Australian Meteorological and Oceanographic Journal 62 (2012) 277–285

Observational constraints on parameter estimates for a simple climate model

Roger W. Bodman[1], David J. Karoly[1], Susan Wijffels[2] and Ian G. Enting[3]
[1]School of Earth Sciences, The University of Melbourne, Melbourne, Australia
[2]CSIRO Wealth from Oceans Flagship, Hobart, Australia
[3]MASCOS, The University of Melbourne, Melbourne, Australia

(Manuscript received June 2012; revised August 2012)

Observations of ocean temperature and ocean heat content changes are investigated in order to better estimate the primary ocean parameters in a simple climate model, namely MAGICC (Model for the Assessment of Greenhouse gas Induced Climate Change). A re-examination of the simulated 20th century ocean temperature changes has been made possible by the release of new observational data, which indicates that complex climate models and MAGICC are mixing too much heat into the deeper ocean. Goodness-of-fit testing between the simulated and observed 1960–2008 world ocean temperature change leads to a revised set of parameters for the simple climate model that include a value for the ocean effective vertical diffusivity that is nearly a quarter of that used in the IPCC Third and Fourth Assessment Report versions of the model. Testing an independent constraint based on the ratio of changes in sea surface temperature to 700 m ocean heat content changes produces similar results. The lower ocean diffusivity affects the surface temperature results and alters the best estimate for the climate sensitivity parameter. The projected temperature changes for a high-growth emissions scenario show a larger increase in temperature by 2100 even with a reduced climate sensitivity.

Introduction

Simple climate models have been used in each of the IPCC assessment reports to estimate future global mean temperature changes from a range of emission scenarios. Such models continue to be widely used in integrated assessment models and by policymakers as they provide a flexible and economical alternative to AOGCMs (Atmosphere/Ocean General Circulation Models). A model such as MAGICC can, when tuned appropriately, closely emulate the global mean temperature projections of much more complex models (Meinshausen et al. 2011; Wigley and Raper 2001). The model can then provide insight into how key global processes interact to produce warming in the climate system.

There are a number of sources of uncertainty that apply to MAGICC and its ability to project temperature changes, principally climate sensitivity, ocean effective vertical diffusivity, aerosol forcing and the carbon cycle, as well as the structural simplifications of the model (Meinshausen 2006; Wigley and Raper 2001). These parameter estimates can also have large impacts on the economic assessment of mitigation policies from integrated assessment models that are built on simple climate models, such as MAGICC (van Vuuren et al. 2011). Here we focus on constraining the model's ocean diffusivity parameter and explore the implications that follow from revising its previous standard value.

This investigation begins by recognising the significance of the ocean's role in future global mean temperature changes and therefore in MAGICC, and it identifies the key climate system parameters that need to be estimated for the model to simulate 20th century global mean temperature changes. Methods for estimating these parameters are then applied that are designed to isolate important individual parameters in the simple climate model using largely independent observational constraints. This helps to avoid the problem of how to deal with cross-correlations and weighting of different observations that arises in previous studies. As well, we address the mismatch between the observed and modelled ocean temperature change profile.

Corresponding author address: Roger Bodman, Centre for Strategic Economic Studies, Victoria University, Melbourne, Victoria, 8001, Australia
Email: roger.bodman@vu.edu.au

The MAGICC simple climate model

This study uses the latest version of MAGICC, version 6 (Meinshausen et al. 2011), a simplified earth system model (ESM) based on a four-box energy balance model for the climate system to represent the hemispheric land and ocean regions. A carbon cycle model is incorporated that tracks changes in carbon between the atmosphere, ocean and terrestrial biospheres from emissions due to the burning of fossil fuels and land use changes.

The change in energy balance from a perturbation in radiative forcing ΔQ results in a global mean surface temperature change ΔT together with atmospheric feedback $\lambda\Delta T$, accompanied by a transfer of energy from the ocean's mixed-layer into the deep ocean of ΔF. The expression for the mixed-layer heating rate is (based on Wigley and Raper 1990):

$$\phi\rho ch\Delta T + \lambda\Delta T = \Delta Q - \Delta F \quad \text{...(1)}$$

where λ is the climate feedback parameter, ϕ is a factor accounting for land ocean differences in heat capacity, ρ is ocean density, c is the ocean heat capacity and h is the mixed-layer depth. The transfer of heat ΔF is simulated using a simple diffusion equation (as detailed later). Climate sensitivity is inversely proportional to this climate feedback parameter, and constitutes one of MAGICC's critical parameters.

The ocean is then central to the transient response of global mean temperatures caused by changes in radiative forcing. In MAGICC, the climate system's response is determined by the upwelling-diffusion equations that describe the movement of energy between the atmosphere and ocean. The model's ocean parameters need to be carefully estimated since they determine the thermal inertia of the climate system. This thermal inertia, along with the cooling effect of aerosols, is protecting society from realising the full level of global warming due to current atmospheric greenhouse gas concentrations.

