignac et al. (10) table 1. We use the 1993–2008 error  
311 of  $\pm 0.13$  W m $^{-2}$  in Lyman et al. (35) as the  $2\sigma$ -error of the  
312 in-situ OHU rate, because it accounts for a comprehensive  
313 list of uncertainties. In addition, we assume that the in-situ  
314 error of  $\pm 0.13$  W m $^{-2}$  is constant in time. We note that  
315 this choice likely underestimates the in-situ error before the  
316 1990s (36), but using a larger in-situ error does not affect our  
317 discussion below.

318 The OHU rate has exhibited a robust acceleration since the  
319 1960s (36–38). The GF OHU rate (this study) increased from  
320  $0.12 \pm 0.23$  W m $^{-2}$  in 1960–1980 to  $0.63 \pm 0.23$  W m $^{-2}$  in 2000–  
321 2020 (Fig. 1c, black line), i.e. a linear trend of  $0.12 \pm 0.07$   
322 W m $^{-2}$  per decade over 1960–2020. The Cheng estimate  
323 shows a similar OHU rate increase over the same period,  
324 from  $0.10 \pm 0.13$  W m $^{-2}$  to  $0.60 \pm 0.13$  W m $^{-2}$ . The in-situ  
325 OHU rates may be underestimated before 1990 because of  
326 linear vertical interpolation and the XBT data biases (39).  
327 The in-situ OHU rates differ from one another regarding

328 detailed time evolution, but the difference is not significant  
329 considering their uncertainties ( $\pm 0.13$  W m $^{-2}$ ). The Zanna  
330 OHU rate exhibits a weaker upward trend than the in-situ  
331 estimates in 1980–2020, while the Gebbie OHU rate exhibits  
332 a downward trend after 1990 (Figs. 1c and S6c). Note that  
333 the Gebbie estimate was built to study OHU on a much  
334 longer timescale than the one focused here (past 2000 years  
335 vs. past 140 years).

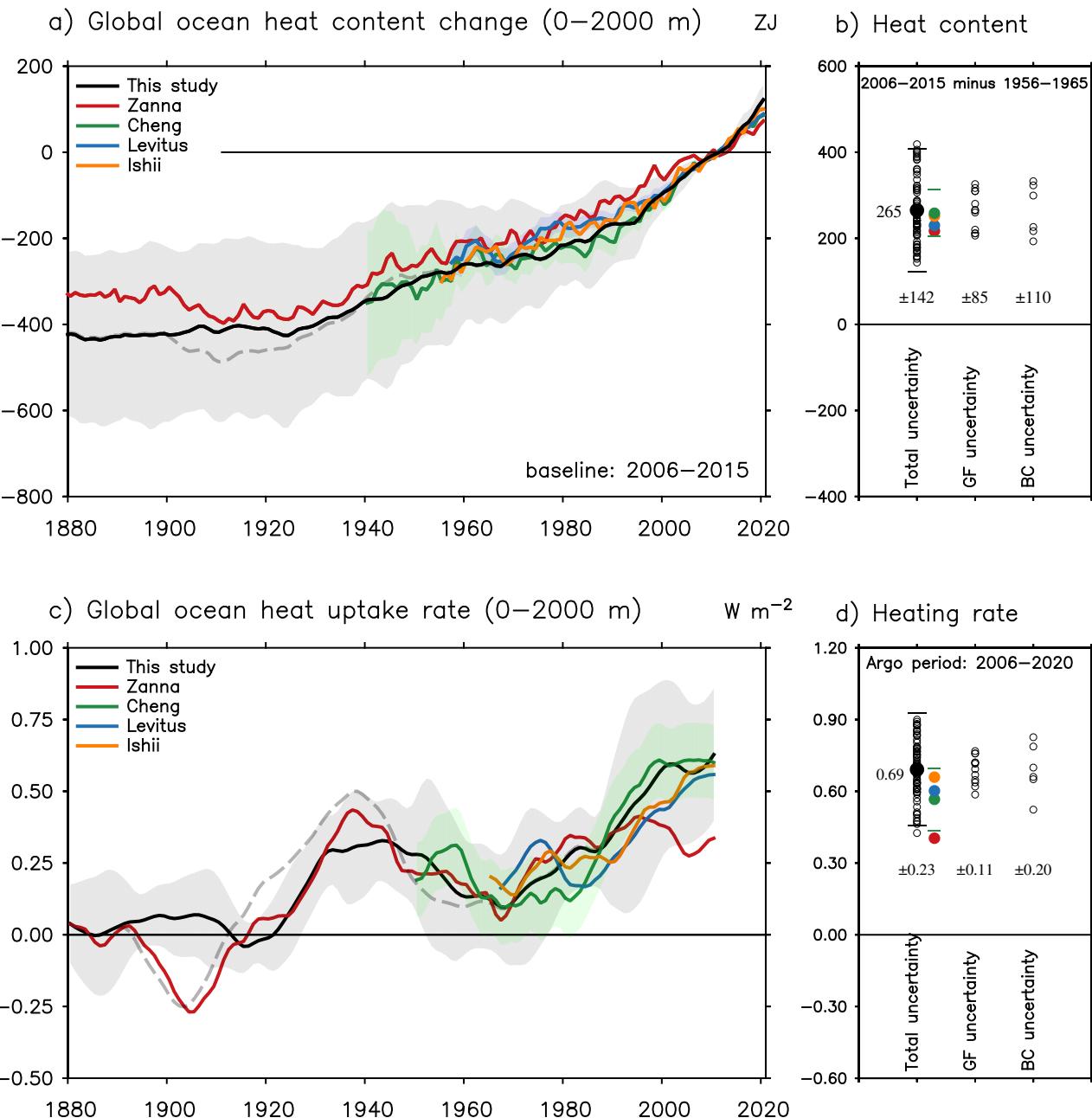
336 Prior to 1960, the GF estimate (this study) suggests that  
337 the OHU rate was accelerating in 1920–1940 (central years),  
338 and decelerating in 1950–1970 (Fig. 1c, black line). The  
339 transition between the two episodes coincides with the ramp-  
340 up of anthropogenic aerosol emission (40, 41).

341 The potential biases in SST datasets have a marked impact  
342 on the GF OHU rate prior to 1960 (Fig. 1c compare the  
343 black solid and dashed line). Removing the cold excursion in  
344 1900–1920 changes the OHU rate in 1900 from  $-0.21 \pm 0.19$  to  
345  $0.06 \pm 0.12$  W m $^{-2}$ . Halving the World War 2 warm anomaly  
346 reduces the OHU rate in 1940 from  $0.47 \pm 0.19$  to  $0.31 \pm 0.17$  W  
347 m $^{-2}$ . Whether the above bias corrections can be justified is  
348 examined later through the lens of the global energy budget.  
349 The Zanna and Gebbie estimates both show a reversal in  
350 the trend of OHU rate between 1920–1940 and 1950–1970,  
351 similar to our estimate (Fig. S6c). However, the peak OHU  
352 rate at 1940 is higher in their estimates compared to ours;  
353 this difference is potentially related to the World War 2 SST  
354 biases discussed above.

