



What can decadal variability tell us about climate feedbacks and sensitivity?

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Received: 2 February 2017 / Accepted: 29 January 2018 / Published online: 26 February 2018
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Abstract

Radiative feedbacks are known to determine climate sensitivity. Global top-of-atmosphere radiation correlations with surface temperature performed here show that decadal variability in surface temperature is also reinforced by strong positive feedbacks in models, both in the long wave (LW) and short wave (SW), offsetting much of the Planck radiative damping. Net top-of-atmosphere feedback is correlated with the magnitude of decadal temperature variability, particularly in the tropics. This indicates decadal-timescale radiative reinforcement of surface temperature variability. Assuming a simple global ocean mixed layer response, the reinforcement is found to be of a magnitude comparable to that required for typical decadal global scale anomalies. The magnitude of decadal variability in the tropics is uncorrelated with LW feedbacks, but it *is* correlated with total SW feedbacks, which are, in turn, correlated with tropical SW cloud feedback. Globally, water vapour/lapse rate, surface albedo and cloud feedbacks on decadal timescales are, on average, as strong as those operating under climate change. Together these results suggest that some of the physical processes responsible for setting the magnitude of global temperature change in the twenty-first century and climate sensitivity also help set the magnitude of the natural decadal variability. Furthermore, a statistically significant correlation exists between climate sensitivity and decadal variability in the tropics across CMIP5 models, although this is not apparent in the earlier generation of CMIP3 models. Thus although the link to sensitivity is not conclusive, this opens up potential paths to improve our understanding of climate feedbacks, climate sensitivity and decadal climate variability, and has the potential to reduce the associated uncertainty.

1 Introduction

While further human-forced global average warming appears inevitable (IPCC 2013; Peters et al. 2013), the magnitude of projected late twenty-first century warming (ΔT_{Global} say) for a given scenario of future greenhouse gas emissions is uncertain (Meehl et al. 2007a; Collins et al. 2013). Despite major efforts to understand and reduce this uncertainty (Boucher et al. 2013; Collins et al. 2013), it remains large. This complicates decisions relating to climate change adaptation and mitigation, and adds hundreds of billions of dollars to the associated cost (Hope 2015).

Future climate will also depend on natural decadal climate variability (DCV; Hawkins and Sutton 2009, 2011; Kirtman et al. 2013; Power et al. 2006; Deser et al. 2012)—and includes processes such as the Interdecadal Pacific Oscillation (Power et al. 1999, 2006; Folland et al. 1999; Kosaka and Xie 2013). Despite the importance of this *internally-driven* DCV to climate and life on earth, relatively little is known about the physical processes underpinning it and the factors that determine its magnitude (Liu et al. 2012). A key feature of coupled model DCV is that the range in models is enormous. The standard deviation (SD) of global decadal variability ($SD_{G_{10y}}$) differs by a factor of more than four across Coupled Model Intercomparison Project phase 5 (CMIP5, Taylor et al. 2012) models—see below. What causes this range?

Differences in the El Niño–Southern Oscillation (ENSO) of course will play a role in decadal variability. Middlemas and Clement (2016) found around half the variance in the frequency of significant warming/cooling decades per century across CMIP5 models could be explained by the magnitude of decadal variations in their Niño3 sea surface

Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s00382-018-4113-7>) contains supplementary material, which is available to authorized users.

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temperatures (SST). Importantly ENSO variability is itself associated with strong radiative feedbacks, both regionally (Bellenger et al. 2014; Li et al. 2015) and globally (Colman and Power 2010; Colman and Hanson 2016), suggesting it has the potential for a significant role in stochastic radiative forcing and decadal radiative feedback.

Although coupled ocean/atmosphere processes such as ENSO likely play a role in determining the magnitude of DCV, they are unlikely to be the whole story. It is notable that ocean models with only mixed layer physics can also show strong variability (Middlemas and Clement 2016; Xie et al. 2016). Thus, although fully coupled models, as expected, do show larger variances across most timescales in both radiation and global temperature (Xie et al. 2016), the differences are relatively small at decadal and longer timescales. For example, there is only around 5% difference in the decadal SD of global temperature in mixed layer/fully coupled pair of models considered by Middlemas and Clement (2016). Consistent with this, a review by Liu (2012) concludes that processes involving ocean/atmosphere dynamical feedbacks play only a relatively minor role globally, although they may be important regionally [e.g. in the North Atlantic (Chen and Tung 2014)]. What other processes may be critical?

Following Roe (2009), *radiative feedbacks* may play a significant role in determining decadal variability of surface temperature. Xie et al. (2016) infer that short wave (SW) stochastic radiative forcing plays a potentially important role in DCV as they find it typically leads temperature by around 1 year. They find, however, that the correlation of *total* global averaged radiation with global surface temperature on decadal timescales is relatively weak—peaking at around -0.4 at a lag of around 2 years, due to strongly offsetting long wave (LW) and SW responses. They deduce a net radiative feedback under variability that peaks at only around half the magnitude of the climate change feedback (-0.5 versus $\sim -1 \text{ W/m}^2/\text{K}$), arguing that differences in temperature and radiation patterns drive a different feedback response to that of climate change (see also Zhou et al. 2015).

The Xie et al. (2016) analysis does not clarify the reasons underlying the very large range in variability in models, however. Nor does it preclude an important role for radiative feedback in amplifying DCV, given such feedbacks oppose what would otherwise have been a strongly damping Planck¹

¹ The Planck cooling refers to the hypothetical TOA LW radiative cooling that would take place for the climate system under a given surface warming if the atmosphere warmed uniformly with height at the same rate the surface temperature change (i.e. no lapse rate changes), and there were no changes to other radiatively sensitive parameters in the atmosphere/surface, such as to water vapour, clouds or surface albedo. The Planck cooling is not strictly a climate ‘feedback’ but instead represents the radiative damping of the climate system that would occur *in the absence of feedbacks* (Bony et al. 2006).

cooling term, analogous to the case under climate change (Bony et al. 2006; Roe 2009). Indeed the weaker net negative feedback noted by Xie et al. (2016) indicate there are *as strong or stronger* positive feedbacks than under climate change—as noted previously by Colman and Hanson (2013). Furthermore the small total feedbacks identified by Xie et al. (2016) are the net result of very strong, but offsetting LW ($R = -0.8$) and SW ($R = +0.7$) correlations, confirming that strong radiative feedback processes are indeed operating in these models. Consistent with this view, a coupled model run with suppressed water vapour feedback, was found to have significantly lower *interannual* variability (Hall and Manabe 1999).

Considering the radiative contributions to decadal-long warming trends in CMIP5 models, Brown et al. (2014) concluded that typically around half the global average warming may be attributable to the net top of atmosphere radiative feedback (with the SW dominating the response)—although with large variation between decades and an uncertain role for LW feedback. The remaining global warming was associated with non radiative-feedback related processes, such as redistribution of heat within the climate system (Brown et al. 2014).