The ocean circulation is represented in MAGICC by narrow sinking cool branches at high latitudes balanced by broadscale uniform upwelling in the rest of the ocean. The upper ocean vertical temperature gradient is maintained

Table 1. MAGICC climate system parameters.

Abbreviation	*Description*	*Units*	*Standard*	*Revised*
ΔT_{2x}	Climate sensitivity	°C	3.0	2.2
K	Ocean effective vertical diffusivity	$cm^2 s^{-1}$	2.3	0.6
R_{lo}	Land/ocean warming ratio		1.3	1.6
α	Ratio of air temperature to mixed-layer temperature†		1.25	1.25
κ_{lo}	Heat exchange coefficient land-ocean	$W m^{-2} °C^{-1}$	1.0	2.0
h	Mixed layer depth†	m	60	60
T_{moc}	Temperature change threshold at which minimum meridional overturning is reached	°C	8.0	8.0
w_0	Initial upwelling velocity†	$m\ yr^{-1}$	4.0	4.0
β	Ratio of polar sinking water to mixed layer temperature†		0.2	0.2
κ_{ns}	Heat exchange coefficient North-South	$W m^{-2} °C^{-1}$	1.0	1.0
w_{var}	Variable upwelling fraction†		0.7	0.2

†Not included in calibration process by Meinshausen et al. (2011).

Table 2. Climate parameters and their relative contribution to temperature change uncertainty in 2100.

Parameter name	*Uncertainty Contribution,* σ	*% of total*
Climate sensitivity, ΔT_{2x}	0.33	95.97%
Ocean vertical diffusivity, K	0.49	2.73%
Ratio of air temperature to mixed-layer temperature, α	0.14	0.47%
Land ocean heat exchange coefficient, κ_{lo}	0.70	0.40%
Land/Ocean warming ratio, R_{lo}	0.23	0.17%
Variable upwelling fraction, w_{var}	0.20	0.12%
North/South heat exchange coefficient, κ_{ns}	0.91	0.10%
Polar water temperature ratio, β	0.20	0.02%
Mixed layer depth, h	18.3	0.02%
Initial upwelling velocity, w_0	0.35	0.00%

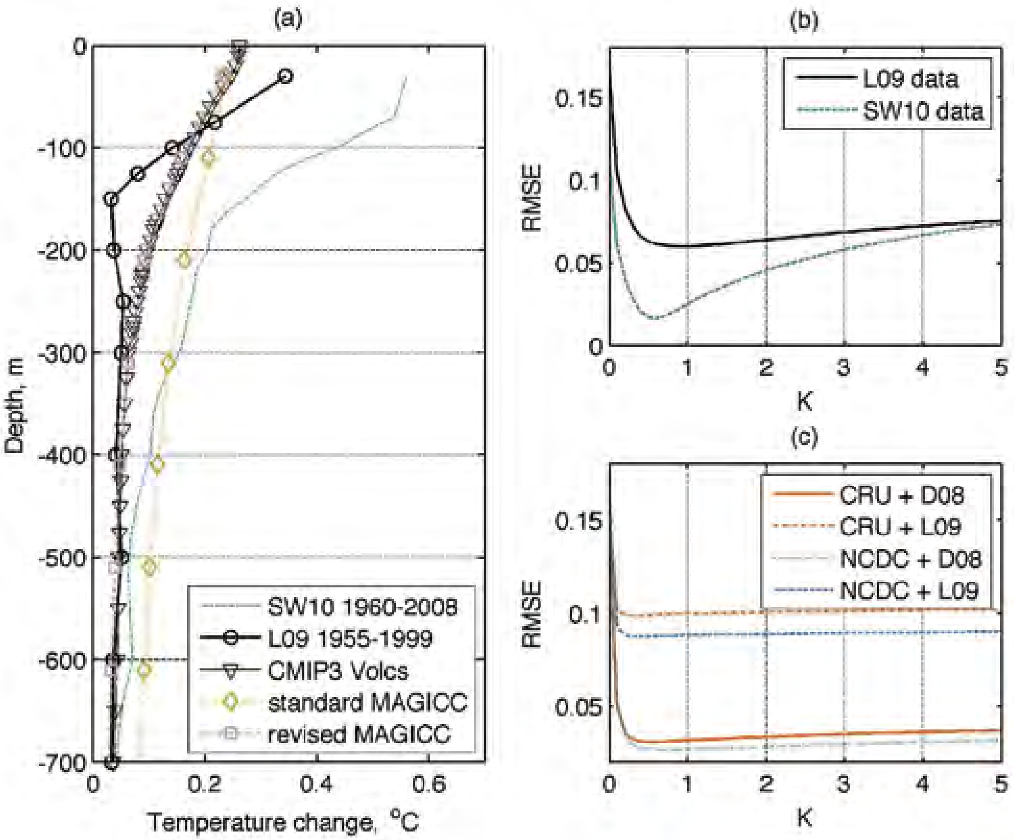
by uniform vertical mixing, scaled by the ocean effective diffusivity parameter *K*. However, in the real ocean, the vertical temperature gradient in the upper 1000 m is largely maintained by wind-driven ocean subduction of the meridional temperature gradient (Luyten et al. 1983) and interior ocean mixing actually plays little role in setting the vertical scale of this gradient. Consequently, the upwelling-diffusion balance in MAGICC should be regarded only as a proxy for the ocean subduction process.