355 **The Argo Era.** We compare the OHU rate from different  
356 estimates for 2006–2020, when the Argo floats have achieved  
357 a near-global coverage in 0–2000 m. During 2006–2020, the  
358 GF estimate (this study) suggests an OHU rate of  $0.69 \pm 0.23$   
359 W m $^{-2}$ , consistent with the in-situ estimates of  $0.57 \pm 0.13$ ,  
360  $0.60 \pm 0.13$ ,  $0.66 \pm 0.13$  and  $0.59 \pm 0.13$  W m $^{-2}$  from Cheng,  
361 Levitus, Ishii and Bagnell, respectively (Figs. 1d and S6d).  
362 Different choices of SST dataset and excess temperature  
363 estimate (MM C) result in  $\pm 0.20$  W m $^{-2}$  spread in the GF  
364 OHU rate, while uncertainties in the GF kernel lead to  $\pm 0.11$   
365 W m $^{-2}$  spread (Fig. 1d). Note that the GF OHC uncertainty  
366 is no smaller during the Argo era than in earlier periods (Fig.  
367 1c grey shading). This is because the GF method uses the  
368 full SST history to infer OHC change (Eq. 1), i.e. the OHU  
369 rate at any time is affected by SSTs at all previous times,  
370 including their uncertainties. During the Argo era, the Zanna  
371 OHU rate sits near the lower limit of our estimate (Fig. 1d);  
372 this difference is mostly due to our use of excess temperature  
373 for the boundary condition (Fig. S8). The Gebbie estimate is  
374 excluded for this comparison because it is not available after  
375 2015.

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**Fig. 1.** Global ocean heat uptake during the historical period (0–2000 m). Different estimates are color coded. “This study” and “Zanna” are based on the Green’s function (GF) method; the other three are in-situ estimates. a) time evolution of ocean heat content change relative to the 2006–2015 baseline ( $1 \text{ ZJ} = 10^{21} \text{ J}$ ). b) ocean heat content change between 2006–2015 and 1956–1965. c) time evolution of ocean heat uptake rate per unit area of Earth’s surface. d) ocean heat uptake rate during the Argo period (2006–2020). In (c), the rate of change is computed as linear trends of a 20-year running window. In (b) and (d), the spread of our GF estimate is decomposed into that due to the GF kernel  $G$  and that due to the boundary condition  $\Theta_e^*$ ; individual members are shown as circles. Shading and error bars indicate the  $2\sigma$ -error. In (a) and (c), the dashed black line is the same as the solid black line, except that it is computed from SST datasets without bias corrections.

## 497 Global Energy Budget

498 In this section, we analyse the global energy budget since  
499 1880 using our GF OHU reconstruction. Methods for deriving  
500 the energy budget terms and associated uncertainties are  
501 summarised in Table 2. All the energy budget terms are  
502 shown as anomalies with respect to the 1870–1880 time mean.  
503

504 **Observation-Based Data.** We derive Earth’s energy imbalance  
505  $N$  from our GF OHU reconstruction, because heating rates  
506 in other Earth system components are poorly known prior to  
507 1960. We do not use the GF estimate for OHU below 2000 m  
508 because the GF kernel is poorly constrained by observations  
509 at those depths (SI Appendix 1C). We obtain the full-depth  
510 OHU rate by combining: (i) the GF OHU rate for 0–2000 m  
511 depth with (ii)  $0.07 \pm 0.04 \text{ W m}^{-2}$  from Johnson et al. (42)  
512 for below 2000 m; the latter only applies to the 1980–2020  
513 period. Earth’s heat inventory in recent decades (e.g. 1971–  
514 2020) suggests that OHU accounts for  $90 \pm 6\%$  of  $N$  (2, 4, 8).  
515 We therefore divide the full-depth OHU rate by  $90 \pm 6\%$  to  
516 derive  $N$ . Note that, due to insufficient observations, we  
517 assume that: 1) OHU below 2000 m is negligible before 1980  
518 and 2) the fraction of  $N$  stored in the ocean is constant in  
519 time. These assumptions should be revisited in the future  
520 when extended records of Earth’s heat inventory become  
521 available.

522 We derive the radiative forcing  $F$  and the radiative  
523 response  $R$  using methods that are independent of the global  
524 energy budget, that is  $N = F + R$  is not guaranteed by  
525 construction.  $F$  is obtained from the assessed range in the  
526 IPCC sixth assessment report (AR6) (2), which combines lines  
527 of evidence from models and observations.  $R$  is computed  
528 by two methods. The first method ( $R_{\text{simple}}$ ) considers  $R$   
529 due to the global-mean surface warming  $T$  and a constant  
530 climate feedback parameter  $\alpha$  (i.e.  $R_{\text{simple}} = \alpha T$ ). The mean  
531 and  $2\sigma$  of  $T$  are derived from the HadCRUT5 dataset (43)  
532 using its 200 ensemble members. The feedback parameter  
533  $\alpha = -1.16 \pm 0.79 \text{ W m}^{-2} \text{ K}^{-1}$  is obtained from the assessed  
534 range in the IPCC AR6 (2). The uncertainty of  $R_{\text{simple}}$  comes  
535 from propagation of error. The second method ( $R_{\text{spatial}}$ )  
536 considers  $R$  due to spatially-varying SST and sea ice changes  
537 in observations using 3D atmosphere general circulation  
538 models. The Cloud Feedback Model Intercomparison project  
539 (44) specifically designed an experiment (amip-piForcing)  
540 to diagnose  $R_{\text{spatial}}$ ; we use the results of eight atmosphere  
541 models to compute the mean and  $2\sigma$  of  $R_{\text{spatial}}$  (MM E).

542 The energy imbalance  $N$  is derived from the 20-year  
543 running window used to compute the OHU rate. For  
544 consistency, the radiative forcing  $F$  and radiative response  
545  $R$  are smoothed by a 20-year running mean. Note that this  
546 makes dips in  $F$  after volcanic eruptions less obvious.  
547

548 **Budget Closure.** Our estimate of Earth’s energy imbalance  $N$   
549 (Fig. 2a blue line) agrees with the sum of the TOA radiative  
550 forcing  $F$  and radiative response  $R$  within uncertainties all  
551 the time since 1880, indicating a closure of the global energy  
552 budget. This conclusion is robust regardless of (i) the choice  
553 of the  $R$  estimate (Fig. 2a black and gray line) and (ii) whether  
554 OHU is derived from SST with bias corrections (compare  
555 Figs. 2a with S9a). We also use the Zanna and Gebbie  
556 OHC estimate to derive  $N$  estimates following the method  
557 described above. The resulting  $N$  estimates agree with  $F + R$   
558

559 during 1880–2020 when considering uncertainties estimated  
560 in this study (Fig. S10).

