

Nonlinear regional warming with increasing CO₂ concentration

Article

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1 **Nonlinear regional warming at higher CO₂**
2 **concentrations**

3

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39 In the debate on acceptable levels of climate change, and for planning adaptation
40 measures, stakeholders need regional-scale climate projections including the range of
41 plausible warming rates. To assess the benefits of mitigation, it is important to
42 understand whether some locations may see disproportionately high or low warming
43 from additional forcing above targets such as 2 K¹. There is an urgent need to narrow
44 uncertainty² in this nonlinear warming, which requires understanding how climate
45 changes as forcings increase from medium to high levels. However, quantifying and
46 understanding regional nonlinear processes is challenging. Here we show that
47 regional-scale warming can be strongly super-linear to successive CO₂ doublings,
48 using five different climate models. Ensemble-mean warming is super-linear over
49 most land locations. Further, the inter-model spread tends to be amplified at higher
50 forcing levels, as nonlinearities grow – especially when considering changes per K of
51 global warming. Regional nonlinearities in surface warming arise from nonlinearities
52 in global-mean radiative balance, the Atlantic Meridional Overturning Circulation,
53 surface snow/ice cover and evapotranspiration. In quantifying and understanding the
54 benefits of mitigation, potentially-avoidable climate change (the difference between
55 business-as-usual and mitigation scenarios) and unavoidable climate change (change
56 under strong mitigation scenarios) may need different treatments.

57

58 Linear assumptions affect stakeholder advice in various ways^{1,3-7}. Fast simplified
59 models^{1,5,7} (especially integrated assessment models), for quantifying climate change
60 under many policy scenarios, often assume climate change is the same for each CO₂
61 doubling. Some studies make a less strong assumption: that regional climate is linear
62 in global warming^{3,4,6}. Also, studies of physical mechanisms often explore just one
63 time period of one forcing scenario. An implied linear assumption here is that the

64 physical mechanisms are similar under other scenarios or for other time periods (not
65 necessarily true in a nonlinear system).

66

67 To quantify nonlinearities, the linear response must first be carefully defined. Even in
68 a linear system the spatial patterns of climate change (per CO₂ doubling or per K of
69 global warming) can be different in different forcing scenarios or evolve during a
70 given scenario. This is because of different timescales of response within a system⁸⁻
71 ¹⁰. For example, warming over the Southern Ocean lags the global mean¹⁰. Therefore,
72 the spatial pattern of warming just after a CO₂ change is different than that several
73 decades later.

74

75 Our experimental design is chosen to separate linear and nonlinear mechanisms. We
76 use abruptCO₂ experiments, initialized from a pre-industrial control experiment. The
77 CO₂ concentration is changed abruptly, then held constant for 150 years, revealing the
78 model response over different timescales. The abrupt4xCO₂ experiment (with CO₂
79 quadrupled from pre-industrial levels) has similar forcing magnitude as a business-as-
80 usual scenario by 2100¹¹. The abrupt2xCO₂ experiment is identical to abrupt4xCO₂
81 but with half the CO₂ concentration (with forcing between that reached under RCP2.6
82 and RCP4.5 scenarios by year 2100¹¹). A transient forcing experiment ('1pctCO₂'),
83 where CO₂ is increased by 1% per year, is also used. We start with results from the
84 HadGEM2-ES climate model.

85

86 The abruptCO₂ experiments are highly idealised. Therefore, we first show that their
87 behaviour is comparable to the more policy-relevant 1pctCO₂ experiment, and detect
88 nonlinearities in the 1pctCO₂ response. It is possible to use a simple linear

89 combination of abruptCO₂ responses to estimate climate change under a transient
90 forcing experiment^{12,13}. This linear method performs well when the end of the
91 1pctCO₂ experiment (near 4xCO₂) is reconstructed from the abrupt4xCO₂ response
92 (Figure 1b). This shows that the abrupt4xCO₂ experiment features realistic physical
93 mechanisms. It does not mean that temperature responses are linear (conceptually, it
94 is like a local linear approximation to a curve). The importance of nonlinearity is
95 revealed in the relatively poor performance when the abrupt2xCO₂ response is used
96 instead (Figure 1a); while for the middle of 1pctCO₂ (near 2xCO₂), the reconstruction
97 using abrupt4xCO₂ is much worse than that using abrupt2xCO₂ (compare Figures
98 1c,d). The linear method is only accurate for periods in the transient experiment with
99 forcing matching that of the abruptCO₂ experiment: climate patterns are therefore
100 different for different CO₂ concentrations – which is evidence of nonlinearity.

101

102 Having detected nonlinearities in the 1pctCO₂ experiment, we characterise them more
103 clearly by analysing the abruptCO₂ experiments directly. This experimental design
104 has two significant advantages over the 1pctCO₂ scenario. First, temperature
105 responses in the two abruptCO₂ experiments may be compared at the same timescale
106 after CO₂ is changed (eliminating complications due to linear effects from different
107 timescales of response). Secondly, noise from internal variability may be reduced
108 through long-term means. Assuming that the balance of mechanisms should be stable
109 after the initial ocean mixed-layer warming, we average over years 50-149 of each
110 experiment (Supplementary Figure 1). For abrupt2xCO₂, these 100-year means
111 correspond roughly to the results for year 2100 of a CO₂-only version of rcp4.5 (and
112 about double this for abrupt4xCO₂).

113

114 We compare temperature responses to a first and second CO₂ doubling. Current
115 linear methods that parameterise forcing (most integrated assessment and energy
116 balance models) assume that radiative forcing is exactly linear in log(CO₂) – and
117 equivalently, that each CO₂ doubling produces the same forcing change^{1,5}. In
118 HadGEM2-ES, the two doublings give very similar forcing changes¹⁴. The response
119 to the first doubling is given by abrupt2xCO₂ minus the pre-industrial control; that for
120 the second doubling by abrupt4xCO₂ minus abrupt2xCO₂ (both are averaged over
121 years 50-149). We quantify nonlinearities by the 'doubling difference': the response
122 to the second doubling minus that for the first (Figure 2a); and the 'doubling ratio': the
123 second doubling divided by the first (Figure 2b). Current linear models would have
124 zero doubling difference everywhere.

125

126 The doubling ratio in global-mean warming is 1.18 (the second CO₂ doubling
127 produces more warming than the first). Global-scale nonlinearity has been attributed,
128 in other models, to changes in water-vapor and cloud feedbacks, opposed by changes
129 in albedo and lapse-rate feedbacks¹⁵⁻¹⁷. In some climate models, variation in forcing
130 per CO₂ doubling would also affect the global doubling ratio¹⁵⁻¹⁷. Regional variation
131 in doubling ratio is broad, however: 5% of the land surface has a doubling ratio
132 outside the range 0.9-1.65 (Supplementary Figure 5a). Gradients of the doubling ratio
133 across continents are strong (Figure 2b), notably over the Americas and Europe,
134 pointing to important regional mechanisms.

135

136 We scale out global-mean nonlinearity (Methods) and then focus on the remaining
137 features (see Figure 2c) one by one. The positive area in the north Atlantic, near
138 Greenland, appears to be associated with a nonlinear response of the Atlantic

139 Meridional Overturning Circulation (AMOC)¹⁸. In HadGEM2-ES, the maximum
140 Atlantic overturning near 30N weakens about 35% less under a second CO₂ doubling
141 than under the first (a positive doubling difference). We can estimate the effect on
142 surface temperature by scaling the regional temperature response in a separate
143 freshwater hosing experiment (where freshwater is added to the high-latitude north
144 Atlantic to induce AMOC weakening). We multiplied this temperature response
145 pattern by the ratio: (doubling difference for AMOC index) / (AMOC index response
146 in the hosing experiment). The resulting pattern (Figure 2d) features a north Atlantic
147 anomaly similar to that in Figure 2c. This suggests that the north Atlantic nonlinearity
148 is indeed driven by the nonlinear AMOC response. AMOC nonlinearity may arise
149 from variation in the salt-advection feedback (which affects the AMOC
150 strength)¹⁹. The AMOC transports heat to the North Atlantic, so a positive doubling
151 difference in the AMOC causes positive doubling differences in North Atlantic
152 surface temperatures.