The model calculates 20th century temperature changes by considering a comprehensive set of historical forcings, including changes in greenhouse gases concentrations, anthropogenic aerosol components, volcanic aerosols and solar insolation up to 2005. Model results were extended to 2009 using emissions interpolated from the SRES A1FI emission scenario as this provides a reasonable approximation pending updates to the historical data files. Direct and indirect aerosol forcing values correspond with the IPCC Fourth Assessment Report estimates (IPCC 2007).

Identifying key climate parameters

The relative importance of MAGICC's combined climate system parameters was tested by assessing the contribution each of the parameters makes to MAGICC's global mean temperature change results. The model was first run with a standard set of initial parameter values to establish a reference temperature change, then re-run for each parameter in turn, with the parameter value changed by one per cent of its standard deviation. An initial range of values for each parameter and standard deviation was obtained from previous settings and the CMIP3 calibrated values (from Meinshausen et al. 2011). The difference in the year 2100 temperature change results, derived based on the SRES A1FI emission scenario, was then used to provide a measurement of the uncertainty from the model outputs for each of the input parameters (the Jacobian of the model, Rayner et al. 2010). The variance of each parameter provides the content for the covariance matrix *C(v)* and the calculated

Fig. 1. (a) Global average ocean temperature change profiles as a function of depth from observations, multi-model mean de-drifted CMIP3 models (1950–1999), and standard and revised MAGICC model (1955–1999). Observations from S.E. Wijffels (unpublished data; SW10) for 1960–2008 and 1955–1999 from Levitus et al. (2009) (L09); CMIP3 data from Sen Gupta et al. (2010). 'Volcs' indicates the ten models that included volcanic forcings; MAGICC profiles using standard and revised parameters as listed in Table 1; (b) RMSE results between two sets of observed ocean temperature changes (L09 and SW10) and MAGICC with variable *K*; (c) RMSE results for SST/OHC ratio using observed SSTs (CRU; (Rayner et al. 2006) and NCDC; (Smith et al. 2008)), observed OHC (L09 and D08), and MAGICC with variable *K*.



sensitivities assume a linear error propagation from the input parameters to the model results based on the relationship:

$$\mathrm{U} = \mathrm{JC}(v)\mathrm{J}^{\mathrm{T}} \qquad \text{...(2)}$$

where, for a random vector v with multivariate normal distribution described by the covariance matrix $C(v)$, and the J is any linear mapping, then U is also a multivariate normal which provides an uncertainty estimate for the parameters. The superscript represents the transpose of the matrix J.

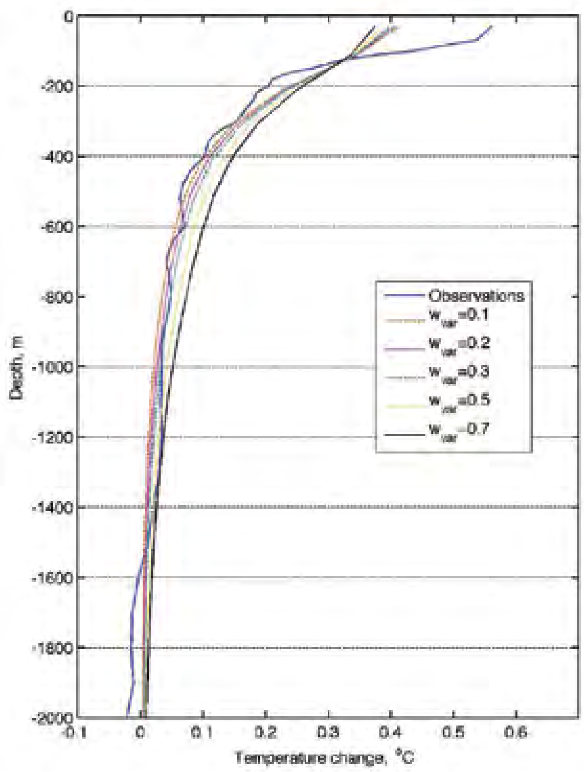
There are 11 parameters that determine the climate system's response (Table 1) (excluding three new optional parameters introduced by Meinshausen et al. 2011 related to additional features). K, h, w_0, w_{var}, β, and T_{moc}, are the ocean parameters that control the rate at which heat is moved downwards into the ocean. Results for global mean temperature are most sensitive to fractional changes in climate sensitivity ΔT_{2x} and ocean vertical diffusivity K, which account for almost 99 per cent of the total uncertainty for the modelled temperature change in 2100, followed by α, κ_{lo}, R_{lo}, w_{var}, and κ_{ns} (Table 2). The values for h, w_0 and β have a negligible impact on global mean temperature changes. These results then provide a basis for focusing on a subset of the climate parameters.