561 **Central Estimate.** We compare  $N$  against  $F + R$  for the central  
562 estimate. Our estimate of  $N$  closely follows  $F + R_{\text{spatial}}$  (Fig.  
563 2a blue and black line); both feature a weak positive trend  
564 before 1950 and a stronger one after 1980. The root-mean-  
565 squared error between them is  $0.14 \text{ W m}^{-2}$  over 1880–2014.  
566 In comparison, the Zanna and Gebbie  $N$  estimates do not  
567 track  $F + R_{\text{spatial}}$  as closely as our estimate does; both of them  
568 suggest a strong decadal variability in  $N$  during 1900–1960,  
569 which is not seen in  $F + R_{\text{spatial}}$  (Fig. S10). The root-mean-  
570 squared error between  $N$  and  $F + R_{\text{spatial}}$  is  $0.17$  and  $0.28 \text{ W m}^{-2}$   
571 for the Zanna and Gebbie estimates, respectively.  
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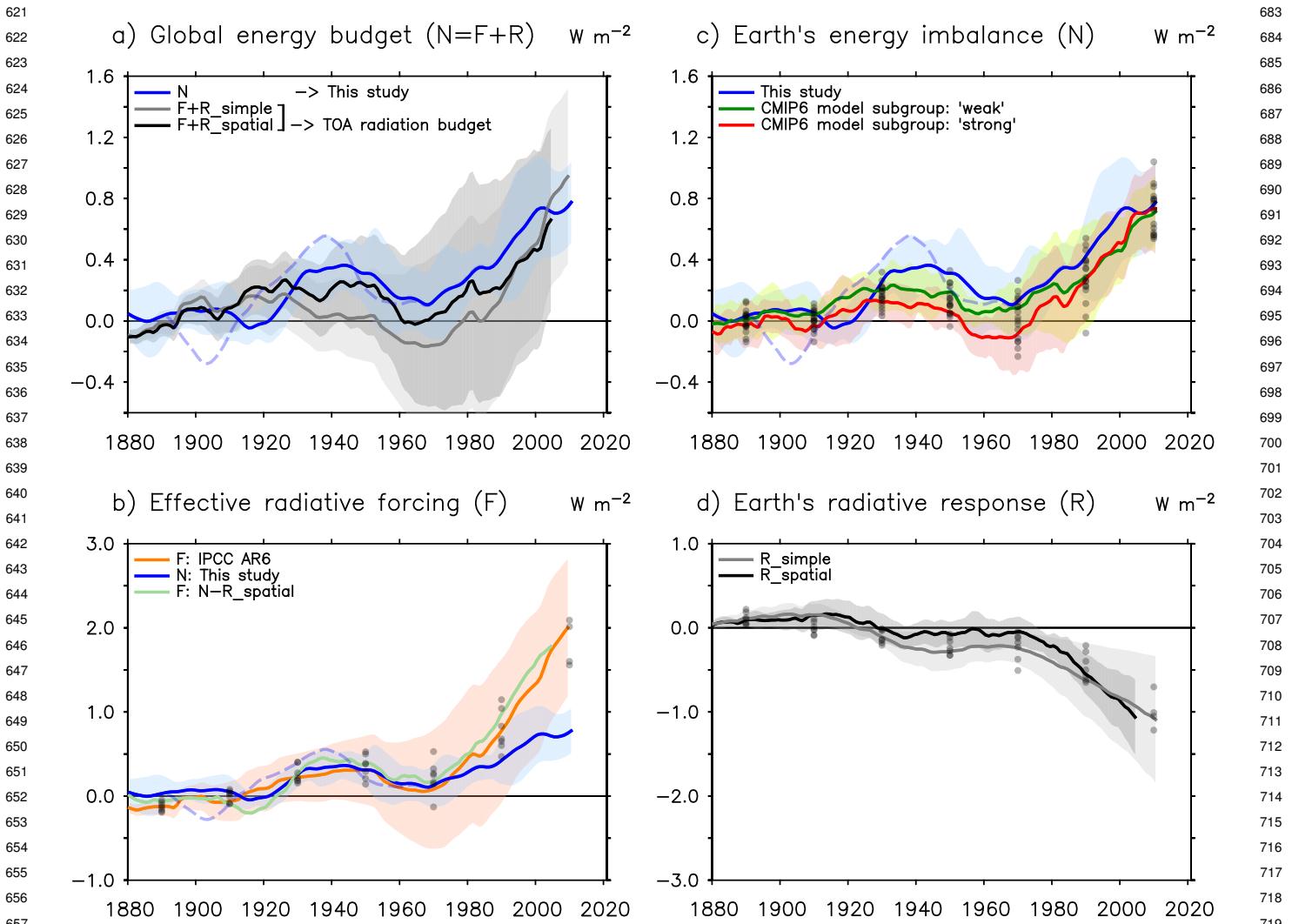
573 Our estimate of  $N$  (Fig. 2a blue line) agrees better with  $F + R_{\text{spatial}}$   
574 (black line) than with  $F + R_{\text{simple}}$  (grey line), wherein  
575  $R_{\text{simple}}$  and  $R_{\text{spatial}}$  are derived from  $R = \alpha T$  and atmosphere  
576 models, respectively. This suggests that atmosphere models  
577 provide a more realistic estimate of  $R$  than the simple model  
578 with a constant  $\alpha$ . Recent studies have shown that surface  
579 warming at different locations affects  $R$  differently (45, 46);  
580 this mechanism is resolved in  $R_{\text{spatial}}$ , but not in  $R_{\text{simple}}$ .  
581

582 **Distinct Phases.** We find two distinct phases in the global  
583 energy budget. Before 1980, the evolution of Earth’s energy  
584 imbalance  $N$  (Fig. 2b blue line) closely followed that of the  
585 radiative forcing  $F$  (orange line); the two are not significantly  
586 different, considering their uncertainties. Deriving  $N$  from  
587 SST datasets without bias corrections does not alter this  
588 finding (compare Figs. 2b with S9b). After 1980, however,  
589 the energy imbalance  $N$  started to increase at a slower rate  
590 than the radiative forcing  $F$ , and the two became significantly  
591 different in 2010 (Fig. 2b).  $N/F$  measures the fraction of the  
592 forcing that went into heating the Earth. The  $N/F$  ratio is  
593 close to unity before 1980, but gradually decreases after that,  
594 reaching  $38 \pm 15\%$  in 2010 (Table 2). Note that  $N/F$  is highly  
595 uncertain before 1980 because  $F$  is not significantly different  
596 from zero during that time.  
597

598 **Reduced Historical Forcing Uncertainty.** We infer the radiative  
599 forcing  $F$  as the difference between  $N$  and  $R$  following  
600 previous studies (7, 47), and compare the result against the  
601  $F$  estimate in the IPCC AR6. The uncertainty of the inferred  
602  $F$  is derived via propagation of error.  
603

604 We focus on the 1960–1980 period, for which the  $F$  in  
605 the IPCC AR6 has a large uncertainty ( $0.08 \pm 0.71 \text{ W m}^{-2}$ ). The  
606 inferred  $F$  range is  $0.38 \pm 0.29 \text{ W m}^{-2}$  from  $N - R_{\text{simple}}$  and  
607  $0.17 \pm 0.29 \text{ W m}^{-2}$  from  $N - R_{\text{spatial}}$ . In both cases, the lower  
608 bound of the inferred  $F$  is substantially less negative than the  
609 IPCC AR6 estimate, and the range is about 60% narrower.  
610 This uncertainty reduction is comparable to that found by  
611 Andrews and Forster (47), who consider the 2005–2015 period.  
612 The inferred  $F$  also has a smaller uncertainty than the  $F$  of  
613 IPCC AR6 in 1920–1940 and 2000–2020 (Table 2), but the  
614 improvement is less pronounced than in 1960–1980.  
615