The preceding discussion indicates that significant uncertainties remain in the role of radiative feedback (including the relative roles of LW/SW) in the magnitude and inter-model range of DCV, both globally and in the tropics. Understanding the causes of this large range is not simply of importance for evaluating and improving models—but also for understanding recent climate trends and the role of radiative reinforcement, and how ‘typical’ this may be (e.g. Brown et al. 2014). Recent findings (Andrews et al. 2015; Zhou et al. 2016; Gregory and Andrews 2016) suggest that large scale cloud redistributions, in the recent period have been responsible for global radiative responses which have suppressed warming, inconsistent with long term climate change feedbacks, or even typical decadal feedbacks (Brown et al. 2014). Since tropical variability has been identified as an important driver of global-scale temperature variability (Kosaka and Xie 2013; Dai et al. 2015; Meehl et al. 2012), a particular focus will be on tropical decadal variability, and the associated radiative feedbacks. If radiative feedbacks play a key role in amplifying decadal temperature variability then there arises the important question of possible links between the magnitude of DCV and climate change.

This paper addresses the following questions:

Footnote 1 (continued)

Here it is listed in tables as a ‘feedback’ for simplicity of presentation.

- How large is the spread in DCV in models, globally and in the tropics/extra-tropics? How large is the influence of ENSO variability on this range?
- How strong are the LW/SW and net decadal radiative feedbacks in models on decadal timescales? Are these correlated with the magnitude of the variability, and are they of a sufficient magnitude to ‘explain’ the range? Which feedbacks are most important globally and in the tropics/extra-tropics?
- How large are climate feedbacks under DCV compared with climate change?
- Are there links between the magnitude of DCV, either globally or in the tropics, with either temperature change projected over the next century or with climate sensitivity?

The paper is laid out as follows: the methodologies for calculation of variability and feedback, and the models used are described in Sect. 2. Section 3 contains results and discussion, with conclusions in Sect. 4.

2 Analysis of variability and radiative feedbacks

Up to 41 models from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012) archive were used for the calculation of variability and feedbacks from pre-industrial runs. The full list used is given in supplementary material Table S1. 200 years of data were used for all models except for MIROC4h (100 years available). Not all models provided the fields needed for the calculation of all top of atmosphere (TOA) radiative feedbacks. Model data was first re-gridded to a common 2.5°latitude/longitude grid; global/tropical/extra-tropical annual means calculated were then detrended by removal of a linear fit, to eliminate any drift. For most models this had little impact on calculated variability. Decadal SDs were calculated following application of a 10 year running mean. Eighteen models from the Coupled Model Intercomparison Project Phase 3 (Meehl et al. 2007b) were also used. These are listed in Table S2 of the supplementary material. Equilibrium climate sensitivity (ECS) values were obtained from Randall et al. (2007) and Flato et al. (2013) for CMIP3 and CMIP5 respectively.

Decadal (or interannual) LW/SW/Net radiative feedbacks were calculated as follows. For the interannual case, global annual means were calculated for surface temperature and for TOA LW, SW and net radiation (e.g. see Forster and Gregory 2006). The (200) radiation values were then regressed against the corresponding surface temperatures, to give the global feedback. For tropical feedback, the calculation was repeated, but with averages for both TOA radiation and surface temperatures calculated over the tropics only. Decadal feedbacks were

calculated using an identical approach, following the application of a 10-year running mean to the radiation and temperature fields. Error bars shown throughout were determined from the 80% confidence interval from standard regression. More sophisticated fitting can be applied using a Bayesian approach which samples the uncertainty range in the data point. This approach has been found to provide similar confidence spread for these feedbacks (Colman and Hanson 2013). We show 80% rather than, say, 95% confidence range in these plots, as it is illustrative of the uncertainty in calculation for the feedbacks and how that varies/differs between models and feedbacks, but avoids the visual clutter of showing larger error bars.

Individual process feedbacks (Table 2) were calculated using “radiative kernels” (Soden et al. 2008; Shell et al. 2008). The kernels used here were derived from the BMRC/CAWCR model (see Soden et al. 2008) and vary as a function of month, latitude, and (apart from surface albedo) atmospheric level. For the preindustrial runs, relevant fields were first averaged into decadal monthly means, then the radiative kernel applied to pairs of corresponding months between adjacent decades. Decadal annual means were then calculated, and global or tropical averages regressed against corresponding average temperature changes. Details of the methodology are described in Colman and Hanson (2013). For the calculation of climate change feedbacks, kernels were applied to pairs of months selected from decades beginning 2010 and 2090. After calculation of annual means, feedbacks were then calculated by normalising radiation change by global mean surface air temperature change.

‘Scaled’ decadal feedbacks (see Table 2 and associated discussion) were calculated following Armour et al. (2013) and Colman and Hanson (2016). The assumption here is that feedbacks are (to first order) invariant for a given geographic location—i.e. the same locally for both climate change and DCV. To calculate the implied decadal global or tropical feedback, local feedbacks obtained from kernel calculations under RCP8.5 were ‘scaled’ by the relative surface temperature variations that occur under DCV. Details on the approach are provided in Colman and Hanson (2016), and it is discussed further below. An important caveat is that some processes will not be expected to be only locally temperature dependent. For example Zhou et al. (2016) argue that East Pacific tropical cloud changes are affected by changes in West Pacific temperatures through changes in free tropospheric temperatures affecting inversion strength.

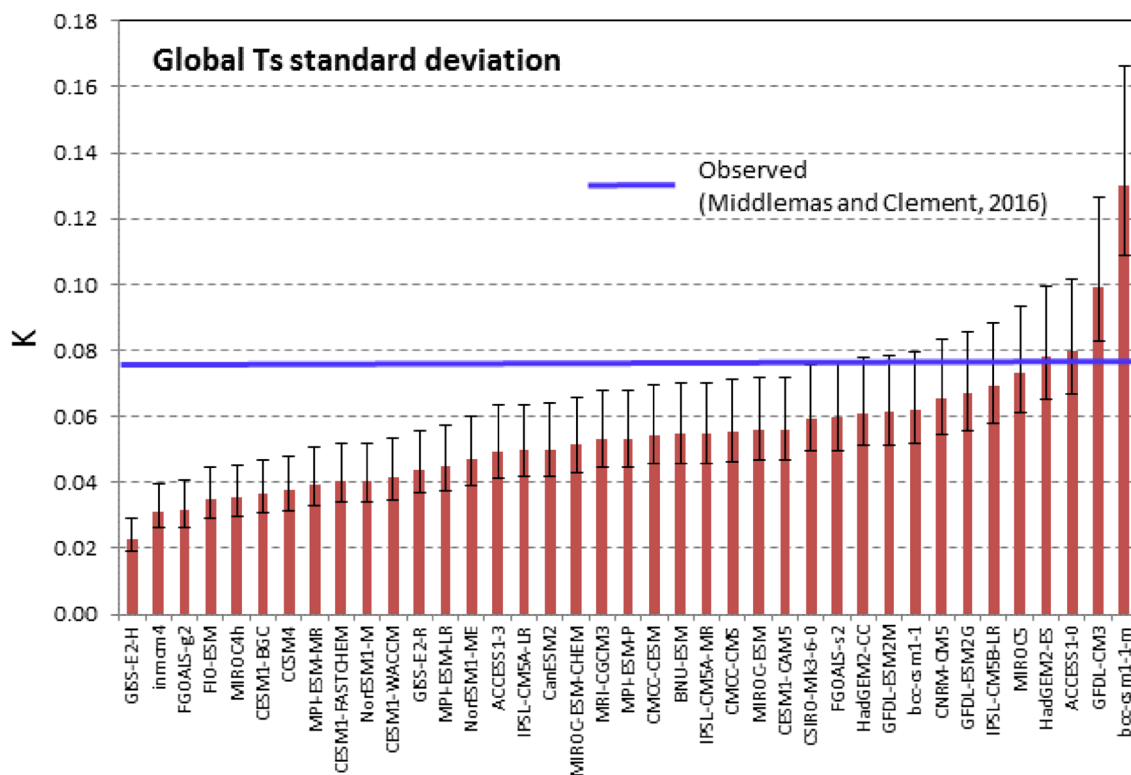


Fig. 1 Decadal global SD of surface temperature for the CMIP5 models (K), listed in order of increasing SD. Names of models (and the corresponding modelling institutions) are listed in Table S1. Error

bars indicate 80% confidence range (Sheskin 2016) from the 200 year pre-industrial experiment sample. Also shown is the observational estimate from Middlemas and Clement (2016)