This parameter uncertainty analysis found that the ocean effective vertical diffusivity parameter K is the most important ocean parameter, with the remaining ocean parameters having little influence on global mean temperature changes. Indeed, in the recent work of Meinshausen et al. (2009), some of the relevant parameters were not included in the parameter estimation process (w_0, w_{var}, α, h, and β—refer Table 1). However, our investigations also found that some of these parameters influence the shape of the ocean temperature change profile, determining the rate at which heat is redistributed into the deep ocean, and therefore need to be reassessed.

In addition, there is evidence that climate models are not representing the temperature change in the ocean's upper layers particularly well. The observed change is larger and more surface trapped than seen in the CMIP3 models and MAGICC with its standard parameter settings (Fig. 1(a)). Forest et al. (2008) arrived at a similar conclusion. This has implications for estimating projected surface temperatures since, if the upper ocean layers remain warmer than indicated by models, the overall future global mean surface temperature may be somewhat greater. Here we investigate MAGICC's ocean parameters in order to consider the adjustments that yield an improved fit between its results and observations, and then consider the implications this may have for projections of future global mean temperatures.

The values used for modelling results with the early version of MAGICC reported in the IPCC First Assessment Report were K = 0.62 and 1.27 cm^2 s^{-1} (IPCC 1990). A change to K = 2.3 cm^2 s^{-1} occurred around the time of the IPCC Third Assessment Report (IPCC 2001) as a result of tuning to CMIP2 models (Second Coupled Model Intercomparison Project; Meehl et al. 2000). This was the default setting used

Fig. 2. Ocean temperature change profile comparison between observations (solid blue line, SW10 data) and MAGICC for different settings of the variable upwelling fraction, w_{var}.



for the Third and Fourth Assessment work, and remains so in versions four and five, and, hence, the standard for most of the integrated assessment models that incorporate MAGICC as their 'temperature calculator'. The more recent tuning to 19 CMIP3 models (Third Coupled Model Intercomparison Project; Meehl et al. 2007) was introduced subsequently, as reported in Meinshausen et al. (2009). The latter has values for K that range from 0.43 to 2.6 cm^2 s^{-1}, with an average value of 1.30 cm^2 s^{-1}, while the value for the aggregate CMIP3 temperature response is 1.1 cm^2 s^{-1}.

The ocean parameters

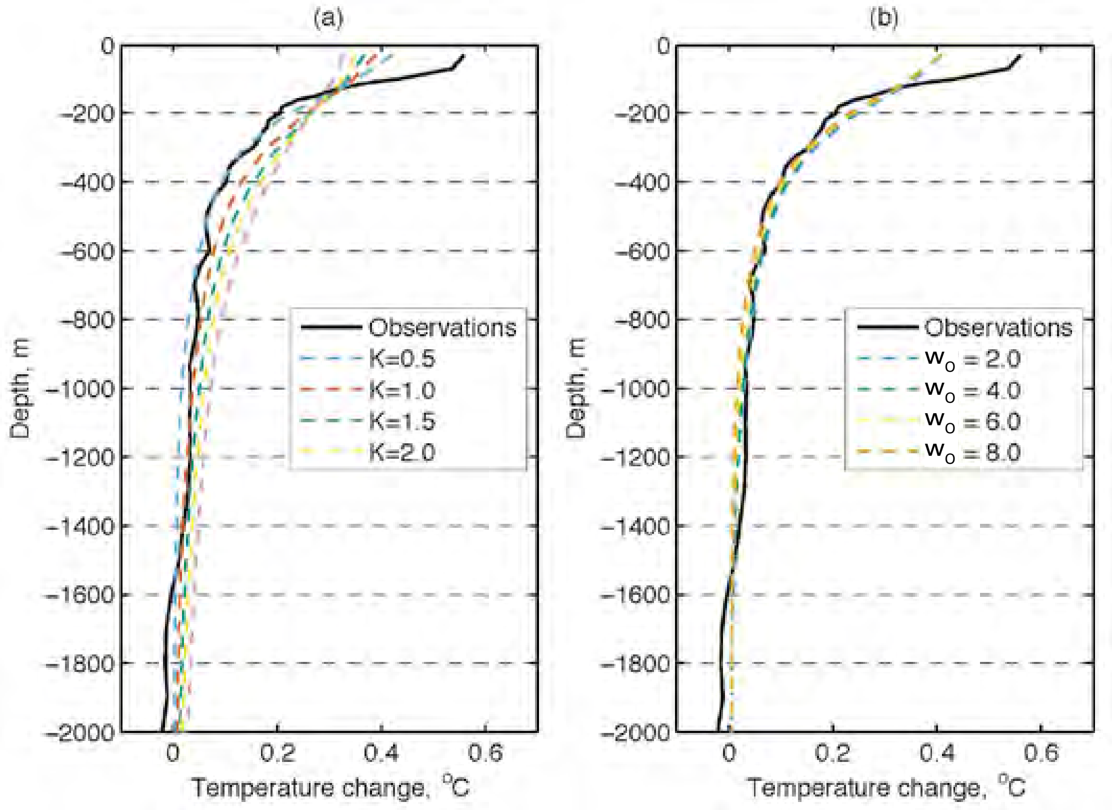
According to MAGICC, heat due to a change in radiative forcing travels through the ocean mixed layer and diffuses down into the deep ocean. The strength of mixing depends primarily on the vertical diffusivity K and upwelling velocity w. The basic ocean equation for ocean temperature change $\Delta\theta$ is given by Wigley and Raper (1990):