153

154 To reveal other nonlinear mechanisms, we subtract the AMOC pattern (Figure 2d)
155 from that in Figure 2c. The residual (Figure 2e) is associated with mechanisms other
156 than those in the global mean energy balance or the AMOC. The North Atlantic
157 positive feature has been effectively removed.

158

159 The remaining high-latitude temperature nonlinearities are largely driven by a
160 nonlinear albedo feedback^{18,20} (which is dominated by changes in ice and snow cover).
161 It is nonlinear²¹ as it becomes zero when ice/snow is either absent or so thick that its
162 extent changes little under warming. The patterns in the doubling difference of sea ice
163 fraction (Figure 2f) match closely the high latitude patterns of temperature doubling

164 difference (Figure 2e), with sea-ice albedo feedbacks driving temperature nonlinearity
165 (supplementary material).

166

167 The final mechanism we study involves land evapotranspiration. Soil moisture-
168 temperature feedbacks can be nonlinear²²: feedback is small when soil moisture is
169 saturated, or so low that moisture is tightly bound to the soil (in both regimes,
170 evaporation is insensitive to change in soil moisture)²³. Nonlinear behaviour could
171 also occur through the response of plant stomata (and hence transpiration) to
172 increased CO₂²⁴, or through nonlinear precipitation change^{25,26}. To investigate this
173 type of effect, we calculate the ratio of mean surface sensible heat and mean surface
174 latent heat fluxes (the Bowen ratio) in the two abruptCO₂ experiments. Much of the
175 temperature nonlinearity over mid/low latitude land (Figure 2g) is associated with
176 change in the Bowen ratio (see Figure 2h). Regions where the Bowen ratio is
177 substantially larger at 4xCO₂ than at 2xCO₂ (red in Figure 2h) have more restricted
178 evaporation: more incident heat is lost as sensible heat, causing further warming. This
179 does not occur where the Bowen ratio is already larger than 1 at 2xCO₂ (e.g. the
180 Sahara, where most turbulent heat is sensible even at 2xCO₂). These regions are
181 masked in Figure 2h. The most strongly superlinear warming occurs over the
182 Amazon in this model (doubling ratios of 80% are driven by the response of forest
183 tree stomata to CO₂, with a longer-term response from reduced vegetation
184 productivity - supplementary material; these mechanisms are highly uncertain).

185

186 Further to our analysis of HadGEM2-ES we find that nonlinearity is similarly
187 important in four other climate models: NCAR-CESM1, IPSL CM5A-LR, MIROC5
188 T42 and HadCM3. These models show doubling ratios over land comparable to those

189 in HadGEM2-ES (supplementary Figure 5a). Over most land locations, the ensemble
190 mean doubling difference is comparable to the ensemble standard deviation for
191 warming from the first doubling (supplementary Figure 5b). That is, the range of
192 warmings simulated by this ensemble is quite different for the first and second CO₂
193 doublings. The models do show differences in spatial patterns of nonlinear warming.
194 Consequently, the ensemble mean pattern (Figure 3) is smoother than that of any
195 individual model. However, some continental-scale patterns across Europe, North
196 and South America and tropical Africa are similar between Figures 2b and 3.
197
198 Nonlinearity has implications not just for the ensemble mean, but also for the spread
199 of model projections. In general, an increased spread at higher forcing should be
200 expected: the relative importance of nonlinear mechanisms grows with increasing
201 forcing, so their contribution to model spread does likewise. Conceptually, this is like
202 including an extra uncertain process at higher CO₂ concentrations. This inflation in
203 model spread at higher forcing is large when nonlinearities are uncertain
204 (supplementary material), and appears to be especially relevant for change per K of
205 global warming. We calculated the ensemble standard deviation in regional warming
206 per K of global warming. Over 30% of land, the ensemble spread is at least 40%
207 larger for the second doubling than for the first doubling (not driven by internal
208 variability – Supplementary Material). This corresponds to a doubling of variance -
209 driven by uncertain nonlinear mechanisms. This finding is important for work
210 quantifying and reducing model uncertainty. It implies that the additional regional
211 warming under a business-as-usual scenario (over and above that in a mitigation
212 scenario) may be more uncertain than the warming under a mitigation scenario - a fact
213 missed by previous linear impacts assessments^{1,3,4}. Secondly, different techniques

214 may be needed to reduce model uncertainty in these two aspects of climate change:
215 uncertainty from nonlinear mechanisms being relatively more important at higher than
216 at lower forcing levels.

217

218 The mechanisms of nonlinear warming identified in HadGEM2-ES also operate in the
219 other four models studied. All have a positive global-mean temperature nonlinearity
220 (Supplementary Table 1). As done for HadGEM2-ES, we scale this global-mean
221 nonlinearity out and discuss regional patterns. Most of the remaining temperature
222 nonlinearities over North-West Europe are associated with the AMOC: the magnitude
223 of this nonlinearity is predicted simply by scaling the HadGEM2-ES hosing
224 experiment by the AMOC doubling difference from each model (Figure 4a). While
225 there is significant model spread in sea-ice nonlinearity (Supplementary Figure 6),
226 Arctic temperature doubling differences averaged across the four extra models align
227 closely with the sea-ice albedo doubling differences (Figure 4b,c), with patterns
228 similar to those for HadGEM2-ES (Figure 2f). Similar comments apply to the
229 evaporation mechanism at lower latitudes (Figure 4d,e; Supplementary Figure 7),
230 especially over the Americas, Africa and Arabia, although not all of the pattern is
231 explained this way (nonlinear dynamical processes and internal variability may also
232 contribute).

233

234 The implications of nonlinearity for individual studies will be application-specific,
235 and should be considered alongside other issues, such as impacts model uncertainty.
236 Further differences in patterns of 'potentially-avoidable' and 'unavoidable' warming
237 may arise from linear mechanisms. The abruptCO2 experiments are powerful for
238 separating mechanisms and identifying where nonlinearity is largest or smallest.

239 Where available, transient projections from state-of-the-art climate models remain
240 preferable for direct policy advice.
241
242 Work is needed to reduce uncertainty in these nonlinear mechanisms. Our
243 experimental design could usefully be applied to other models. Some policy advice
244 based on linear methods³ may need to be reconsidered, while studies of physical
245 processes controlling both temperature and precipitation^{25,26} should account for a
246 different balance of mechanisms under different forcing scenarios or for different time
247 periods.

248

249 **Methods**

250

251 **HadGEM2-ES model and experiments**

252

253 The Hadley Centre Global Environmental Model version 2 Earth System
254 configuration (HadGEM2-ES)^{27,28} has an atmospheric resolution of 1.25x1.875° and
255 38 vertical levels, and a 1° ocean (reaching 1/3° near the equator) with 40 vertical
256 levels. NCAR CESM1, HadCM3, IPSL CM5A-LR and MIROC5 are described in
257 supplementary Table 2.

258

259 All models ran a fixed-forcings pre-industrial control, and both abruptCO₂
260 experiments. Each abruptCO₂ experiment was initialised from the same point in the
261 control run, and CO₂ was abruptly changed (to twice pre-industrial levels for
262 abrupt2xCO₂ and four times for abrupt4xCO₂), and then held constant for 150 years.

263

264 The hosing experiment, run for HadGEM2-ES only, involved addition of 0.1Sv
 265 freshwater near the coast of Greenland for 100 years. This produced a modest (30%)
 266 slowdown in the AMOC (measured by maximum overturning near 30N). Results
 267 from this experiment were averaged over years 50-149.