3 Results and discussion

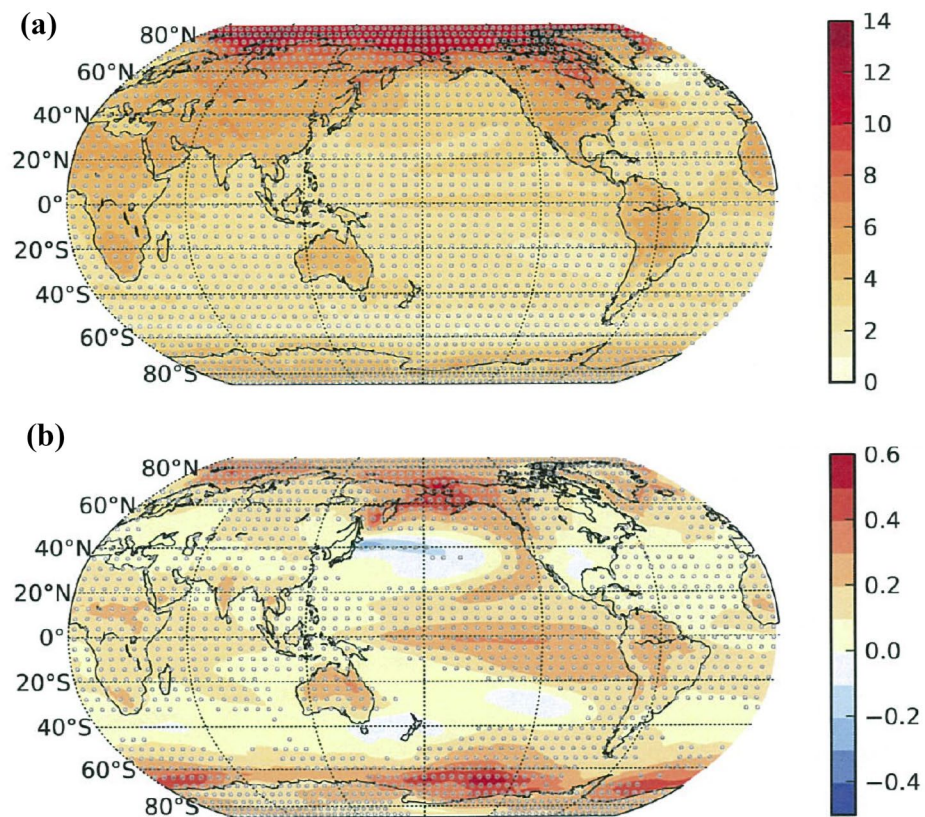
3.1 Magnitude and pattern of decadal variability in models

Figure 1 shows the SD of decadal global mean variability in surface air temperature in the CMIP5 models, ordered from lowest to highest. Values of SD range from 0.023 to 0.13 K. The range from the earlier CMIP3 models (Meehl et al. 2007b) was comparable: from 0.021 to 0.11 K (not shown). The processes resulting in this range remain unclear (Liu et al. 2012). For comparison, an observational estimate from Middlemas and Clement (2016) of DCV, obtained by removing estimates of forced changes to the GISTEMP data set (Hansen et al. 2010), is around 0.078 K, i.e. towards the top of the model range (Fig. 1), therefore most models underestimate DCV (see also discussion in Laepple and Huybers 2014; Fredrissen and Rypdal, 2016).

What does DCV look like spatially in the models and how does it compare to the patterns of climate change? Figure 2a shows the multi-model mean (MMM) of the change in local surface air temperature (for 2081–2100 relative to 1986–2005) under the RCP8.5 emissions

scenario (van Vuuren et al. 2011). Figure 2b shows point-by-point regression of temperature against tropical mean temperature from the pre-industrial experiments (after application of a 10 year running mean)—i.e. the MMM DCV pattern *relative to tropical mean temperature change* (30°N–30°S). Stippling indicates > 70% of models agree on the sign of the change, which indicates statistical significance at the 95% level under the assumption of model independence (see supplementary material). Figure 2b shows a surprisingly high degree of coherence in internally generated DCV in T with variability in T averaged over the tropics. In the vast majority of locations, the models tend to warm when the tropics are warm, with out-of-phase temperature variations restricted to a relatively small region in the North Pacific. The spatial correlation coefficient between the two plots is 0.24. Figure 2b is overall consistent in pattern with findings elsewhere from regression of local temperature against decadal global temperature, or from clustering of warming/cooling decades, suggesting that models reproduce IPO-like SST patterns under unforced DCV (Middlemas and Clement 2016; Brown et al. 2015; Power et al. 2016).

Fig. 2 a Multi-model average of local temperature change (2010–2100) under RCP8.5 (K); **b** multi-model average of regression coefficient of the 10-year running mean local temperature against the 10-year running mean tropical mean temperature, multiplied by 1 SD of DCV (unit, K). Calculations are made using 200 years of the pre-industrial experiments (where available). Stippling indicates that in excess of 70% of models agree on the sign of the change (see supplementary material for discussion on choice of stippling threshold)



3.2 Decadal variability and tropical Pacific variability

How important is ENSO variability for DCV? Figure 3 shows a plot of global and tropical variability against decadal NINO3.4 variability. Very little global variance can be explained by NINO3.4 (in agreement with the findings of Middlemas and Clement 2016), but this increases to around 1/3 when only the tropics are considered. Other ENSO indices (NINO3, NINO4) give similar results to those of Fig. 3 (not shown). Note, however that all models produce NINO3.4 decadal SD below the estimated observational value from Middlemas and Clement (2016) of around 0.3 K, so models may be underrepresenting the influence of ENSO on decadal variability. This view is consistent with Kociuba and Power (2015), who showed that models seemed to underestimate tropical DCV because of deficiencies in simulated ENSO characteristics. For *interannual* variability, the current analysis gives, as expected, much higher explained variances of 38 and 48% for model global and tropical variability magnitudes respectively, consistent with strong ENSO influence on interannual variability (e.g. Pan and Oort 1983), but with decadal variations being less strongly associated with dynamical ocean/atmosphere feedback processes (Liu et al. 2012).

3.3 Decadal radiative feedbacks in models

Which global and tropical mean TOA radiative feedbacks are associated with decadal variability? Before examining individual feedbacks, the *total* LW, SW and net radiative feedbacks are considered. These were determined from calculating 20 10-year averages for each model using their pre-industrial runs, then regressing net TOA radiative variations against global average surface air temperature (see supplementary Fig. S1 for an example). It is found (consistent with Xie et al. 2016) that strong correlations occur for both LW and SW with global mean temperature, but that the correlations are weaker when net feedback is considered, due to the offsetting nature of the LW/SW (e.g. supplementary Fig. S1).