616 **Pre-1880 Period.** Our global energy budget analysis assumes  
617 that Earth’s climate is near equilibrium in 1870–1880,  
618 consistent with the IPCC AR6 (48). However, some studies  
619 argue that an earlier baseline should be used because  $\text{CO}_2$   
620 concentration increases started before 1870 (49). As a  
621 sensitivity test, we evaluate the global energy budget for  
622



**Fig. 2.** Evaluating the global energy budget since 1880 using observation-based data. The three components examined here are: Earth's energy imbalance  $N$ , the radiative forcing  $F$ , and Earth's radiative response  $R$ . Methods for deriving  $N$ ,  $F$  and  $R$  are summarised in Table 2. In all panels, shading indicates the  $2\sigma$ -error.  $F$  and  $R$  are both smoothed by a 20-year running mean. The  $N$  estimate of this study is shown as the blue line in (a-c), the same in each panel. The  $N$  estimate in the dashed blue line is the same as that in the solid blue line, except that it is computed from SST datasets without bias corrections. In (b-d), simulations from climate models are shown as pale dots, plotted every 20 years for clarity; different panels contain different numbers of model results due to data availability. In (c), the models are split into those with a "weak" and "strong" response to anthropogenic aerosol forcing, respectively.

1700–1880 using surface temperature change reconstructed from palaeoclimate records (MM D). The result shows that Earth's energy imbalance  $N$  is dominated by responses to volcanic eruptions in 1700–1800, without a clear sign of long-term increase (Fig. S11). In 1860–1880, the energy imbalance  $N$  is close to zero, consistent with our choice of the reference period, i.e. 1870–1880.

### Evaluating Climate Model Simulations

In this section, we evaluate the radiative forcing  $F$ , the radiative response  $R$  and the energy imbalance  $N$  simulated in 17 climate models (i.e. atmosphere–ocean general circulation models) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) (50) against the observation-based estimates described in the previous section. The energy imbalance  $N$  is available for all 17 models up to 2020, while the radiative forcing  $F$  and radiative response  $R$  are available

for 7 models only (up to 2014 in 3 models and 2020 in 4) because they are low priority outputs. We focus on the 1920–1940 and 2000–2020 periods, which sample distinct phases in the observed energy budget. Model results are shown as pale dots in Figs. 2b-d and individually in Figs. S12–15. Methods for deriving the global energy budget from climate models are described in MM E and summarised in Tables 2 and 3. All model results are smoothed by a 20-year running mean to be consistent with the observation-based estimates.

The CMIP6 simulations of  $F$ ,  $R$  and  $N$  agree with the observation-based estimates within the  $2\sigma$  inter-model spread (Figs. 2b-d and Table 2). Notably, CMIP6 models tend to simulate a more negative  $R$  than  $R_{\text{spatial}}$  in 1920–1940 ( $-0.10$  vs.  $0.00 \text{ W m}^{-2}$ ) and a less positive  $F$  than the  $F$  of IPCC AR6 in 2000–2020 ( $1.71$  vs.  $2.02 \text{ W m}^{-2}$ ) (Table 2).

We next compare the CMIP6 simulations of  $F$ ,  $R$  and  $N$  in individual models against the observation-based estimates.

745 **Table 2.** Radiative forcing  $F$ , radiative response  $R$  and Earth's energy imbalance  $N$  from observation-based estimates and climate model  
 746 simulations. The rate of ocean heat uptake is denoted as “dOHC/dt”. All quantities are in units of  $\text{W m}^{-2}$  of Earth's surface area. The 1920–1940  
 747 and 2000–2020 averages are selected to demonstrate two distinct phases in the global energy budget. The two  $R$  estimates,  $R_{\text{simple}}$  and  $R_{\text{spatial}}$ ,  
 748 are both computed from observed surface warming; the difference is that  $R_{\text{simple}}$  only considers the global-mean warming, whereas  $R_{\text{spatial}}$   
 749 considers the spatially-varying warming using 3D atmosphere models. For climate model simulations, the data source shows the experiment  
 750 name, with the ensemble size denoted in parentheses. The  $2\sigma$ -error is derived from various sources/approaches for observation-based  
 751 estimates, but it is always computed from the inter-model spread for climate model simulations. Different climate model experiments are  
 752 contrasted in Table 3.

Observation-based estimates				
Variable	1920–1940	2000–2020	Data source	Uncertainty
dOHC/dt 0–2000 m	$0.25 \pm 0.13$	$0.63 \pm 0.23$	GF method	perturbation of inputs
dOHC/dt >2000 m	negligible	$0.07 \pm 0.04$	Johnson et al. (42)	Johnson et al. (42)
dOHC/dt full depth	$0.25 \pm 0.14$	$0.70 \pm 0.23$	sum of previous two	propagation of error
Imbalance $N$	$0.28 \pm 0.16$	$0.78 \pm 0.27$	$\text{dOHC/dt} \div (0.90 \pm 0.06)$	propagation of error
Forcing $F$	$0.23 \pm 0.28$	$2.02 \pm 0.82$	Forster et al. (2)	Forster et al. (2)
Response $R_{\text{simple}}$	$-0.11 \pm 0.11$	$-1.07 \pm 0.74$	simple model $R = \alpha T$	propagation of error
Response $R_{\text{spatial}}$	$0.00 \pm 0.17$	$-1.15 \pm 0.51$	atmosphere models	inter-model spread
$N \div F$	$1.22 \pm 1.28$	$0.38 \pm 0.15$	$N$ and $F$	propagation of error
Inferred $N$	$0.23 \pm 0.20$	$0.87 \pm 0.58$	$F + R_{\text{spatial}}$	propagation of error
Inferred $F$	$0.28 \pm 0.21$	$1.93 \pm 0.54$	$N - R_{\text{spatial}}$	propagation of error
Inferred $R$	$0.05 \pm 0.24$	$-1.25 \pm 0.71$	$N - F$	propagation of error
Climate model simulations				
Variable	1920–1940	2000–2020	Data source	CMIP6 variable
dOHC/dt full depth	$0.15 \pm 0.14$	$0.71 \pm 0.29$	historical (17)	hfds
Imbalance $N$	$0.16 \pm 0.15$	$0.72 \pm 0.28$	historical (17)	rsdt, rsut, rlut
Forcing $F$	$0.26 \pm 0.19$	$1.71 \pm 0.54$	piClim-histall (7)	rsdt, rsut, rlut
Response $R$	$-0.10 \pm 0.15$	$-0.98 \pm 0.45$	$N$ and $F$ (7)	N/A
$N \div F$	$0.61 \pm 0.58$	$0.43 \pm 0.17$	$N$ and $F$ (7)	N/A

781 For a given model, uncertainties of  $F$ ,  $R$  and  $N$  are obtained  
 782 as the standard deviation of the TOA radiative flux in its  
 783 pre-industrial simulation, after applying the 20-year running  
 784 mean. This accounts for the fact that model simulations may  
 785 differ from observations because their unforced variability are  
 786 in different phases.