268

269 **Scaling the global-mean nonlinearity out of the regional temperature doubling**
 270 **differences**

271

272 Figure 2c shows doubling differences after the global-mean nonlinearities (except
 273 those due to the AMOC) are scaled out. The calculation of doubling differences with
 274 global non-linearities scaled out (denoted DD_{noglob}) is described below. The small
 275 global-mean nonlinearity associated with the AMOC is not scaled out here. This is
 276 because the global-mean AMOC effect is included in Figure 2d (the scaled hosing
 277 response), and is therefore removed when Figure 2d is subtracted from Figure 2c: to
 278 give the residual in Figure 2e. DD_{noglob} is given by:

279

$$280 \quad DD_{noglob} = T_{42} - T_{21,scaled}$$

281

282 where T_{42} is the warming from the second doubling, and:

283

$$284 \quad T_{21,scaled} = T_{21} \cdot \frac{(\overline{T_{21}} + \overline{DD_{noAMOC}})}{\overline{T_{21}}}$$

285

286 where T_{21} is the warming from the first doubling. The overbar indicates a global

287 mean. $\overline{DD_{noAMOC}}$ is the global mean doubling difference from processes other than
288 the AMOC:

289

$$290 \quad \overline{DD_{noAMOC}} = \overline{DD} - \overline{DD_{AMOC}}$$

291

292 \overline{DD} is the global mean of Figure 2a and $\overline{DD_{AMOC}}$ is the global mean of Figure 2d.

293

294

295

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297

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391

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401

402 ***Author contributions***

403

404 P.G. conceived the study and wrote the paper. All authors contributed to the scientific
405 interpretation and the paper. T.A., M.B.M, J.L.D., J.M.G., N.S. and H.S. performed
406 experiments.

407

408 ***Competing financial interests statement***

409

410 The authors have no competing interests as defined by Nature Publishing Group, or
411 other interests that might be perceived to influence the results and/or discussion
412 reported in this article.

413

414

415 **Figure legends**

416

417 Figure 1. Regional nonlinearity in the transient-forced 1pctCO₂ experiment.

418 Warming (K) simulated directly by HadGEM2-ES (y-axis) is compared with that

419 predicted from the linear reconstruction^{12,13} using (left column) abrupt2xCO₂ and

420 (right column) abrupt4xCO₂ responses. Good performance of the linear

421 reconstruction is indicated by the points lying close to the red line (each point

422 represents one model grid cell). Results are averaged over (top row) years 120-139 of

423 the 1pctCO₂ experiment (near 4xCO₂), and (bottom row) years 61-80 (near 2xCO₂).

424

425 Figure 2. Mechanisms of nonlinear regional warming in HadGEM2-ES. Left

426 column: doubling differences (K); a) unscaled; c) after global-mean nonlinearity is

427 scaled out (Methods); e) as c), but with nonlinearity associated with the AMOC (panel

428 d) subtracted; g) as e) but latitude range matches that of panel h). b) doubling ratio.

429 d) estimated nonlinearity associated with the AMOC. f) doubling difference in sea ice

430 fraction. h) Bowen ratio at 4xCO₂ divided by Bowen ratio at 2xCO₂. All based on

431 means over years 50-149 of the abrupt2xCO₂, abrupt4xCO₂ or hosing experiments.

432

433 Figure 3. Doubling ratio of ensemble mean warming. Ensemble means are taken for

434 each of the first and second CO₂ doublings first, then the doubling ratio calculated.

435

436 Figure 4. Multi-model mechanisms of temperature nonlinearity. All panels: 'scaled

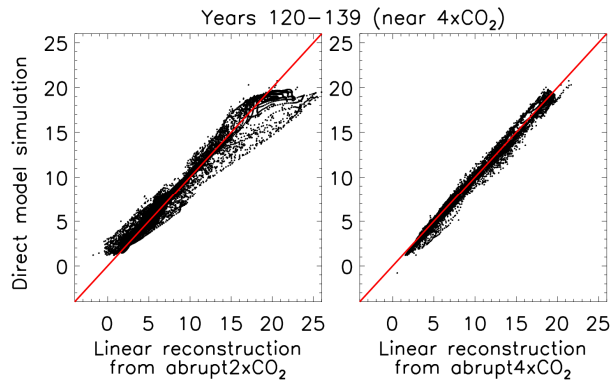
437 temperature doubling differences' have had the global mean nonlinearity scaled out.

438 a) AMOC influence, averaged over NW Europe (land, 10W-20E, 45-70N). Y-axis:

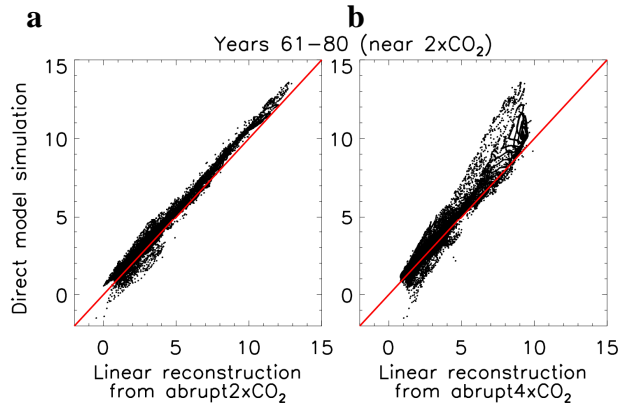
439 scaled temperature doubling difference for each model; x-axis: the HadGEM2-ES

440 hosing temperature response scaled using the doubling difference in AMOC index for
441 each model (as Figure 2d; Pink: HadGEM2-ES; dark blue: HadCM3; light blue:
442 MIROC5; yellow: NCAR CESM1; red: IPSL CM5A-LR). b,c) Sea-ice influence.
443 Ensemble means (excluding HadGEM2), of b: scaled temperature doubling difference
444 and c: albedo doubling difference. d,e) Evaporation influence. d: Ensemble mean
445 (excluding HadGEM2) scaled temperature doubling difference; e: Bowen ratio of
446 ensemble mean surface heat fluxes at $4xCO_2$, divided by the equivalent at $2xCO_2$ (as
447 Figure 2h).
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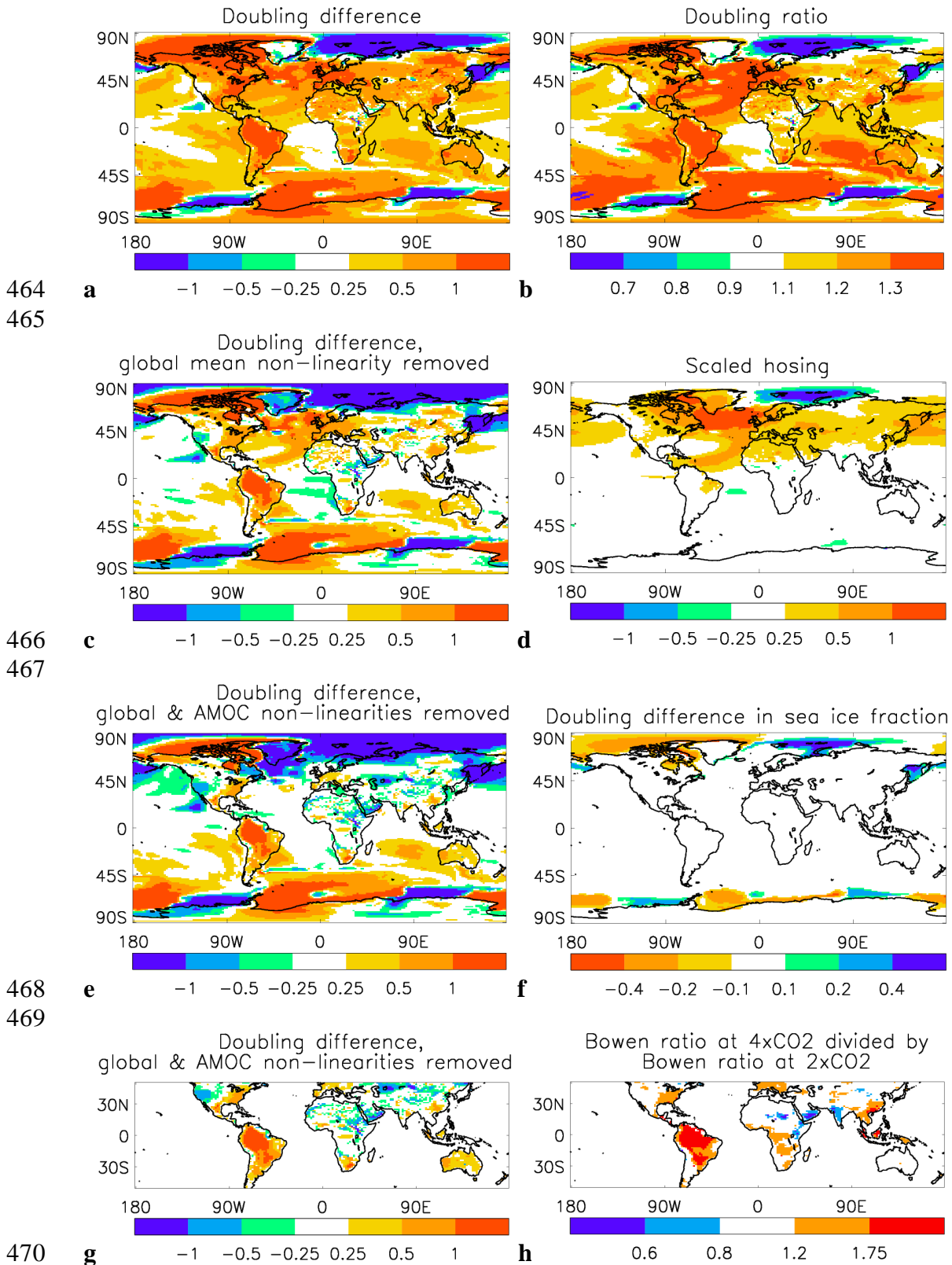