The values of multi-model mean DCV-related global, tropical and extra-tropical LW, SW and Net feedbacks are given in Table 1. The inter-model SD is shown in brackets. Table 1 also shows the decadal LW feedback with the Planck term removed.

It is immediately apparent from Table 1 that setting aside the Planck cooling (see below), decadal feedbacks are strong and positive in both LW and SW, and make a close-to-equal contribution to positive feedback globally. Including the Planck cooling results in a ‘total response’ MMM radiative feedback of only $-0.24 \text{ W/m}^2/\text{K}$, close

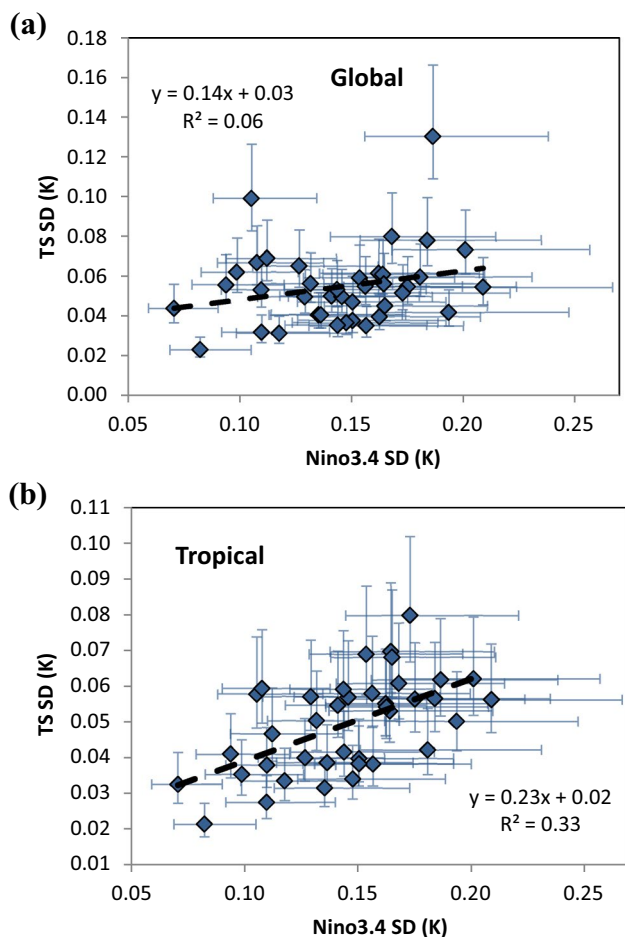


Fig. 3 SD of **a** global, and **b** tropical decadal temperature versus decadal NINO3.4 SDs. Each point represents a CMIP5 model, and the error bars show estimated 80% confidence ranges. Lines of best fit and explained variance are also shown from standard regression

Table 1 Global, tropical (30°N–30°S) and extra-tropical (poleward of 30°) multi-model mean LW, SW and net feedbacks under decadal and interannual variability. Also shown is the LW with the Planck cooling term removed. Units are W/m²/K. Feedbacks are calculated by regressing area mean TOA radiation changes against corresponding area mean temperature. Numbers in brackets represent 1 SD of model spread

	Global	Tropics	Extra-tropics
Decadal			
LW	- 1.52 (0.32)	- 2.07 (0.72)	- 0.90 (0.27)
SW	1.28 (0.47)	1.58 (0.93)	0.88 (0.35)
Total	- 0.24 (0.40)	- 0.48 (0.88)	- 0.02 (0.21)
LW (no planck)	1.39 (0.28)	1.36 (0.62)	1.51 (0.39)
Interannual			
LW	- 1.57 (0.44)	- 2.49 (0.80)	- 0.89 (0.23)
SW	0.81 (0.64)	1.56 (0.98)	0.71 (0.29)
Total	- 0.76 (0.62)	- 0.93 (0.94)	- 0.18 (0.31)

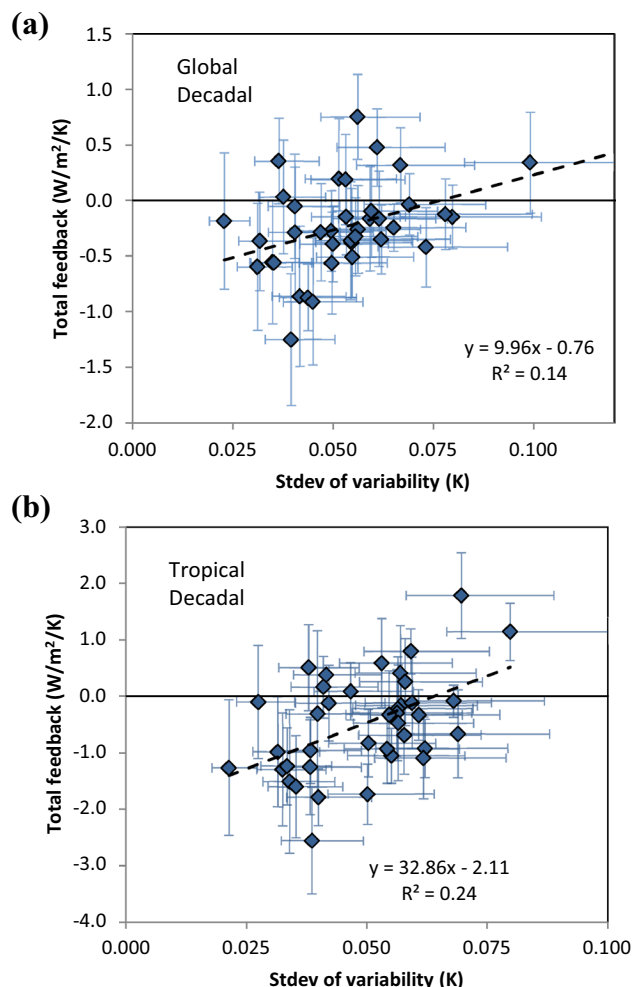


Fig. 4 a Total TOA radiative feedback (W/m²/K), versus SD of global temperature (K). **b** Tropical TOA radiative feedback versus tropical temperature SD. Each point represents a CMIP5 model, and x and y error bars show 80% confidence on SD from the PI sampling and feedback from decadal regression respectively. Lines of best fit and explained variance are also shown

to radiative neutrality, and with significantly less radiative damping than for forced climate change (Bony et al. 2006; Flato et al. 2013). Interestingly, the MMM extra-tropical LW feedback is less radiatively damping than tropical, despite the low latitude maximum of the dominant water vapour feedback (Colman and Hanson 2016). Because of this the extra-tropics play a larger role than the tropics in setting the overall strength of the global feedback. This is consistent with Brown et al. (2015) (their Fig. 5) that the extra-tropics are important for explaining spread in radiative contributions to decadal warming/cooling trends.