787 For the energy imbalance  $N$ , we split the 17 models into  
 788 those with a “weak” response to anthropogenic aerosol forcing  
 789 (9 models), and those with a “strong” one (8 models) (MM E);  
 790 their respective multi-model means are shown as the green  
 791 and red line in Fig. 2c. Eight of the nine “weak” models  
 792 simulate  $N$  that agrees with the observed  $N$  (within the  
 793  $2\sigma$ -range) over 90% of the time in 1880–2010 (Fig. S12), but  
 794 only two of the eight “strong” models do so (Fig. S13). The  
 795 agreement between the observation-based and simulated  $N$   
 796 is worse when the former is computed from SST datasets  
 797 without bias corrections (Fig. 2c compare the blue solid and  
 798 dashed line).

799 The radiative forcing  $F$  and radiative response  $R$  are  
 800 available for 7 of the 17 climate models. Here we use the  
 801 inferred  $F$  ( $N - R_{\text{spatial}}$ ) and  $R_{\text{spatial}}$  as the observation-based  
 802  $F$  and  $R$ , respectively. Six of the seven models simulate  $F$   
 803 that agrees with the observation about 90% of the time in  
 804 1880–2004 (Fig. S14), while only two do so for  $R$  (Fig. S15).  
 805 Four of the seven models are the “weak” models, while the

806 rest are the “strong” models. The “weak” models have a  
 807 more positive  $F$  and a more negative  $R$  than the “strong”  
 808 models in the model mean (Fig. S16).

## Regional Ocean Heat Uptake

849 The GF OHC estimate, by construction, only accounts for the  
 850 OHC change originating from the surface (16, 23); we refer  
 851 to this as the “excess” OHC change. The difference between  
 852 the observed total OHC change and the excess OHC change  
 853 gives the “redistributed” OHC change, which integrates to  
 854 zero over the global ocean volume (51, 52). In this section,  
 855 we examine the excess and redistributed contributions to the  
 856 observed total OHC change at different latitudes. We focus  
 857 on the zonal-and-depth integrated change over 0–2000 m; a  
 858 change is computed as the linear trend over 1980–2020, when  
 859 greenhouse gas forcing dominates. The observed total OHC  
 860 change is derived from the average of three in-situ datasets:  
 861 Cheng, Levitus and Ishii.

862 **Latitudinal Distribution.** The excess OHC change of this study  
 863 (i.e. the GF OHC change) has two peaks in both the Indo-  
 864 Pacific and the Atlantic, located at around 40°S and 30°N  
 865 (Figs. 3a and b, black line). For the central estimate, the  
 866 excess OHC change at high latitudes is about twice as large  
 867 as at low latitudes (Fig. 3a, black line). The redistributed  
 868 OHC change (Fig. 3a, grey line) is much smaller than the excess  
 869 OHC change, and has a much more uniform latitudinal  
 870 distribution. The total OHC change (Fig. 3a, red line) is  
 871 the sum of the excess and redistributed OHC change, and  
 872 has a similar latitudinal distribution to the excess OHC  
 873 change.

as that at low latitudes. We compare our estimate with the Bronselaer et al. estimate (52) for excess OHC change (Figs. 3a and b, purple line); the latter is inferred from observed anthropogenic carbon change. The two estimates agree with each other broadly; both of them suggest a greater excess OHC change in the Southern Ocean than the Zanna estimate (16) (Figs. 3a and b, red line). We infer the OHC redistribution as the observed total OHC change minus the excess OHC change. The result suggests that OHC redistribution exhibits alternating positive and negative changes across latitudes (Figs. 3c and d), consistent with previous studies (16, 52, 53).

**Regional Integral.** We examine the role of OHC redistribution in shaping the observed total OHC change for the North Atlantic integral ( $30^{\circ}\text{N}$ – $90^{\circ}\text{N}$ ) and the Southern Ocean integral ( $90^{\circ}\text{S}$ – $30^{\circ}\text{S}$ ). In 1980–2020, the observed global OHC change is about 7.1 ZJ per year, equivalent to  $0.45 \text{ W m}^{-2}$  over the Earth's surface. The North Atlantic accounts for about 8% of the global change, while the Southern Ocean account for 40%.

In the North Atlantic (Fig. 3b), the excess change of this study ( $1.5 \text{ ZJ yr}^{-1}$ ), Bronselaer et al. (52) ( $0.9 \text{ ZJ yr}^{-1}$ ) and Zanna et al. (16) ( $1.1 \text{ ZJ yr}^{-1}$ ) all exceed the observed total change ( $0.6 \text{ ZJ yr}^{-1}$ ) for the central estimate; the ratio of excess to total is 2.5, 1.5 and 1.8, respectively. This implies a net southward heat redistribution, or a weakening of the northward heat transport, across  $30^{\circ}\text{N}$ . Note that our estimate of excess change is highly uncertain in the North Atlantic (Fig. 3b), which prevents an accurate estimate of the redistributed change there.

In the Southern Ocean (Figs. 3a and b), the excess change of this study and Bronselaer et al. (52) are about the same as the observed total change, especially in the Indo-Pacific sector (Fig. 3a, numbers). This indicates that the redistributed change is close to zero when aggregated over the Southern Ocean, despite its marked patterns there, in contrast with the North Atlantic case.

## Summary and Discussion

Earth's energy imbalance  $N$ , the radiative forcing  $F$  and the radiative response  $R$  are essential quantities for monitoring the trajectory of anthropogenic climate change; they are linked through the global energy budget  $N = F + R$ . The ocean volume-integrated warming dominates Earth's energy imbalance  $N$  on multiannual timescales. Poor observational sampling prevents an estimate of global ocean warming before 1960, which leaves a gap in the global energy budget record.

In this study, we produce a reconstruction of global ocean heat uptake beginning in 1880 via a Green's function approach that relies on surface observations, hence alleviating the sampling issue in early periods. Our estimate of ocean warming is consistent with those derived from in-situ temperature profiles since 1960. From our estimate we obtain a timeseries of Earth's energy imbalance  $N$ , i.e. the net global-mean top-of-atmosphere (TOA) radiative flux, since 1880.

We highlight two findings in this study. First, our estimate of Earth's energy imbalance  $N$  is consistent with the current best estimates of radiative forcing  $F$  (2) and radiative response  $R$  ( $R_{\text{spatial}}$ ) during 1880–2020. In particular, our  $N$  estimate reduces the discrepancy between  $F+R$  and  $N$  during

1900–1960 in previous studies (Fig. S10), improving the understanding of historical climate change in early periods.