$$\frac{d}{dt}\Delta\theta = K\frac{\partial^2\Delta\theta}{\partial z^2} + w\frac{\partial}{\partial z}\Delta\theta \qquad \text{for } 0 < z < D \qquad \text{...(3)}$$

where z is the depth below the mixed layer and D is the depth of the ocean.

Over the course of developing MAGICC, this simple upwelling-diffusion model has been modified to improve

Fig. 3. Model results with (a) fixed upwelling rate, w_0 = 4.0, and variable ocean vertical diffusivity K and, (b) results with K = 1.0 and variable w_0. w_{var} set to zero in both cases (SW10 observations).



its characteristics relative to AOGCMs. In its most recent form, MAGICC version six uses a trapezoidal ocean cross-section with entrainment from the polar sinking water, and a warming-dependent upwelling rate (Meinshausen et al. 2011).

The formula for the variable upwelling rate is given by:

$$w(t) = w_0\left(1 - w_{var}Tg / T_{moc}\right) \quad \text{...(4)}$$

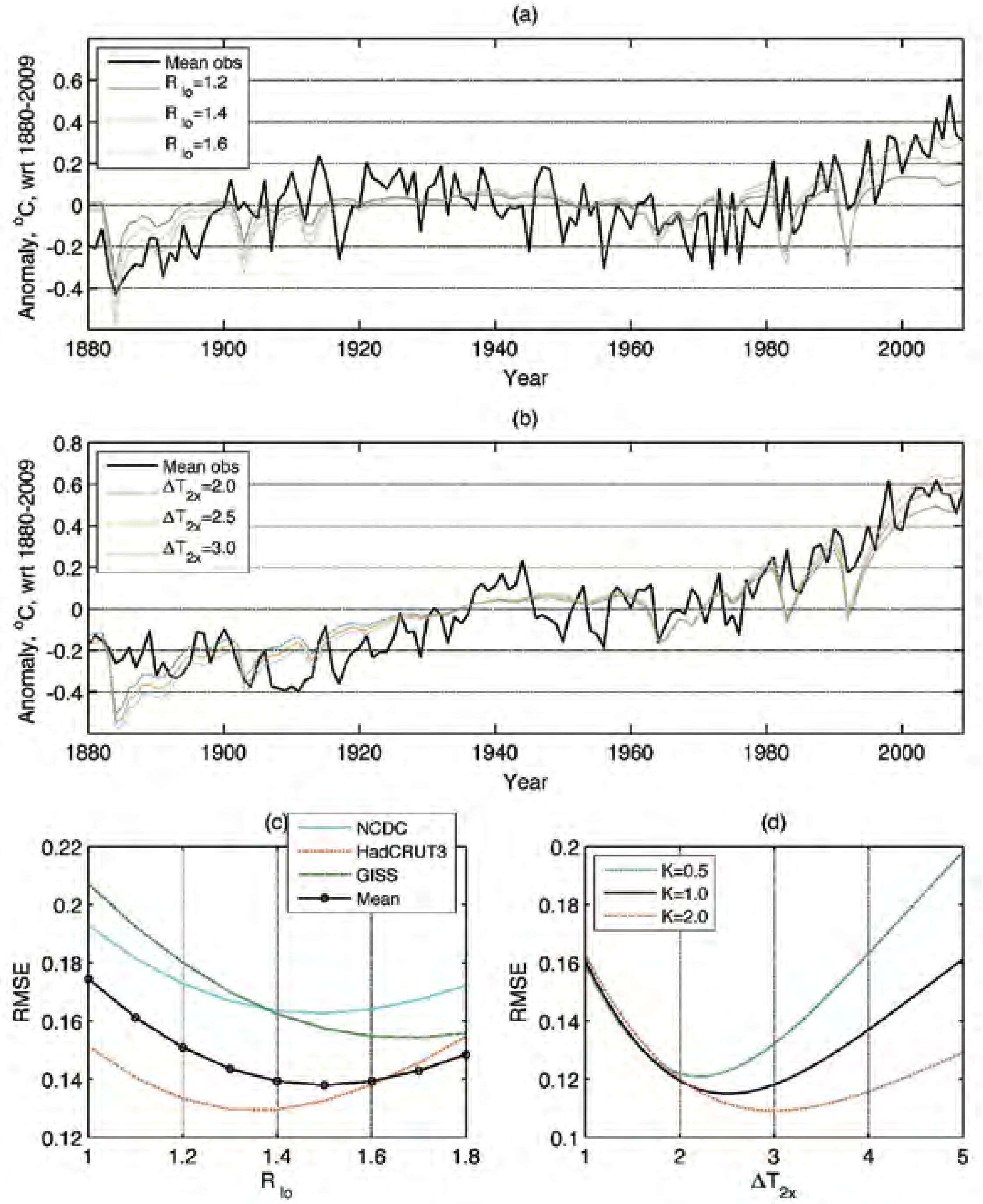
where w_{var} is a fraction of w_0 and Tg is the global temperature anomaly at time t, and T_{moc} is the temperature change threshold at which minimum meridional overturning is reached. This revised method was implemented to better match the ocean heat flux and sea level rise in AOGCMs. The standard value for w_{var} was set to 0.7 for the TAR, as discussed by Raper et al. (2001), and retained for the AR4 version of MAGICC. However, this value appears to be too large. We tested the results if w_{var} is varied and determined that a lower value between 0.1–0.3 provided an improved fit between the observed and modelled ocean temperature change (refer Fig. 2). With w_{var} fixed at 0.2, MAGICC was run for two cases, examining the modelled ocean temperature profile as compared to SW10 observations for (a) different values of K, and (b) different values of w_0, with results as illustrated in Fig. 3. A consistent time interval, 1960 to 2008, was used rather than the different periods for Fig. 1, which were necessitated by the available data.

Estimating ocean diffusivity