Interannual feedbacks (shown in Table 1) tell a similar story, i.e. there are positive LW and SW feedbacks in both the tropics and extra-tropics. On interannual timescales, however, total radiative feedback is more damping than for

Table 2 Multi-model mean decadal and climate change global feedbacks. Numbers in brackets are inter-model SD. Units are $W/m^2/K$. Feedbacks shown are surface temperature (Ts), LW/SW water vapour (q), lapse rate (LR), surface albedo (a) and LW/SW cloud (C). Right-most column shows feedbacks derived by scaling local climate

Feedback	Decadal	Climate change	Decadal derived from scaled climate change
Ts	− 2.94 (0.13)	− 3.07 (0.09)	− 2.83 (0.21)
q (LW)	1.42 (0.49)	1.75 (0.19)	1.43 (0.38)
q (SW)	0.22 (0.05)	0.26 (0.04)	0.26 (0.06)
LR	0.0 (0.48)	− 0.74 (0.23)	− 0.53 (0.40)
a	0.78 (0.38)	0.42 (0.11)	0.70 (0.26)
C (SW)	0.20 (0.52)	0.19 (0.43)	− 0.26 (0.41)
C (LW)	0.23 (0.30)	0.34 (0.20)	0.34 (0.43)
Sum of SW	1.20	0.87	
Sum of LW	− 1.29	− 1.72	
Sum of LW (no planck)	1.65	1.35	

change feedback strength by the ratio of decadal local temperature change per degree of global temperature rise to that from climate change (Colman and Hanson 2016). Bottom two rows show the sum of LW and SW feedbacks for decadal and climate change feedbacks (for comparison with results in Table 1)

DCV (by around $0.5 W/m^2/K$), suggesting radiative feedbacks play a lesser role in amplifying variability at inter-annual compared with decadal timescales (see also Forster 2016). Furthermore, ocean heat capacity is large, so the radiative heating would not change the climate system temperature much on interannual timescales. This is noted here but will not be further quantified in this paper.

How do decadal radiative feedbacks relate to the magnitude of model variability? Global (tropical) DCV is plotted against total global (tropical) TOA radiative feedback across the models in Fig. 4. Error bars show 80% confidence limits from standard regression of the radiative feedback magnitude (discussed in Sect. 2 above) or from the confidence limits in estimating decadal temperature SD from the 200-year pre-industrial experiments (e.g. Sheskin 2016). A modest positive correlation ($R=0.37$) is apparent for global values, stronger ($R=0.49$) for the tropics-only case (i.e. for tropical DCV regressed against tropical radiation). Both regressions are statistically significant at the 95% level. This implies that models with stronger DCV, and particularly tropical variability, tend to have stronger positive (reinforcing) net TOA radiative feedback. By contrast, the equivalent regressions for interannual variability (not shown) are not statistically significant.

Note that two models have net positive feedback at decadal timescales in Fig. 4, raising the issue of their stability under variability. There are two important aspects here. Firstly, when considered at the 95% level only one model (MIROC-ESM) remains statistically greater than zero (not shown)—so further study is needed to confirm that its feedback is indeed positive. Secondly, even if at decadal timescales a model has no net radiative damping (or a small positive radiative feedback) this does not imply that this holds at all timescales—for example there are no positive feedback

models at interannual timescales even at the 80% level (not shown). Physical damping factors that operate between different timescales—e.g. involving deep exchange of heat in the ocean, or involving negative feedbacks which result from differing surface temperature variability patterns, must act to stabilise the long term response. So even if the climate system were to gain energy at decadal timescales, it must lose energy to other timescales. Such interactions are likely complex, and investigation of them lies beyond the scope of this paper.

3.4 Comparing feedback processes under decadal variability and climate change

To understand what sets the magnitude of the SW/LW feedbacks we must examine the contributions from differing processes. Individual (global) MMM decadal feedbacks for surface temperature (Planck), water vapour, lapse rate, surface albedo and clouds, along with their inter-model SD, are provided in Table 2. Also shown, for comparison, are global climate change feedbacks. The bottom two rows show the net feedback calculated by summing the individual feedback terms, and can be compared with the total feedbacks calculated by straight regression of TOA net SW/LW radiation. It can be seen that the numbers are close, although not exact. Uncertainty of kernel calculations (Soden et al. 2008) will play some role in this difference, but differences arise from the uncertainties inherent in the estimation of decadal feedbacks (especially clouds) from the (only) 200 year time-series. Given the independent methods of the two calculations, however, the overall agreement bolsters confidence in the calculations of the individual feedback terms.

The source of the strong decadal feedbacks can be seen in Table 2. LW and SW water vapour feedbacks are, on

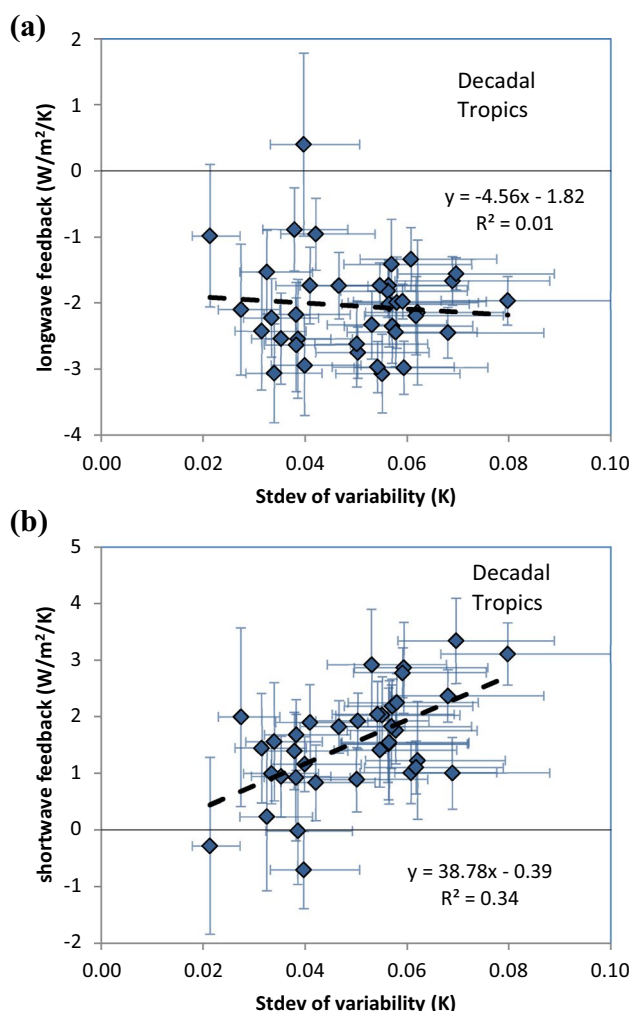


Fig. 5 Total tropical **a** LW and **b** SW feedback (W/m²/K), plotted against SD of tropical temperature variability. Each point represents a CMIP5 model, and the error bars show the 80% confidence limit in estimation of the feedback from standard regression. Lines of best fit and explained variance are also shown from standard regression

average, comparable to those of climate change (LW component around 20% weaker). Together these provide about 60% of the total positive feedback. Decadal lapse rate feedback is close to neutral, compared to a negative climate change feedback of -0.74 W/m²/K, and mean that the combined water vapour/lapse rate feedback contributes a similar fraction of overall positive feedback at decadal timescales as under forced climate change. For clouds, the MMM SW cloud feedbacks are comparable for DCV and climate change. The DCV LW cloud feedback is a little weaker than the corresponding climate change feedback (although still positive). Perhaps surprisingly, the surface albedo feedback is stronger in the decadal case. The inter-model spread of the decadal albedo feedback is very large, and models show an extremely large range in the coverage of sea ice in their pre-industrial climate (Hobbs et al. 2016), so at least part of the spread

may arise from consequent differences in sea ice response. We hope to investigate this in a future study.