Second, our analysis reveals two distinct phases in the global energy budget. In 1880–1980, Earth's energy imbalance  $N$  closely followed the radiative forcing  $F$ . After 1980, however, the imbalance  $N$  increased at a slower rate than the forcing  $F$ ;  $N$  only amounts to  $38 \pm 15\%$  of  $F$  in 2000–2020. While the causes of those distinct phases are unclear, this finding is consistent with recent studies showing that the climate feedback parameter  $\alpha$  has been more negative (stable) since 1980 than it was in the preceding decades (45, 46). That is, Earth's radiative response  $R$  per unit global warming is increasing, which promotes a more negative  $R$ , hence a lower  $N/F$  ratio. The change in  $\alpha$  is linked to the change in SST warming pattern; the recent La-Nina-like pattern makes  $\alpha$  more negative because it increases low cloud cover (54).

A major consequence of OHU is sea-level rise through ocean thermal expansion. The ocean thermal expansion derived from the GF OHC estimate (this study) agrees with that derived from the total sea-level rise minus ocean-mass change, considering uncertainties (Fig. S17a, MM F). This indicates that the GF OHC estimate is consistent with the sea-level budget. Nonetheless, we note there are marked differences in the central estimates of thermal expansion derived from the above two approaches (Fig. S17a). This hinders a tight constraint on OHC change from the sea-level budget in the early 20th century.

Any systematic error in SST datasets will result in systematic errors in our estimate of Earth's energy imbalance  $N$ , because SST errors are propagated to  $N$  via the Green's function. Past studies suggest that the cold excursion in 1900–1920 and the World War 2 warm anomaly in 1939–1945 may be artefacts of the SST datasets, due to poor sampling coverage and inhomogeneity of instrumentation (24–28). We find that removing those two features produces a  $N$  estimate that agrees better with: 1) the observation-based TOA radiation budget ( $F+R$ ) and 2) the historical simulation of  $N$  in climate models.

## Materials and Methods

**A. Excess Heat and Green's Function.** Excess heat is the additional heat entering the ocean from the surface. The governing equation of excess heat, written in terms of excess temperature  $\Theta_e$ , is given by:

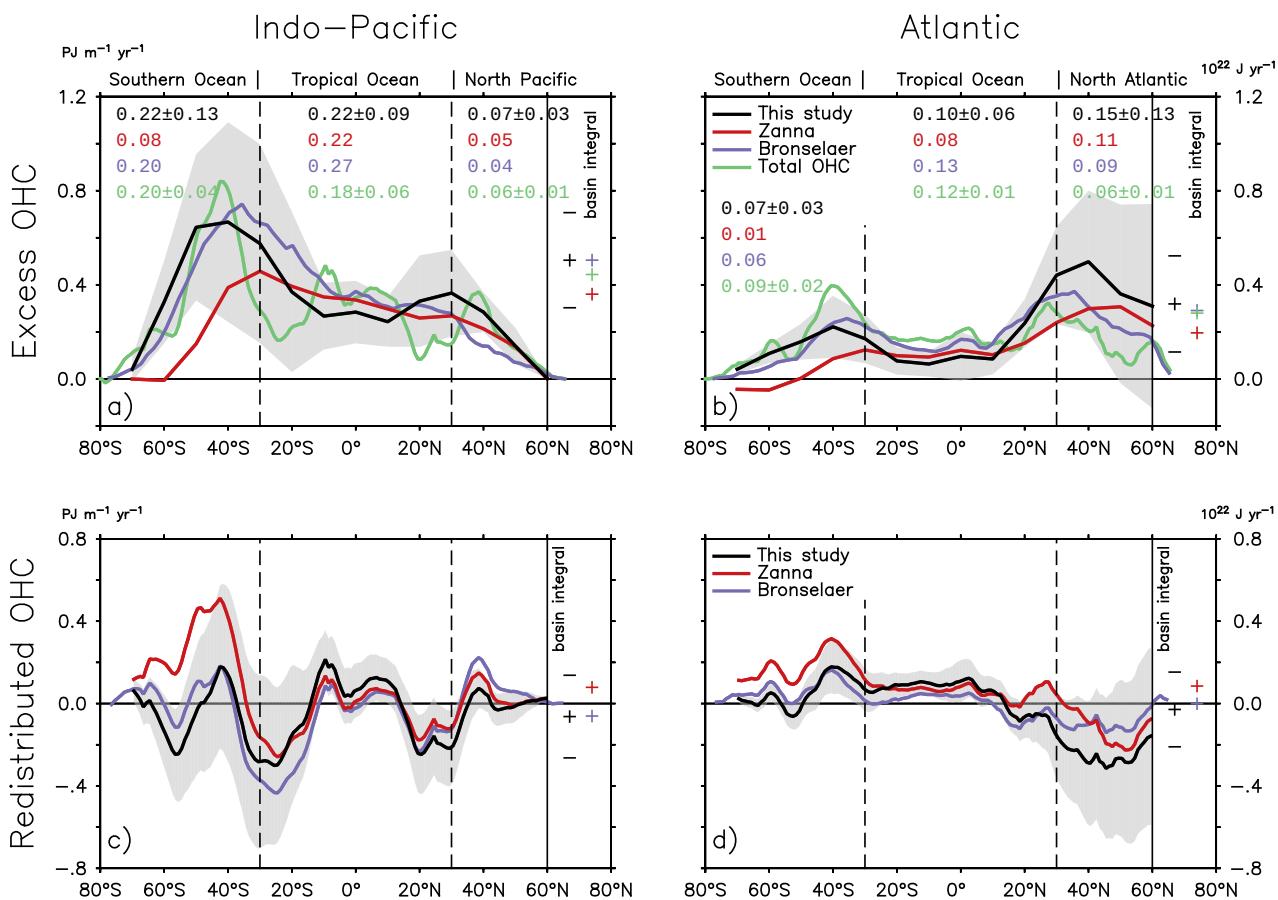
$$(\frac{\partial}{\partial t} + L)\Theta_e(\mathbf{r}, t) = Q_a(\mathbf{r}, t), \quad [2]$$

Initial condition:  $\Theta_e(\mathbf{r}, 0) = 0$ ,

where  $t$  is time and  $\mathbf{r}$  a 3D position vector in the ocean.  $Q_a$  is the surface heat flux anomaly relative to the climatology.  $L$  is the 3D ocean transport operator, which evolves an ocean tracer field forward in time; it encodes the net effect of ocean transport, from large-scale advection to small-scale mixing. Multiplying  $\Theta_e$  with the specific heat and density of seawater gives excess heat. Integrating excess heat over the global ocean volume gives global ocean heat content (OHC) change. Diagnostics similar to  $\Theta_e$  have been used in the literature, for instance, the fixed-circulation temperature change in Winton et al. (55), the added temperature in Gregory et al. (51) and the material warming in Zika et al. (53).