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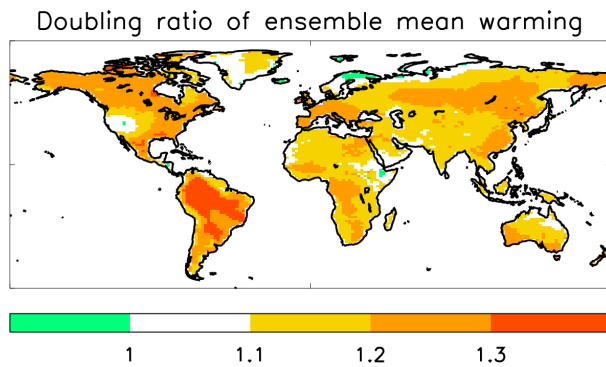
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456 Figure 1. Regional nonlinearity in the transient-forced 1pctCO₂ experiment.
457 Warming (K) simulated directly by HadGEM2-ES (y-axis) is compared with that
458 predicted from the linear reconstruction^{12,13} using (left column) abrupt2xCO₂ and
459 (right column) abrupt4xCO₂ responses. Good performance of the linear
460 reconstruction is indicated by the points lying close to the red line (each point
461 represents one model grid cell). Results are averaged over (top row) years 120-139 of
462 the 1pctCO₂ experiment (near 4xCO₂), and (bottom row) years 61-80 (near 2xCO₂).
463



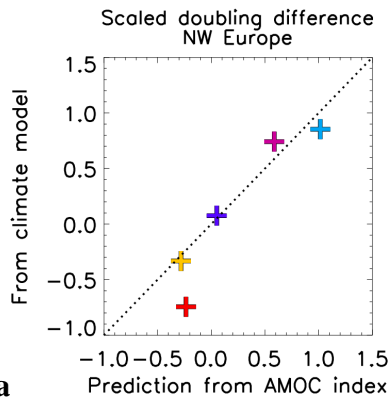
472 Figure 2. Mechanisms of nonlinear regional warming in HadGEM2-ES. Left
 473 column: doubling differences (K); a) unscaled; c) after global-mean nonlinearity is
 474 scaled out (Methods); e) as c), but with nonlinearity associated with the AMOC (panel
 475 d) subtracted; g) as e) but latitude range matches that of panel h). b) doubling ratio.
 476 d) estimated nonlinearity associated with the AMOC. f) doubling difference in sea ice

477 fraction. h) Bowen ratio at $4xCO_2$ divided by Bowen ratio at $2xCO_2$. All based on
478 means over years 50-149 of the abrupt $2xCO_2$, abrupt $4xCO_2$ or hosing experiments.
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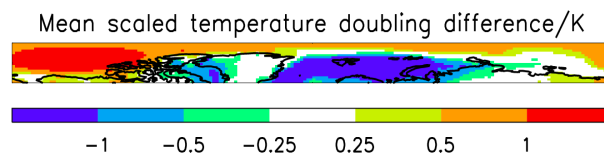


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490 each of the first and second CO_2 doublings first, then the doubling ratio calculated.
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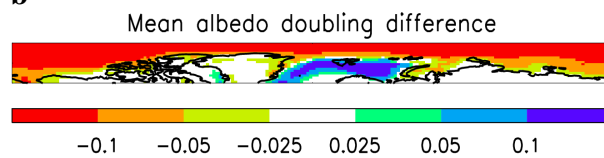
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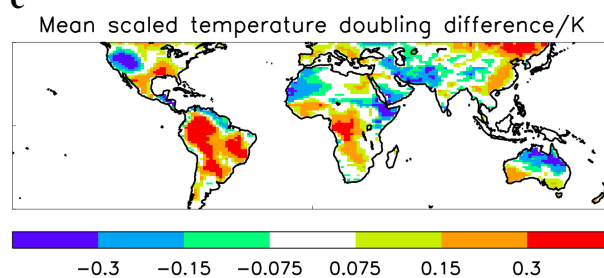
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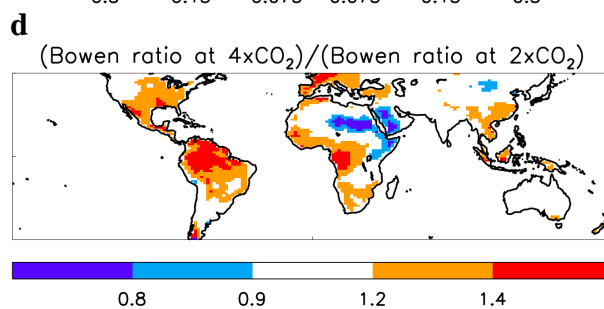
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e

505 Figure 4. Multi-model mechanisms of temperature nonlinearity. All panels: ‘scaled
506 temperature doubling differences’ have had the global mean nonlinearity scaled out.
507 a) AMOC influence, averaged over NW Europe (land, 10W-20E, 45-70N). Y-axis:
508 scaled temperature doubling difference for each model; x-axis: the HadGEM2-ES
509 hosing temperature response scaled using the doubling difference in AMOC index for
510 each model (as Figure 2d; Pink: HadGEM2-ES; dark blue: HadCM3; light blue:
511 MIROC5; yellow: NCAR CESM1; red: IPSL CM5A-LR). b,c) Sea-ice influence.
512 Ensemble means (excluding HadGEM2), of b: scaled temperature doubling difference
513 and c: albedo doubling difference. d,e) Evaporation influence. d: Ensemble mean
514 (excluding HadGEM2) scaled temperature doubling difference; e: Bowen ratio of

515 ensemble mean surface heat fluxes at 4xCO₂, divided by the equivalent at 2xCO₂ (as
516 Figure 2h).