The reasons for these overall similarities in climate change/decadal feedback strength are not immediately clear, but the similarities in the temperature response to global or tropical temperature change under climate change and DCV (Fig. 2) may imply similar radiative feedback responses. Recent results (Armour et al. 2013) have found that treating feedbacks as ‘locally unchanging’ (that is, fixed in strength at particular locations, with the global feedback strength then dependent on the contribution of local feedbacks) can explain the evolution of global feedbacks in long climate change experiments from changes in the global surface temperature pattern. Colman and Hanson (2016) performed calculations for decadal feedbacks following this approach based on ‘local’ feedbacks derived from RCP8.5 experiments. The MMM strength (and intermodel variation) of feedbacks from the decadal Planck response, LW and SW water vapour and surface albedo feedbacks (Table 2) are indeed recovered from the scaling. LW cloud feedback is also reasonably reproduced, but lapse rate and SW cloud feedbacks show significant differences. These results suggest that the patterns of warming in Fig. 2 may be ‘similar enough’ for common processes to be operating for most radiative feedbacks under both climate change and decadal variability (Colman and Hanson 2016).

Further evidence of the similarities in processes between feedbacks operating under climate change and DCV come from: (i) common patterns of vertical contributions to water vapour and lapse rate feedbacks (Colman and Power 2010; Colman and Hanson 2013); (ii) a water vapour feedback that is consistent with unchanged relative humidity (Colman and Hanson 2013); and (iii) an inverse relationship between lapse rate and (LW) water vapour feedback (Colman and Hanson 2013). Correlations have also been found between the strength of interannual and climate change net cloud feedback across models (Zhou et al. 2015). Finally, global variability on interannual timescales has also been shown to be reduced when global radiative feedbacks are suppressed (Hall and Manabe 1999; Hall 2004), and ENSO-associated variability reduced when cloud feedbacks are suppressed (Ying and Huang 2016; Radel et al. 2016). Overall then, there is evidence for strong positive radiative feedbacks operating in models as well as similarities in the feedback strengths and structures between decadal (and interannual) variability and climate change.

But are inter-model decadal feedback differences enough to explain (or at least contribute substantially to) the range in DCV? Table 2 shows a MMM positive feedback of around $+2.5$ W/m²/K, with a range of ~ 2 W/m²/K—see Fig. 4. This variation comes from the terms offsetting the Planck cooling; as the latter is tightly clustered around -2.95 W/m²/K with relatively small SD across models. Assuming the

simplest possible (zero dimensional) feedback reinforcement of temperature deviations (see supplementary material) under a global ΔT of 0.05K (MMM SD of DCV—Fig. 1), a positive feedback of $2 \text{ W/m}^2/\text{K}$ is sufficient to provide reinforcing warming of $\sim 0.075 \text{ K}$ to a global mix-layer of 100 m depth on decadal timescales. There will be some sensitivity of this warming figure to assumptions about factors like the mixed layer depth, but the figure chosen here is consistent with those chosen elsewhere in decade timescale changes under global warming (Geoffroy et al. 2012; Brown et al. 2014). This temperature change is the same order as the SD of temperature variation itself and provides *prima facie* evidence that positive feedbacks in the models can induce temperature excursions of the appropriate magnitude for DCV (consistent with the results of Brown et al. 2014).

We would expect several factors to contribute to the magnitude of variability that are not considered here. Theoretical arguments (e.g. Roe 2009) indicate variability should increase with the magnitude of stochastic forcing (such as from ENSO variability, Trenberth et al. 2002 or from short timescale cloud variations, 2014), and decrease with ocean thermal inertia and radiative damping. For example, CMIP5 models show a broad range of effective ocean depth, on climate change timescales at least (Geoffroy et al. 2012), and are likely to do so on interannual and decadal timescales. However in the present study we only consider the influence of the radiative damping term. A consideration of the roles of oceanic mixing and magnitude of stochastic forcing in determining model interannual/decadal variability is to be the subject of a follow up study.

It is known that clouds and SW cloud feedbacks in particular are responsible for much of the range in total feedback under climate change (Bony and Dufresne 2005; Boucher et al. 2013). What individual feedbacks are most important for the range in decadal net feedback? The separate variation of tropical SW and LW total decadal feedback against tropical DCV (Fig. 5.) reveals no relationship between variability and LW feedback, but a strong (and statistically significant at the 95% level) positive correlation in the SW ($R=0.58$). The situation is qualitatively similar at global scales, although the SW correlation with variability is weaker ($R=0.33$) and not statistically significant in this case (not shown). Therefore, although LW feedback plays a roughly equal role with the SW in the overall amplification of the variability of DCV, the SW is primarily responsible for the differing responses in net feedback between models.

The total SW tropical feedback is in turn correlated with strength of the SW cloud feedbacks in models ($R=0.56$, Fig. 6). This provides evidence that differences in cloud responses on decadal timescales may provide an important mechanism for net tropical variability, and echoes the role that SW cloud responses—particularly in the tropics—play in determining climate change sensitivity (Bony and

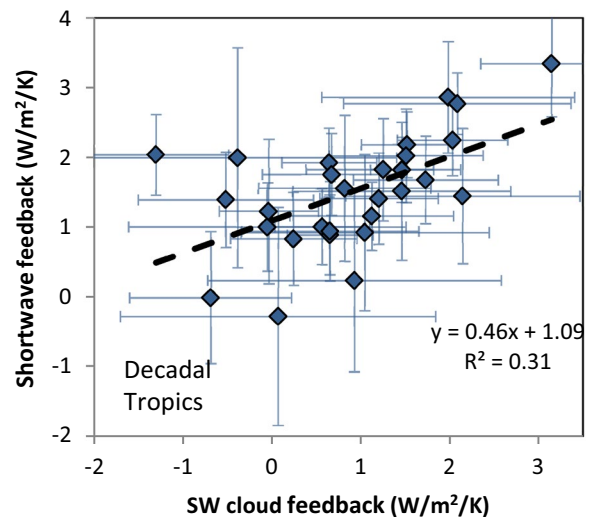


Fig. 6 Net SW feedback, plotted against SW cloud feedback (both $\text{W/m}^2/\text{K}$) for the tropics. Each point represents a CMIP5 model, and the error bars show the 80% confidence limit for standard regression. A line of best fit is also shown, along with explained variance

Dufresne 2005; Andrews et al. 2012; Webb et al., 2015; Zelinka et al. 2013). A statistically significant (at the 95% level) offsetting relationship is also apparent between total LW and SW feedbacks both for the tropics and globally: Fig. 7 ($R = -0.41$, and $R = -0.56$, respectively). This means that the net feedback range is smaller than it would otherwise be, since stronger (positive) feedback in the SW implies stronger (negative) feedback in the LW. The correlations found here are suggestive of an important role of radiative feedbacks and in particular of tropical clouds in decadal timescale tropical variability, but do not conclusively establish it. Furthermore, there is no significant negative correlation between LW/SW cloud feedbacks themselves across models (not shown), so the causes of the inverse LW/SW radiative feedback relationship remain unclear and require further investigation.