The Green's function (GF) approach solves  $\Theta_e$  in Eq. 2 by propagating its boundary condition  $\Theta_e^s$ . The propagation is done via the boundary GF  $G$ , which encodes the ocean's surface-to-interior transport (advection+mixing). The above process can be

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**Fig. 3.** Excess and redistributed OHC change integrated zonally and vertically (0–2000 m) for ocean basins. The change is computed as the linear trend over 1980–2020, and refers to the left-hand axis. The excess OHC change is from: this study (black), Zanna et al. (16) (red) and Bronselaer et al. (52) (purple). The observed total OHC change (green) is included for comparison. The redistributed OHC change is computed as the difference between the observed total and excess change. The basin-integrated change is shown by the “+” sign in the rightmost portion of each panel, referring to the right-hand axis. The numbers show the changes integrated over three latitude bands, separated by vertical dashed lines, in units of  $10^{22} \text{ J yr}^{-1}$ . The colors of the numbers and the plus signs match those of the lines, indicated in the legends. Shading, horizontal bar and the “ $\pm$ ” sign indicate the  $2\sigma$ -range.

written as the following sum over space and time:

$$\Theta_e(\mathbf{r}, t) = \int_{\Omega} d^2 \mathbf{r}_s \int_{-\infty}^t G(\mathbf{r}_s, t - t_s | \mathbf{r}) \Theta_e^s(\mathbf{r}_s, t_s) dt_s, \quad [3]$$

where  $\Omega$  denotes the global ocean surface and  $(\mathbf{r}_s, t_s)$  are coordinate variables for surface quantities. Note that Eq. 3 is a generalisation of Eq. 1.

The GF approach is useful because it can provide an OHC estimate without subsurface temperature measurements; it only requires surface temperature as input, given that the GF  $G$  is known. For this reason, the GF approach has been used to reconstruct OHC in the past 2000 years (56). The GF approach, however, has a number of limitations. First, the GF is assumed to be stationary in time, ignoring potential changes in ocean transports due to changes in climate states. Second, estimating the GF from observations is a highly underdetermined problem as there are many more unknowns than tracer constraints, a challenge compounded by poor sampling of ocean transient tracers in space and time. Lastly, the boundary condition  $\Theta_e^s$  is not observable and must be partly inferred from model simulations.

**B. Observational Green's Functions.** To infer the GF  $G$  from observations, we first rewrite Eq. 3 into a general form

$$X(\mathbf{r}, t) = \int_{\Omega} d^2 \mathbf{r}_s \int_{-\infty}^t G(\mathbf{r}_s, t - t_s | \mathbf{r}) X^s(\mathbf{r}_s, t_s) dt_s, \quad [4]$$

where  $X$  is the concentration of a given tracer; e.g.  $\Theta_e$  or CFC-11.  $X^s$  is  $X$  at the surface. Eq. 4 holds because all tracers in the ocean experience the same ocean transports (i.e. velocities and diffusivities) (17). Each tracer observation, i.e.  $X(\mathbf{r}, t)$ , forms a constraint on  $G$  at  $\mathbf{r}$  via Eq. 4. Here  $\mathbf{r}$  and  $t$  are the location and time of observations, respectively. A collection of  $n$  observations at  $\mathbf{r}$  thus forms  $n$  equations for  $G$  there. In practice, observations are insufficient constraints of  $G$ , because the number of observations is much smaller than the number of unknowns in  $G$ . Note that  $G$  is a function of ocean surface locations and transit times. We solve this underdetermined problem using the Maximum Entropy method (18, 20). Among infinitely many  $G$  solutions that satisfy observations, the Maximum Entropy method chooses the one that is the most “similar” to a prior estimate of  $G$  (measured by their “relative entropy”). This procedure can be cast into a constrained optimisation problem and solved using standard numerical routines.

Details on formulating and solving the Maximum Entropy problem are documented in Wu and Gregory (23) and summarised in Fig. S1. We use four observations of tracers to infer  $G$  at every  $\mathbf{r}$ ; they are CFC-11 and CFC-12 in the GLODAP data (57) (observed at 1994) and the climatological temperature and salinity. We combine these tracers together because their distributions are primarily controlled by the climatological ocean transport. Treatment of the observations is described in SI Appendix 1. We generate four realisations of the GLODAP data by randomly perturbing the central estimate with the standard error of the data. We use  $G$  computed from two climate models and an ocean state estimate as first-guess solutions for inferring  $G$  from observations. The climate models are HadCM3 ( $1.25^\circ \times 1.25^\circ$ ) (58) and FAMOUS ( $3.75^\circ \times 2.50^\circ$ ) (59). The state estimate is ECCO-GODAE ( $1^\circ \times 1^\circ$ ) (29). The 4 sets of observational constraints and 3 first-guess solutions result in 12 sets of observational GFs.

A lack of diversity in the first-guess solution of  $G$  is a limitation of this study. We only use three first-guess solutions here because computing  $G$  requires carrying out customised ocean tracer simulations, which have not been done in other models.

None of our first-guess solutions is derived from eddy-resolving models. In all of them, horizontal eddy mixing of tracers is parameterised using the Redi (60) and Gent and McWilliams (61) schemes. Errors in eddy parameterisation affect our results by affecting the first-guess solutions. Although observational constraints would correct some of the errors, it is unclear how much still remains. In future studies, deriving  $G$  with different eddy parameterisation schemes and model resolutions would help to address this question.

The GF OHC estimate and the Cheng OHC estimate (31) are not fully independent, because HadCM3 is used in both, although

in different ways. To test the impact of this dependency, we have re-computed the GF OHC estimate using the first guess from FAMOUS and ECCO-GODAE, i.e. removing the HadCM3 information. This results in little change in our OHC estimate.

**C. Ocean Heat Uptake Boundary Conditions.** We refer  $\Theta_e^s$  as “sea surface excess temperature” (SSTe) to correspond with “sea surface temperature anomaly” (SSTA) used in Zanna et al. (16). The main difference between SSTA and SSTe is that the latter does not contain ocean temperature redistribution (51). Keeping redistributed temperature in the boundary condition may bias the GF OHC estimate. This is because the GF method only accounts for tracers originating from the surface, but redistributed temperature has sources/sinks throughout water columns (23).

We estimate SSTe by combining three SSTA datasets from observations with two SSTe simulations from climate models (SI Appendix 2, summarised in Fig. S3). Specifically, we replace the global mean of SSTe from climate models with the global mean of SSTA from observations. That is, we only use the spatial anomalies (relative to global mean) from model simulations, not their global means. Note that we omit the difference between SSTe and SSTA in the global mean. A model simulation suggests that SSTe is about 0.1 K warmer than SSTA in the global mean after 1960 (23), probably due to reduced ocean convection. This suggests that our SSTe boundary condition may contain a cold bias in recent decades. Both SSTA and SSTe are expressed as anomalies relative to the 1870–1880 time mean, assuming that the ocean is near equilibrium during that period. Our result is not sensitive to small changes in the baseline. For instance, adding a constant offset of 0.1 K to SSTe, as suggested by Jarvis and Forster (62), only increases our estimate of Earth’s energy imbalance  $N$  by  $\sim 0.01 \text{ W m}^{-2}$  after 1930 (Fig. S18).

We process the global mean of SSTA in two steps. The first step applies a low-pass filter to reduce the impact from interannual heat redistribution. The second step removes two potential biases in SST datasets before 1960 (shown in Fig. S5), which are discussed in the main text. See SI Appendix 2 for further information of the two-step processing.