517

518

519

520

1 **Supplementary material for ‘Nonlinear regional**
2 **warming at higher CO₂ concentrations’**

3

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5 **Chadwick¹, Jeff K Ridley¹, Matthew B Menary¹, Nathaëlle Bouttes², Jean Louis**
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7

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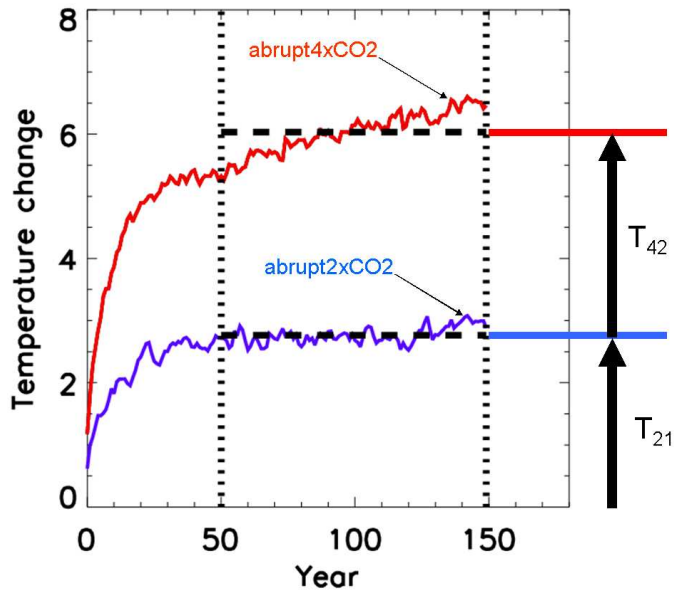
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19 *To be submitted to Nature Climate Change*

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Supplementary Figure 1. Illustrating the doubling difference and doubling ratio calculations. The main results are averaged over years 50-149 – see vertical dotted lines. The red and blue curves show global mean warming timeseries for illustration. The doubling difference is given by $T_{42} - T_{21}$, the doubling ratio by T_{42} / T_{21} .

32

33 **1. Interpreting averages over years 50-149 of the abruptCO2**
34 **experiments**

35

36 Our analysis focuses on averages over years 50-149 of each abruptCO2 experiment.

37 This section discusses how these results may approximately be related to policy-

38 relevant scenario projections. This does not mean that the results are substitutes for

39 scenario projections (in particular, the distinct effects of non-CO2 forcings are

40 absent): it just gives a rough context. The main paper states that, "For abrupt2xCO2,

41 these 100-year means may roughly be interpreted as the results for year 2100 of a

42 CO2-only version of rcp4.5." This statement arises from the method behind Figure 1,

43 as follows.

44

45 Supplementary Figure 2 shows the timeseries of global mean radiative forcing for

46 rcp4.5 (blue). It also shows an idealised transient scenario (black line) that is roughly

47 similar to rcp4.5. We show below that the mean over years 50-149 of the

48 abrupt2xCO2 experiment represents an estimate of the response at year 2100 of the

49 scenario represented by the black line.

50

51 As demonstrated in the main paper (Figures 1b,c) and in previous literature¹⁻³, it is

52 possible to use a simple linear combination of abruptCO₂ responses to estimate

53 climate change under a transient forcing experiment. This method works well (Figures

54 1b,c) when it is used to simulate periods in the transient experiment when the forcing

55 matches that of the abruptCO₂ experiment.

56

57 The method we use to estimate the response to a transient experiment from an
58 abruptCO2 experiment is a linear response function approach. It is given simply by
59 the following equation:

60

61
$$y_i = \sum_{j=0}^i \frac{\Delta F_{i-j}}{\Delta F_a} x_j$$
 supplementary equation 1

62

63 where y_i is the estimated transient temperature response at year i and x_j is the
64 temperature response at year j of the CO₂ step experiment. ΔF_{i-j} is the annual step
65 change in radiative forcing during year $i-j$ of the scenario. ΔF_a is the radiative
66 forcing change in the abruptCO₂ experiment. (Essentially, this treats the transient
67 scenario as a series of small annual step changes in forcing: the response to each step
68 is estimated by scaling the abruptCO₂ response).

69

70 The black line in Supplementary Figure 2 represents an experiment where CO₂ is
71 increased by 0.7% per year for 100 years, then held constant for 50 years (reaching a
72 peak CO₂ concentration of double the pre-industrial level). This corresponds to an
73 approximately constant rate of forcing increase during the ramp-up period. As this
74 experiment takes 100 years to double CO₂, the annual change in forcing is equal to
75 the abrupt2xCO₂ forcing divided by 100. Therefore, the ratio $\Delta F_{i-j}/\Delta F_a$ is set equal
76 to 1/100 for the first 100 years (i.e. for $i-j \leq 99$ in supplementary equation 1); and
77 equal to zero for the last 50 years (i.e. for $i-j > 99$). To obtain the warming at the end
78 of the scenario, we set $i=149$ (the scenario is 150 years long). Therefore, $\Delta F_{i-j}/\Delta F_a$
79 is equal to 1/100 for $j \geq 50$; and equal to zero for $j < 50$. Using supplementary

80 equation 1, therefore, the response at the end of this experiment may be estimated

81 from the abrupt2xCO2 response as follows:

82

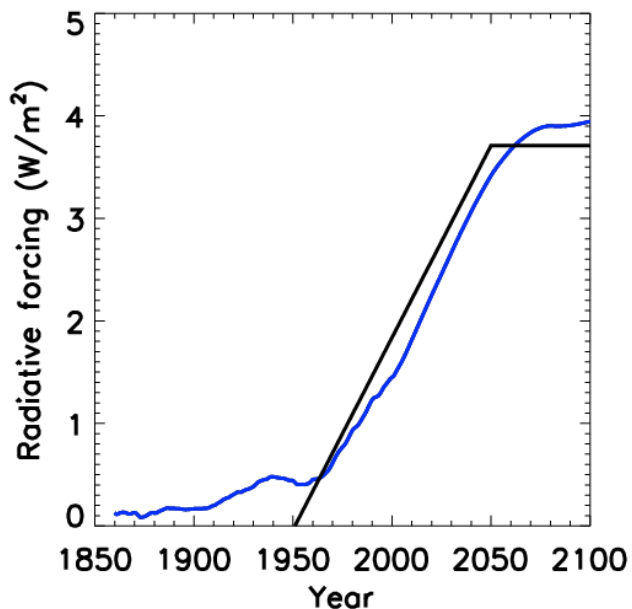
83
$$y = \sum_{j=50}^{149} \frac{1}{100} x_j^{(abrupt2xCO2)}$$
 supplementary equation 2

84 (The summation starts from j=50 because $\Delta F_{i-j} / \Delta F_a$ is zero for j < 50). This is

85 simply equal to the mean over years 50-149 of the abrupt2xCO2 experiment – as used

86 in the main paper.

87



88

89 Supplementary Figure 2. Total global-mean radiative forcing timeseries. Blue: for

90 rc4.5, as estimated by the IAM used to produce the scenario forcing dataset⁴ (from

91 the RCP database: <http://www.iiasa.ac.at/web-apps/tnt/RcpDb>). Black: for a scenario

92 where CO2 is increased by 0.7% per year for 100 years, then stabilised for 50 years.

93

94 **1. Sea-ice non-linearity in HadGEM2-ES**

95

96 The patterns of temperature nonlinearities over high latitude oceans (Figure 2e)
97 correspond closely to nonlinearities in sea-ice cover (Figure 2f). The scale in Figure
98 2f is reversed, because reductions in sea-ice cover tend to drive increases in warming.
99 Here we provide support for the nonlinear albedo feedback being a prominent driver
100 of high-latitude temperature non-linearity..