3.5 Is there a link between decadal temperature variability and climate change?

How do these results relate to climate change? Given the widespread coherence of DCV in surface temperature over the globe with tropical DCV in surface temperature (Fig. 2b), and the apparent role of radiative feedbacks in tropical DCV discussed above, we hypothesize that model-to-model differences in the magnitude of internal DCV might be related to model-to-model differences in the magnitude of ΔT_{Global} . This is confirmed for the CMIP5 models in Fig. 8a, which shows that ΔT_{Global} and the SD of DCV in T_{Tropics} ($\text{SD}_{T_{10y}}$) are linearly correlated, with a correlation coefficient of 0.60 (Table 3), which is

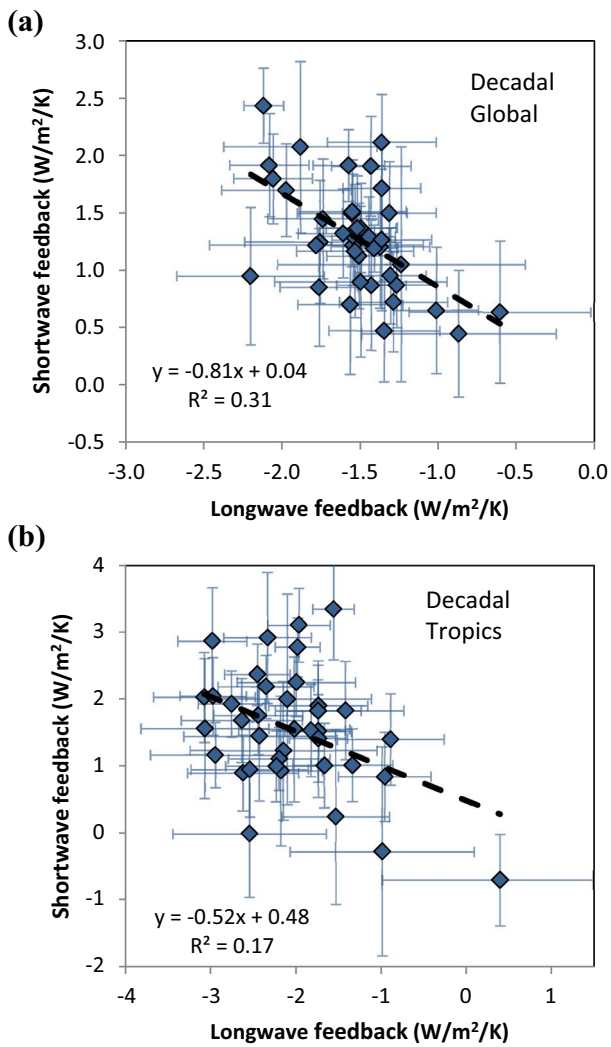


Fig. 7 SW net feedback plotted against LW net feedback **a** globally, and **b** for the tropics only. Each point represents a CMIP5 model, and the error bars show estimated 80% confidence ranges (see Methods for details). Lines of best fit and explained variance are also shown from standard regression

statistically significant at the 95% confidence level. The correlation coefficient increases to 0.73 if attention is restricted to $\Delta T_{Tropics}$, the projected change in tropical temperature (Fig. 8b).

The sensitivity of climate change to imposed anthropogenic forcing can also be measured using the Equilibrium Climate Sensitivity (ECS) and the Transient Climate Response (TCR) indices (Collins et al. 2013). The ECS is plotted against ΔT_{Global} in Fig. 8c, showing a very high correlation coefficient. TCR is, as expected, strongly correlated with ECS, although TCR is less closely correlated with ΔT_{Global} than is ECS (not shown). These findings are consistent with the results of Gregory et al. (2015) and Grose et al. (2016). The relationships between SD_{T-10yr} and all of ΔT_{Global} , ECS and the TCR are consistent in the sense that

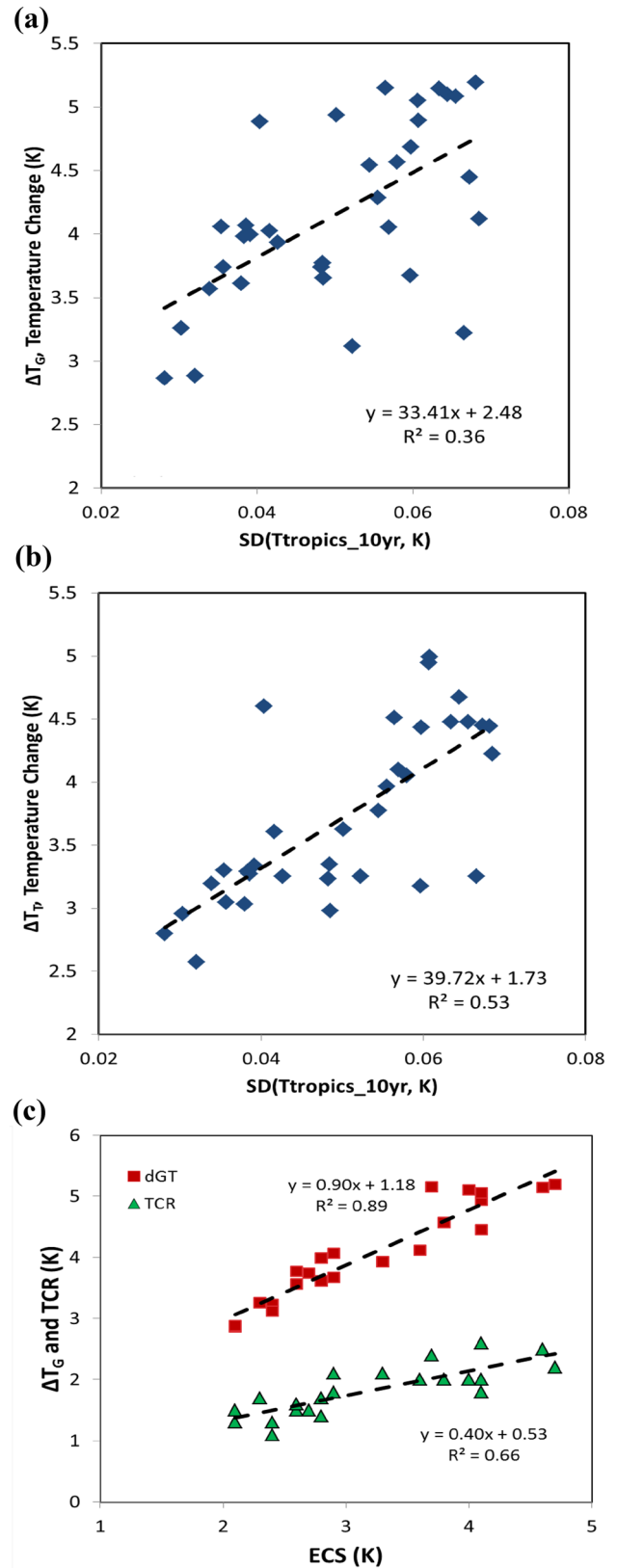


Fig. 8 Scatter plots showing: **a** ΔT_G (global temperature change) versus Tropical (30°S–30°N) temperature decadal SD; **b** tropical temperature change, versus tropical decadal SD; **c** ΔT_G , TCR versus ECS

Table 3 Summary of correlation coefficients and associated information among key variables. Numbers in bold indicate statistical significance at the 5% level. Symbols are as follows: $\Delta T_G/\Delta T_T$, global/tropical surface temperature change over the twentieth century under RCP8.5; $\sigma_T (10yr)$ SD of decadal global variability in models; ECS, equilibrium climate sensitivity