The observed change in ocean temperature as a function of depth was used to constrain the ocean effective diffusivity parameter K. This parameter was varied to estimate what value provides the best model fit to the globally averaged observed 1960–2008 world ocean temperature change profile (with w_{var} = 0.2, all other parameters with standard settings). The ocean data were derived from Levitus et al. (2009) (hereinafter L09) and a second set provided by S.E. Wijffels (unpublished data 2010; hereinafter SW10). Differences between these data sets arise from the selection of instrumental data, the treatment of instrumental biases and methods of temporal and spatial infilling (refer, e.g., Wijffels et al. 2008). Testing for the goodness-of-fit between the modelled and observed ocean vertical temperature change profile, the minimum RMSE (root mean square error) occurs at K = 0.9 cm^2 s^{-1} for the L09 data and K = 0.6 cm^2 s^{-1} for SW10 data; refer Fig. 1(b). This is substantially smaller than the model's standard setting of 2.3 cm^2 s^{-1} used for the TAR and AR4 based on CMIP2 calibration, and in better agreement with the CMIP3 evaluation of Meinshausen et al. (2009).

Another approach to estimating K is to look at changes in ocean heat content (OHC). A number of studies have reported estimates for OHC changes, including Levitus et al. (2009) and Domingues et al. (2008) (hereinafter D08). The

Fig. 4. (a) Mean land minus ocean temperature time series 1880–2009 from CRU (Brohan et al. 2006), NCDC (Smith et al. 2008) and GISS (Hansen et al. 2010) observations with MAGICC results for selected R_{lo} values; (b) Mean of CRU, NCDC and GISS observed 1880–2009 global mean temperatures with MAGICC results for selected ΔT_{2x} values; (c) RMSE results for variable R_{lo} from fitting land minus ocean surface temperatures in (a); (d) RMSE for variable ΔT_{2x} from fitting global mean surface temperatures with K = 0.5, 1.0 and 2.0 in (b); other parameter settings: R_{lo} = 1.6, κ_{lo} = 2.0, w_0 = 4.0, w_{var} = 0.2.