The SSTe used here is physically connected to the SSTA used in MM E to derive Earth’s radiative response  $R_{\text{spatial}}$ . Specifically, SSTe is the part of SSTA that originates from surface heat flux change  $Q_a$  (23). We enforce this relationship by first identifying climate models that well reproduce the observed SSTA trends, and then using their  $Q_a$  fields to carry out SSTe simulations following Eq. 2 (SI Appendix 2).

**D. Global Energy Budget in 1700–1880.** This supplementary analysis uses the same method as the main analysis for 1880–2022. Because temperature datasets used in the main analysis are not available before 1850, we replace them with PAGES2k data (63), which is based on palaeoclimate proxies. The PAGES2k temperature is used for computing Earth’s radiative response  $R$  as well as providing the global mean for the SSTe boundary condition, which is assumed to be globally uniform. PAGES2k data is derived from 7 distinct reconstruction methods, each with 1000 ensemble members. The SSTe boundary condition consists of 7 members, each of which is the ensemble mean of a reconstruction method. This choice is to reduce the cost of evaluating Eq. 3. All 7000 members are used to derive the  $2\sigma$ -range for computing  $R$ . Temperature change is computed with respect to the 1700–1750 baseline.

**E. Climate Model Simulations.** We use four climate model experiments here. They are the coupled atmosphere–ocean experiment **historical** (1850–2020) with its pre-industrial control **piControl**, and the atmosphere-only experiments **piClim-histall** (1850–2020) and **amip-piForcing** (1870–2014). In all of them, the net TOA radiative flux is computed using TOA incoming shortwave flux (**rsdt**), TOA outgoing shortwave flux (**rsut**) and TOA outgoing longwave flux (**rlut**) from CMIP6 standard outputs. The ocean heat uptake (OHU) rate in the **historical** experiment is derived from the net downward heat flux at the sea surface (**hfds**). Note that climate models tend to store a greater fraction of the TOA imbalance in the ocean compare to observations (96% vs. 90%) because their deficiencies in simulating melting of terrestrial ice and

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warming of solid Earth (64). The standard historical experiment stops at 2014; we extend it to 2020 using its SSP2-4.5 (medium emission) extension. The distinguishing features of the experiments and our uses of them are summarised in Table 3.

**E.1. Global Energy Budget Terms.** The global energy budget terms of historical simulations are derived from the historical and piClim-histall experiments. Earth's energy imbalance  $N$  is derived from the net TOA flux in the historical experiment. The contributions of radiative forcing  $F$  and radiative response  $R$  to the energy imbalance  $N$  cannot be separated in the historical experiment. We diagnose  $F$  using the piClim-histall experiment (65), which is a parallel experiment to historical. The piClim-histall, by construction, has the same  $F$  as in historical, but zero  $R$ , because its SST and sea ice are fixed to the pre-industrial condition. We derive  $R$  of the historical experiment as the difference  $R = N - F$ . We use the historical experiment from 17 models, which are listed in Table S1; seven of them have the piClim-histall experiment: CNRM-CM6-1, GISS-E2-1-G, IPSL-CM6A-LR, MIROC6, CanESM5, HadGEM3-GC31-LL, and NorESM2-LM.

The amip-piForcing experiment provides an estimate of the radiative response  $R$  due to observed SST and sea ice changes, which are prescribed as time-varying boundary conditions, with constant pre-industrial forcing (44, 46). We use the amip-piForcing experiment from eight models: CanESM5, CESM2, CNRM-CM6-1, HadGEM3-GC31-LL, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, and TaiESM1. Note that the historical and amip-piForcing experiment with a given model produce different  $R$  because their SST and sea ice fields are different.

**E.2. Model Drifts and Energy Leakage.** Climate model simulations often contain “climate drift” (unforced trends) (66) and non-closure of the energy budget (67, 68), which are collectively referred to as climate drift here. In practice, the climate drift can be estimated from the steady-state simulation, and then removed from the climate change simulation of interest, assuming the same drift to be present in both simulations (66–68).

For the coupled simulation historical, we remove the climate drift by removing its parallel steady-state simulation piControl. The de-drifting substantially improves the energy conservation in climate models. To demonstrate this we compare the TOA radiative flux and the OHU rate (both are global means). Before de-drifting, the TOA radiative flux is much larger than the OHU rate in several models (Fig. S19), suggesting a non-conservation of energy. After de-drifting, the TOA radiative flux closely matches the OHU rate in all 17 models examined here (Fig. S20), implying that the energy leakage is of similar size between the historical and piControl simulation. For piClim-histall and amip-piForcing, we remove the climate drift by removing their 1870–1880 time mean, because they have no parallel steady-state simulations. The late 19th-century is a common choice for defining the steady state climate; e.g. it is used to design the piControl experiment. The 1870–1880 is also used as the steady-state reference for estimating OHU in this study (Table 1).

**E.3. “Strong” and “Weak” Models.** We classify each of the 17 climate models as having a “strong” or a “weak” response to anthropogenic aerosol forcing (Table S1). We classify a model as “strong” if its net surface heat loss relative to the pre-industrial control is stronger than  $2 \text{ W m}^{-2}$ , averaged over the North Atlantic ( $30^\circ\text{N}$ – $65^\circ\text{N}$ ) and 1950–1980, when the aerosol forcing dominates. This gives a similar classification of models as in Robson et al. (69).

**F. Sea Level Budget.** The global-mean sea-level rise can be decomposed into contributions from a) ocean-mass change and b) ocean thermal expansion. Those are termed as the barystatic and thermosteric component, respectively (70). We derive the global-mean sea level and its barystatic component from observation-based reconstructions in Frederikse et al. (71), which covers 1900–2018. Specifically, the global-mean sea level is obtained from tide-gauge and satellite-altimetry observations and the barystatic change is estimated from mass change of glaciers, ice sheets and terrestrial water. We convert OHC change (ZJ) to thermosteric change (mm) via the expansion efficiency of heat,  $0.11 \text{ mm ZJ}^{-1}$ . This

number is derived in Zanna et al. (16) based on climatological ocean temperature and salinity in observations.

**Data and Software Availability.** Ocean heat uptake data of this study is available at <https://doi.org/10.5281/zenodo.11107298>. CMIP6 data is available at <https://esgf-node.llnl.gov>. ECCOv4 data can be downloaded from <https://www.ecco-group.org>. In-situ ocean heat content data are downloaded from: <http://www.ocean.iap.ac.cn> (Cheng), <https://www.data.jma.go.jp> (Ishii), and <https://www.ncei.noaa.gov> (Levitus).

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Table 3. A comparison of climate model experiments used in this study.

name	configuration	atmospheric composition	SST	TOA net radiative flux is	climate change is anomaly wrt
piControl	coupled atmosphere–ocean	pre-industrial	predicted by model	model drift	N/A
historical (1850–2014)	coupled atmosphere–ocean	time-varying historical	predicted by model	model historical <i>N</i>	parallel piControl
piClim-histall (1850–2014)	atmosphere-only	time-varying historical	climatology of piControl	model historical <i>F</i>	its own 1870–1880 time mean
amip-piForcing (1870–2014)	atmosphere-only	pre-industrial	observations, time-varying	observation-based <i>R</i> estimate	its own 1870–1880 time mean

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