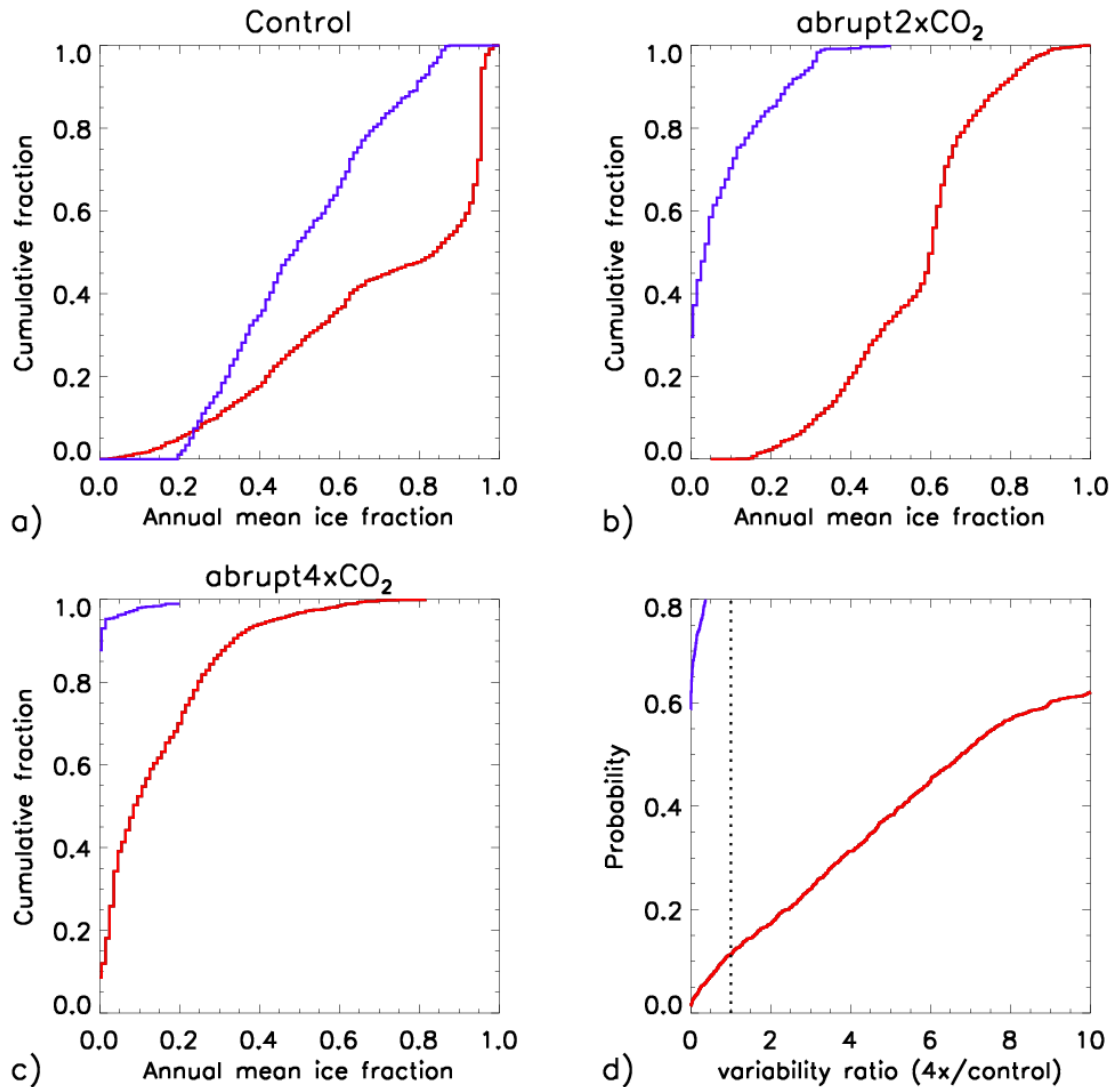
101

102 Supplementary figure 3 shows statistics of the climatological mean and interannual
103 variability in sea-ice fraction. The blue(red) lines show results when only regions with
104 sea-ice doubling difference larger than 0.2(smaller than -0.2) are included. Climate
105 means are shown for the control and each abruptCO2 experiment (panels a-c). Panel d
106 shows the ratio in variability between the abrupt4xCO2 experiment and the control.
107 Regions with positive nonlinearities in sea ice cover (with doubling difference > 0.2 ;
108 c.f. Figure 2f) have intermediate ice cover in the control experiment (Supplementary
109 figure 3a, blue line), but (near) zero ice cover in the abrupt4xCO₂ experiment
110 (supplementary figure 3c, blue line). Correspondingly, the interannual variability in
111 ice cover is much lower at 4xCO₂ than in the control (supplementary figure 3d, blue
112 line). This is consistent with the idea of smaller albedo feedback at 4xCO₂ due to a
113 transition from intermediate to negligible ice cover.

114

115 Regions with negative sea ice nonlinearities (doubling difference < -0.2) have much
116 larger sea ice variability at 4xCO₂ than in the control (supplementary figure 3d, red
117 line), and often have large ice cover in the control (supplementary figure 3a), and non-

118 zero cover even at 4xCO₂ (supplementary figure 3c). This is consistent with the idea
 119 of albedo feedback being higher in the abrupt4xCO₂ experiment.
 120



121

122

123 Supplementary figure 3. Statistics of sea-ice mean (a-c) and variability (d) for regions
 124 with (blue) sea-ice doubling difference > 0.2 and (red) sea-ice doubling difference < -
 125 0.2. Panel d) shows the ratio: (variability in abrupt4xCO₂)/(variability in control),
 126 where variability is quantified as the standard deviation in annual mean sea-ice cover
 127 over years 50-149 of each experiment.

128

129

130

131 **2. Evaporation over the Amazon in HadGEM2-ES**

132

133 The large temperature non-linearities over the Amazon are associated with a
134 substantially larger Bowen ratio at 4xCO₂ compared to 2xCO₂ (Figure 2h). Here we
135 link this to reduced forest tree stomatal conductance at higher CO₂, driven by a direct
136 stomatal response to CO₂, with a secondary effect due to reduced photosynthesis at
137 high temperature. We show results averaged over the western Amazon (72-60W,
138 12S-3N), capturing the main temperature non-linearity.

139

140 Over this region, latent heat flux from evaporation is significantly lower in the
141 abrupt4xCO₂ experiment than in the abrupt2xCO₂ experiment (supplementary figure
142 4a; blue: abrupt2xCO₂; red: abrupt4xCO₂). The total turbulent heat flux is relatively
143 similar in the two experiments (supplementary figure 4b), so the decrease in latent
144 heat flux is balanced by a corresponding increase in sensible heat flux (supplementary
145 figure 4c). This is consistent with the idea of restricted evaporation causing a larger
146 proportion of surface heat to be lost by sensible heat, with a corresponding increase in
147 surface temperature.

148

149 Surface evaporation is determined by atmospheric demand divided by net resistance⁵.
150 The net resistance quantifies limitations on water supply, accounting for soil moisture,
151 biophysical control by plants (via stomata) and the process of transferring moisture
152 from the surface to the lowest atmospheric layer. The decrease in evaporation (at
153 4xCO₂ compared to 2xCO₂) is driven by a relatively large (around 35%) decrease in

154 1/(net resistance) – see Supplementary figure 4d. We plot 1/(net resistance), because
155 evaporation is proportional to 1/(net resistance), at constant atmospheric demand.
156 This decrease in 1/(net resistance) is dominated by a decrease in stomatal conductance
157 associated with the broadleaf tropical forest trees: supplementary figure 4e shows
158 changes due to stomatal conductance alone, and is similar to supplementary figure 4d.

159

160 The difference in stomatal conductance between the two experiments (seen in
161 supplementary figure 4e) is largely due to a fast response of stomata to the different
162 CO₂ levels. This appears in supplementary figure 4e as a difference between the red
163 and blue lines present from the first year. Moisture stress is negligible for forest trees
164 in this region in both experiments (not shown), so regional evaporation is independent
165 of precipitation change.