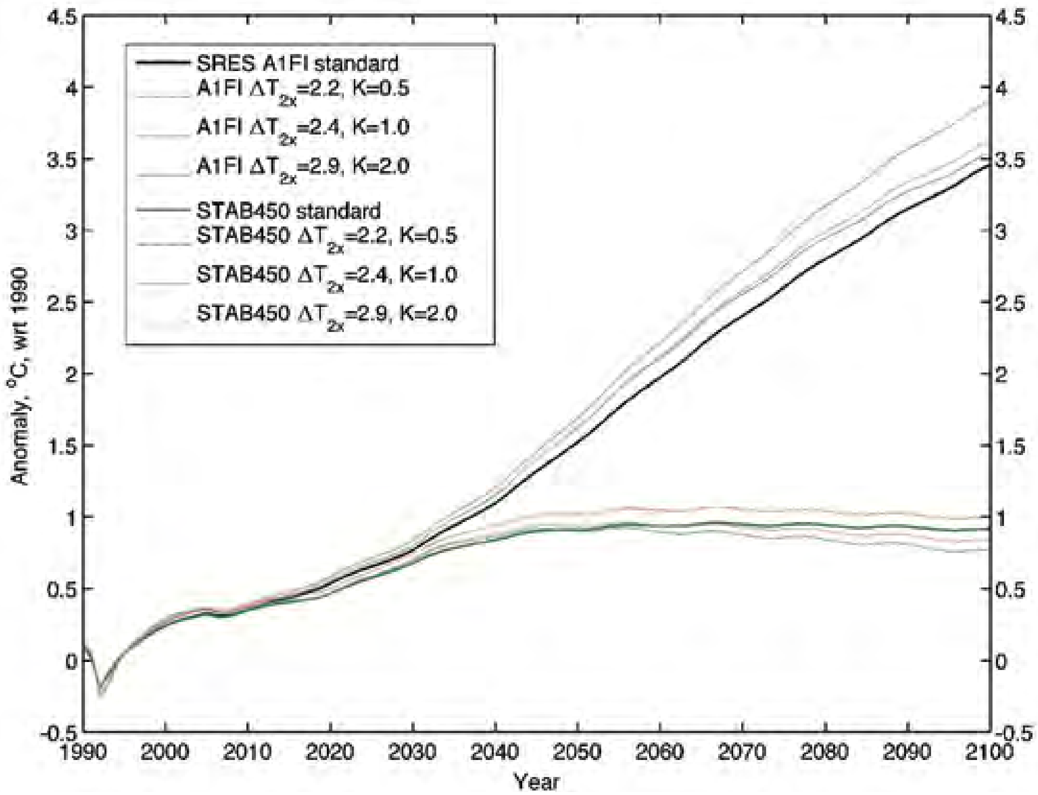


OHC down through the ocean layers is, in effect, a measure of the speed with which heat is transferred into the ocean as a net consequence of the different warming and cooling processes at work.

We have investigated using the ratio between sea surface temperature (SST) changes and OHC changes for the layer to 700 m as a potentially independent constraint for K. This is similar to the effective heat capacity or OHC to global surface temperature ratio used by Frame et al. (2005) and Andrews and Allen (2008), but MAGICC reports separate land-surface and sea surface temperatures, which enables this somewhat different ratio to be used.

The ratio of SST to 700 m OHC changes has almost no correlation with SST changes for two different observed

Fig. 5. MAGICC projected global mean surface temperature changes for SRES A1FI and 450 ppm CO_2-equivalent stabilisation scenarios with standard and revised parameter sets for 1990–2100, with respect to 1980–1999 mean.



SST data sets, CRU HadSST2 (Rayner et al. 2006) and NCDC ERSST3b (Smith et al. 2008), and 700 m OHC (L09 and D08) observations. The MAGICC results exhibit a similar pattern of weak correlations, although the SST to SST/OHC ratio correlation is not as low as in the observations, likely due to the lack of natural variability in the model results.

The low correlation values indicate that this SST/OHC ratio is almost independent of the SSTs, and hence provides a constraint that can be used to estimate K by comparing the observed SST/OHC ratio to modelled SST/OHC ratio. The results point towards low values for K, between 0.3 and 0.8 $cm^2\,s^{-1}$. However, while there is a minimum exhibited in the RMSE results, the range of difference from $K = 0.2$ to 5.0 $cm^2\,s^{-1}$ is very small, as shown in Fig. 1(c).

Both approaches to estimating K point towards a substantially lower value than that used as the default setting in the versions of MAGICC used since the TAR.