	ΔT_G	ΔT_T	$\sigma_T (10yr)$	ECS
ΔT_G	1	0.89	0.60	0.95
ΔT_T		1	0.73	0.89
$\sigma_T (10yr)$			1	0.71
ECS				1

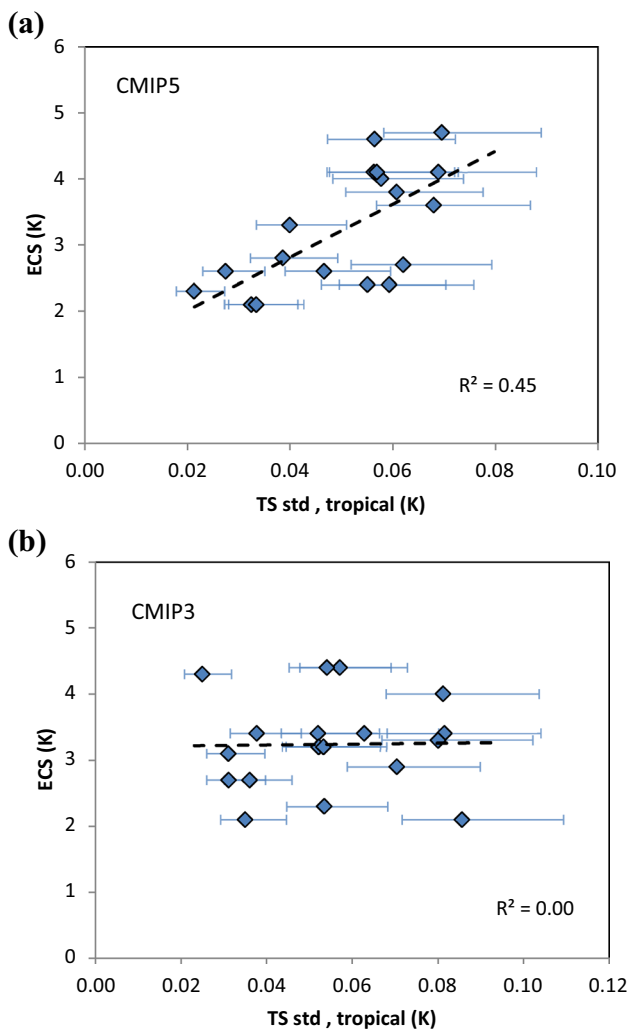


Fig. 9 Scatter plots showing ECS versus tropical SD for **a** CMIP5; **b** CMIP3. Error bars show the 80% confidence range of SD. Also shown are lines of best fit and explained variance from standard regression

the degree of warming and the sensitivity tends to be larger in models with larger values of $SD_{T_{10y}}$.

Correlating $SD_{T_{10y}}$ against ECS in CMIP5 models (Fig. 9a) reveals a statistically significant correlation, with $SD_{T_{10y}}$ explaining nearly half the variance in ECS. A statistically significant correlation also holds between global SD_{10y} and ECS, but it is weaker ($R=0.42$) (not shown). So the CMIP5 models suggest there is indeed a link between $SD_{T_{10y}}$ and climate sensitivity.

As a further test we examined the same issue in CMIP3 models. Despite the relationships found in CMIP5, no such relationships (e.g. between ECS and $SD_{T_{10y}}$) are found for the earlier set of CMIP3 models (Fig. 9b). This does not automatically rule out a relationship between DCV and ECS: CMIP5 models show improvement, including in climate variability, over CMIP3 models (Flato et al. 2013). For example biases in the tropical Pacific mean state are reduced and ENSO related variability better represented (Flato et al. 2013; Bellenger et al. 2014). However there is ‘no quantum leap in ENSO performance’ (Bellenger et al. 2014), nor is there an overall reduction in the range of DCV in CMIP5 compared with CMIP3 (see above). Therefore it remains unclear whether the links between DCV and ECS/ ΔT_{Global} revealed in CMIP5 models are robust. It will be of interest to explore possible decadal variability/ECS correlations within the upcoming CMIP6 group of models, particularly if, as expected, ENSO-related variability is further improved and tropical biases further reduced. The present results suggest, at the very least, that further research is warranted in this area.

4 Conclusions

Ongoing uncertainty in climate change projections arises from the range of model ECS, and this range has not narrowed in the last two decades (Flato et al. 2013). At the same time, DCV varies by at least a factor of 4 across CMIP5 models (and varied by a similar range in CMIP3). Understanding the causes of both of these ranges are critical tasks in climate change science.

The present results provide evidence that global scale radiative feedbacks are playing an important role in the magnitude of global and tropical DCV in CMIP5 models. Both SW and LW feedbacks are positive globally, and LW feedback is as important as the SW in setting the magnitude of the overall feedback. The differences between total feedback globally in models are primarily due to the SW component. The strength of this feedback is, in turn, correlated with SW cloud feedback, and this is particularly strong in the tropics. ENSO related variability certainly plays a role in the spread, with results here suggesting around 1/3 of the tropical variance is related to central Pacific DCV—although very little

global spread is explained. This is consistent with findings elsewhere that deficiencies in representation of ENSO have a substantial impact on tropical temperature DCV (Kociuba and Power, 2014).

SW/LW feedbacks also tend to offset one another both in the tropics and globally. This suggests related but opposing SW/LW processes, particularly from clouds. However, puzzlingly, regressions across models between the strength of the SW/LW cloud feedbacks do not show significant anti-correlations. It should be noted that clouds show high stochastic variability, and that long periods may be required to accurately estimate cloud feedbacks (Colman and Hanson 2013). Further research is needed to clarify the role of clouds in decadal feedback spread, and in the offsetting SW/LW components.

Most radiative feedback components show comparable overall strength in the MMM on decadal and climate change timescales (except most noticeably for global lapse rate). Furthermore the global MMM decadal feedback strength can, for all components except lapse rate and SW cloud, be recovered simply by scaling the climate change feedback by the relative temperature warming found in DCV per degree of global temperature change. A simple zero-dimensional calculation of decadal heating resulting from the positive feedback shows the magnitude of positive feedbacks in models can induce temperature reinforcement of the order of 0.075K in a 100 m deep ocean on decadal timescales, the same magnitude of the decadal temperature deviations themselves.

Taken together this evidence suggests that radiative feedbacks operating on decadal timescales may shed critical light on the processes controlling the magnitude of projected changes. It is suggestive that for the CMIP5 models a correlation exists between ECS and DCV, and this correlation is particularly strong for tropical variability, although earlier CMIP3 models, does not reproduce this relationship. The CMIP3 results lower the confidence in the existence of a link between the magnitude of DCV and climate sensitivity, but does not preclude the possibility, especially since CMIP5 models are superior to CMIP3 models in many respects (Flato et al. 2013). It will be important to retest our key hypothesis with the next generation of models. Further research on decadal radiative feedbacks, their role in variability, and their relationship with climate change feedbacks is needed.

Acknowledgements We thank Greg Kociuba for analysis and generating some of the figures and Guomin Wang, Lawson Hanson and François Delage with assistance with aspects of the analysis, and Josephine Brown, Christine Chung and two anonymous reviewers for helpful comments on the manuscript. This work was supported by the Australian National Environmental Science Programme. We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate

modelling groups for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

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