166

167 The subsequent decline in conductance in the abrupt4xCO₂ experiment
168 (supplementary figure 4e, red line) is driven in this model primarily by a decrease in
169 photosynthesis, with stomata closing to maintain near constant leaf internal CO₂
170 concentration. Evidence for this is given in supplementary figure 4f. This shows that
171 a near constant proportionality is maintained between stomatal conductance and gross
172 primary productivity (GPP, a proxy for photosynthesis, as leaf area is almost constant
173 in this region for these runs). The relationship between photosynthesis and stomatal
174 conductance arises through the transport of carbon through a leaf, which is quantified
175 by the following equation⁶:

176

177
$$A = \frac{g_s (c_c - c_i)}{1.6RT^*}$$

178

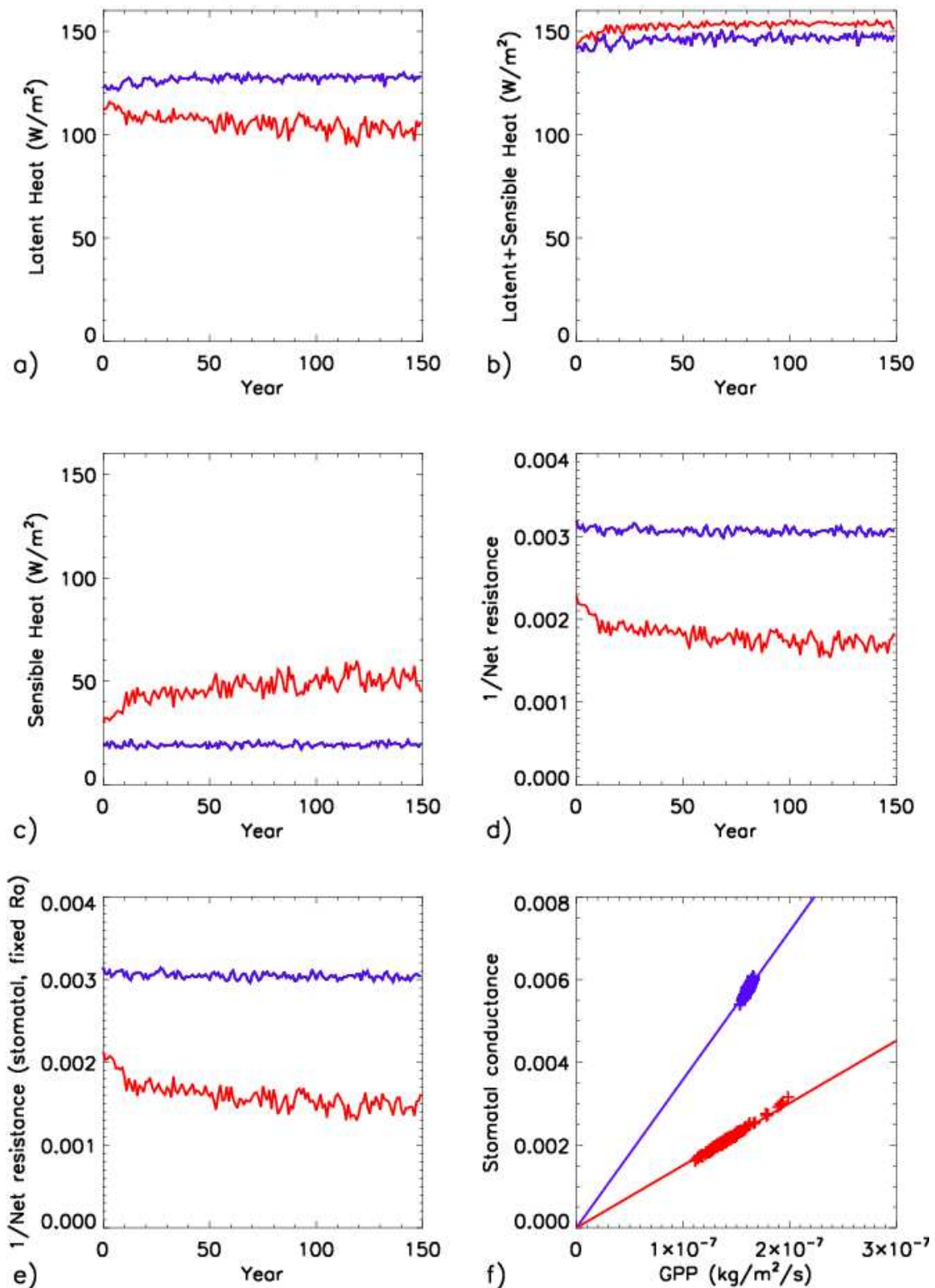
179 A is the leaf photosynthesis rate, g_s the stomatal conductance, $(c_c - c_i)$ is the CO₂
180 concentration gradient across the stomata, R the perfect gas constant and T^* the leaf
181 surface temperature in K (the latter is relatively constant in these runs as it is in units
182 of K). The near-constant proportionality between stomatal conductance and
183 photosynthesis (supplementary figure 4f, red line) means that $(c_c - c_i)$ is
184 approximately constant. That is, the model of stomatal conductance in HadGEM2-ES
185 acts to keep the internal leaf CO₂ concentration (c_i) roughly constant during the
186 abrupt4xCO₂ experiment (c_c , the external CO₂ concentration is approximately
187 constant during the abrupt4xCO₂ run). It does this by closing stomata (decreasing g_s),
188 which in turn reduces water loss.

189

190 Large uncertainties exist in the modelling of stomatal responses to CO₂ increase⁷.
191 HadGEM2-ES does not include photosynthetic acclimation⁸, which could reduce the
192 decrease in GPP at high temperature, potentially reducing the decreases in stomatal
193 conductance. However, the magnitude of this effect is highly uncertain⁹.

194

195



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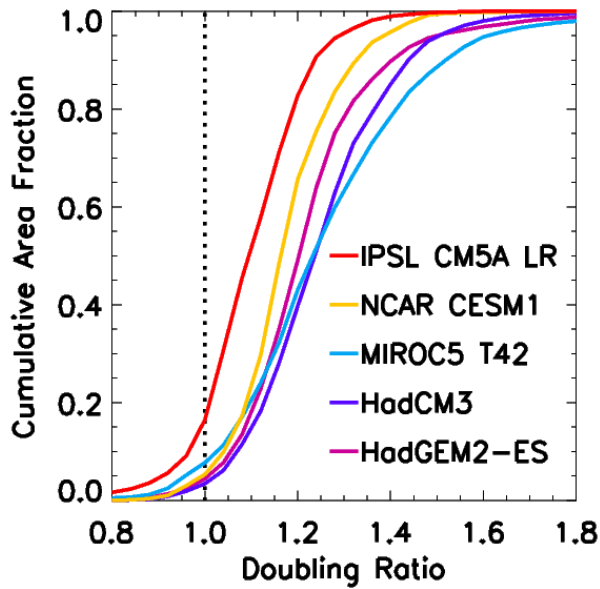
198 Supplementary figure 4. Diagnostics relating to evaporation, averaged over the
 199 Western Amazon, for the abrupt2xCO₂ (blue) and abrupt4xCO₂ (red) experiments.

200 See text for description.

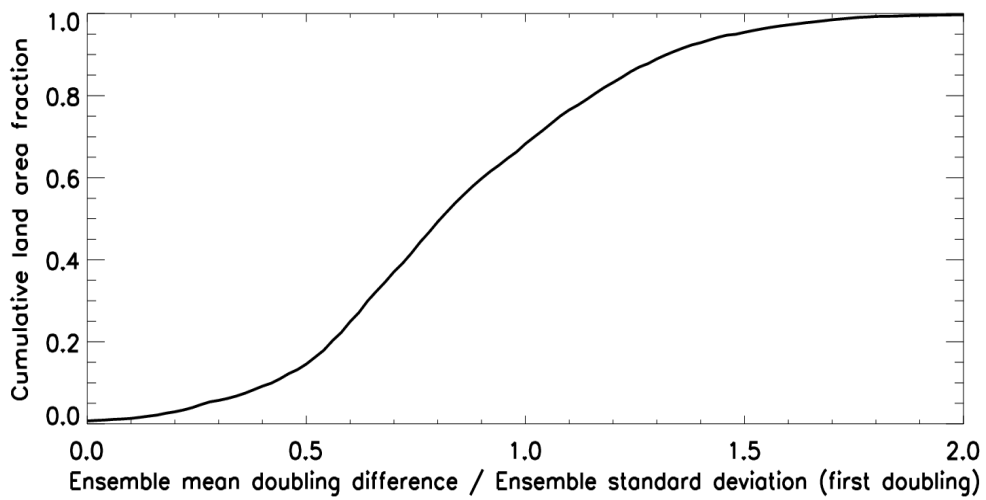
201

202 **3. Multi-model statistics of nonlinearity over land**

203



204 a)



205

206 b)

207 Supplementary Figure 5. a) Cumulative area distribution functions of the temperature
208 doubling ratio over land, for each model. b) Cumulative area distribution function of
209 the ratio: (ensemble mean doubling difference) / (Ensemble standard deviation from
210 the first doubling).

211

212

213 **4. Inflation in model spread for the second CO₂ doubling**

214

215 The main paper reports that, over about 30% of the land area, the model spread in
216 warming per K of global warming is more than 1.4 times larger for the second
217 doubling than for the first. In this section, we will address the possibility of the
218 inflation of model spread being an artifact of internal variability.

219

220 A difference in the standard deviation between two datasets can arise simply from
221 internal variability. This is because the climate state for each model is estimated from
222 the mean over a finite period. Even though 100-year means are used in this study,
223 internal variability may still play a role.

224

225 We denote the ratio between the standard deviation for the second doubling, and that
226 for the first, as R:

227

$$228 \quad R = \frac{\sigma_{42}}{\sigma_{21}},$$

229 where σ_{42} , the ensemble standard deviation for the second doubling (where CO₂
230 changes from 2x to 4x pre-industrial levels) is given by:

231

$$232 \quad \sigma_{42} = \sqrt{V_{42}^{(m)} + V_4^{(i)} + V_2^{(i)}},$$

233

234 where $V_{42}^{(m)}$ is the variance due to model differences alone; $V_4^{(i)}$ is the variance from
235 internal variability in the climate at 4xCO₂; and $V_2^{(i)}$ the equivalent at 2xCO₂.

236 Similarly, σ_{21} , the standard deviation for the first doubling, is given by:

237

238
$$\sigma_{21} = \sqrt{V_{21}^{(m)} + V_2^{(i)} + V_1^{(i)}}$$

239

240 Therefore, R is given by:

241

242
$$R = \frac{\sqrt{V_{42}^{(m)} + V_4^{(i)} + V_2^{(i)}}}{\sqrt{V_{21}^{(m)} + V_2^{(i)} + V_1^{(i)}}}$$

243

244 $V_2^{(i)}$ appears on both top and bottom of this ratio. This means that if $V_2^{(i)}$ was much
245 larger than the other variances, R would tend to 1 everywhere. This cannot explain
246 our finding of large areas with $R > 1.4$.

247

248 If $V_4^{(i)}$ (the internal variability in the mean at 4xCO₂) was increased, however, R
249 would increase everywhere (and so the area with $R > 1.4$ would increase). We tested
250 the importance of $V_4^{(i)}$ by artificially increasing it: by calculating the climate means
251 for abrupt4xCO₂ using shorter averaging periods (but centred on the same year as the
252 100-year means). This has minimal effect on our result: the fraction of land with $R >$
253 1.4 is still 32% even if this averaging period is reduced to 20 years (compared to 30%
254 for 100 year means). This suggests that, for the 100-year means used in the main
255 paper, internal variability has minimal effect on our estimate for the area with $R > 1.4$

256

258

259 **5. Drivers of nonlinearity from individual models**

260

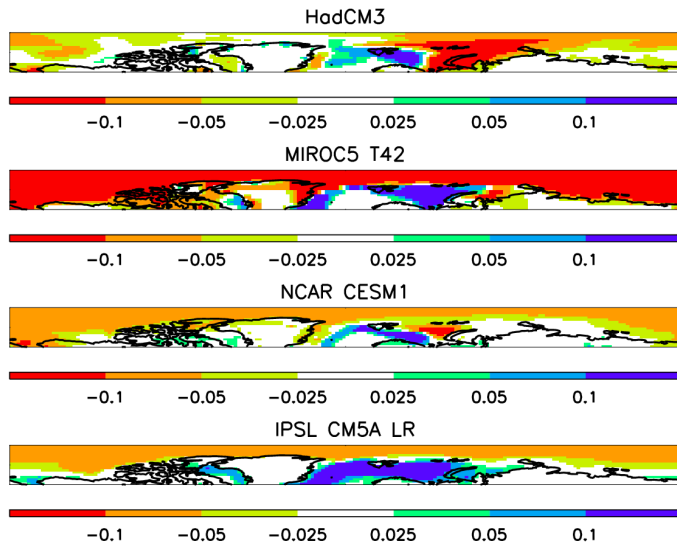
261 The main paper (Figure 4) shows results for the albedo and evapotranspiration drivers
262 averaged over the four additional climate models (NCAR-CESM1, IPSL CM5A-LR,
263 MIROC5 T42 and HadCM3). Here we show results for individual models
264 (Supplementary Figures 6,7). We also give doubling ratios for global-mean warming
265 (Supplementary Table 1). The spread in the AMOC nonlinearity is illustrated in
266 Figure 4a of the main paper.

267

268 As reported in the main paper, the patterns in albedo and evapotranspiration drivers
269 show significant spread across the models. Therefore, their contribution to the overall
270 uncertainty in warming for the second doubling may be substantial in the relevant
271 regions (see discussion on how nonlinearity influences uncertainty in the main paper).
272 The spread in the albedo driver (Supplementary Figure 6) may partly be associated
273 with errors in simulated pre-industrial sea-ice cover (we show above that the sign of
274 the nonlinearity is linked with the control sea-ice cover), so there may be potential for
275 reducing uncertainty using observations. Similarly, the spread in the
276 evapotranspiration driver (Supplementary Figure 7) may partly be associated with
277 errors in pre-industrial soil moisture.

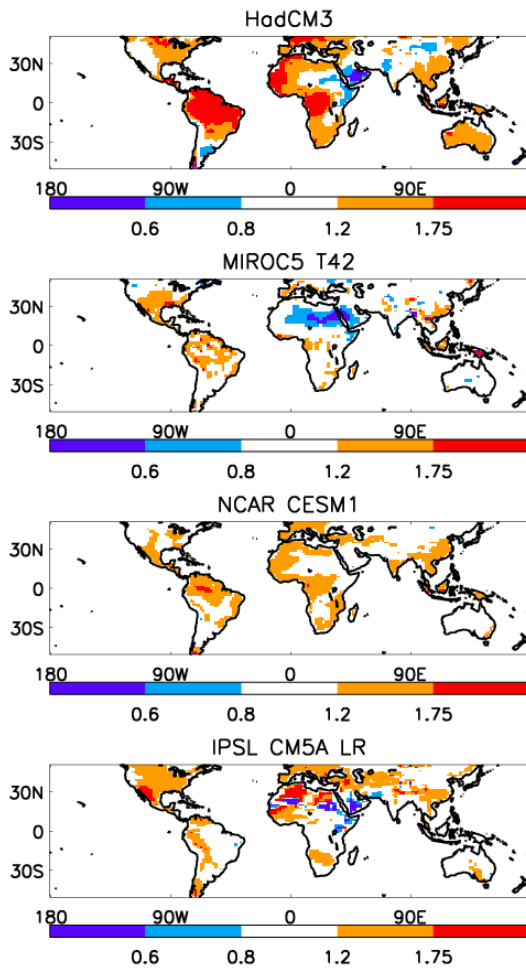
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280

281 Supplementary Figure 6. Albedo doubling differences: as Figure 4c of the main paper,
 282 but for individual models.



283

284 Supplementary Figure 7. Bowen ratio of ensemble mean surface heat fluxes at $4xCO_2$,
 285 divided by the equivalent at $2xCO_2$: as Figure 4e but for each model.

Model	Doubling ratio in global mean warming
NCAR CESM1	1.21
IPSL CM5A-LR	1.05
MIROC5 T42	1.27
HadCM3	1.19
HadGEM2-ES	1.18

286

287 Supplementary Table 1. Doubling ratio in global-mean warming for each model.

288

289 **5. Model descriptions**

290

Model and citation	Resolution	Citation
NCAR CESM1 ¹⁰	0.9° longitude x 1.25° latitude, 26 vertical levels	Gent et al., 2011
IPSL CM5A-LR ¹¹	3.75° longitude x 1.875° latitude, 39 vertical levels	Dufresne et al., 2013
MIROC5 T42 ¹²	T42, 40 vertical levels	Watanabe et al., 2010
HadCM3 ^{13,14}	3.75° longitude x 2.5° latitude, 19 vertical levels	Gordon et al., 2000, Pope et al., 2000

291

292 Supplementary Table 2. Descriptions of models used (HadGEM2-ES is described in

293 Methods of main text).

294

296 **References**

297

298

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