Estimating other key climate system parameters

After revising estimates for MAGICC's ocean parameters, the other key climate system parameters were then examined. The model's land ocean temperature contrast is relatively sensitive to the ratio of land to ocean warming R_{lo} and the heat exchange coefficient κ_{lo}. R_{lo} can be determined from observations using the land-ocean temperature change difference as an independent observational constraint, which leads to a setting of 1.6, rather than the standard value of 1.3. Sutton et al. (2007) obtained values in the range of 1.36–1.84 from CMIP3 AOGCMs, and around 1.5 from observations. Figure 4(a) shows a time series for land-ocean temperatures and the corresponding RMSE plot is included as Fig. 4(c). The parameter κ_{lo} can be investigated in a similar way; the results (not included here) show an almost flat curve for $\kappa_{lo} \geq 1.5$ $Wm^{-2}\,°C^{-1}$; a value of $\kappa_{lo} = 2.0$ $Wm^{-2}\,°C^{-1}$ was selected.

The parameter α, which relates ocean mixed layer temperature changes to sea surface temperature changes, was checked against observed sea surface temperature changes and an equivalent mixed-layer temperature change derived from the L09 ocean temperature data; these findings confirmed the MAGICC standard setting of 1.25.

Revisiting 20th century climate sensitivity

With a revised range for K and revised settings for R_{lo}, κ_{lo} and w_{var}, the climate sensitivity parameter ΔT_{2x} was estimated from the goodness-of-fit between the model's global mean temperature change and 20th century observations (aerosol forcing uncertainties are not addressed here). Time series and RMSE results (Figs. 4(b) and (d)) for values of $K = 0.5$, 1.0 and 2.0 $cm^2\,s^{-1}$ show a best fit to the average of three observational data sets for ΔT_{2x} of 2.2, 2.4 and 2.9 °C respectively. These values are somewhat less than the

standard setting of 3.0 °C, but within the generally accepted range of 2.0 to 4.5 °C (IPCC 2007). The pairs of parameter values for ΔT_{2x} and K of (2.2, 0.5), (2.4, 1.0) and (2.9, 2.0) provide estimates that best fit the observed 20th century global mean temperature changes for 1880 to 2009.

A lower ocean diffusivity means that there is less ability to draw heat down from the atmosphere, so that transient surface temperatures will be warmer. Focusing on matching the modelled ocean temperature change to observations is essential, since this largely informs the thermal inertia and transient response in MAGICC. This also helps to provide a better definition of climate sensitivity. In a stable climate the ocean parameters are not that important, but for the contemporary warming climate they are significant. A better understanding and representation of the ocean's heat uptake characteristics, along with refining the range for climate sensitivity, will help to more rigorously establish at what time temperature change thresholds, such as a 2 °C warming above pre-industrial temperatures, are likely to occur.

Implications for future temperature change

The revised parameter values, derived as explained in the previous sections, have been used to estimate future global mean surface temperature changes for the SRES A1FI emission scenario (Nakicenovic and Swart 2000) and a 450 ppm CO_2-equivalent stabilisation scenario (Garnaut 2008). Projections for standard parameter and revised settings are shown in Fig. 5 for paired sets of ΔT_{2x} and K. Projections using these revised model parameters result in higher global warming estimates than with standard parameters for the A1FI emissions scenario where the change in 2100 is nearly 0.5 °C greater warming than for the standard parameter values when ΔT_{2x} = 2.9 °C and K = 2.0 cm^2 s^{-1}, with smaller changes for the other cases. The reduced ocean diffusivity leads to greater mixed layer warming over time, resulting in increased surface warming; this is amplified by the larger R_{lo} value and is despite a lower climate sensitivity.

For the 450 ppm stabilisation scenario, the impact of the revised parameters is small, around 0.1 °C as indicated in Fig. 5. Improved climate system parameter estimates are less critical for projecting global mean temperatures for scenarios that have small changes in radiative forcing, but these become more significant for high emissions scenarios that result in large radiative forcing.

Conclusions

A revised set of climate system parameters for MAGICC has been determined based on a sequence of systematic testing taking into account parameter uncertainty, observational constraints and RMSE comparisons between observations and model results. The method used here reduced the number of parameters that need to be estimated, since only a few significantly affect global mean temperature changes. It then employed multiple datasets and independent constraints (SST/OHC ratio and land-ocean temperature change difference) that are associated with the model's thermal properties to individually estimate the key parameters independent of the global mean temperature, except for climate sensitivity. This provides a more robust estimate for the oceanic effective vertical diffusivity K (albeit limited by uncertainties in historical observations) without the influence of the climate sensitivity. This does not entirely avoid the problem of cross-correlation between parameters and Bayesian/Monte Carlo approaches to estimate joint probability distributions of the climate system parameters have been adopted by, for example, Forest et al. (2008) and Meinshausen et al. (2009) to combat this issue. However, the results for ocean diffusivity are comparable.

The outcome here is an improved fit between MAGICC's ocean temperature change profile and observations, with a greatly reduced ocean vertical diffusivity setting (K = 0.6–0.9 cm^2 s^{-1} rather than 2.3 cm^2 s^{-1}) and a much smaller variable upwelling component (w_{var} = 0.2 rather than 0.7). Comparisons with OHC observations and an independent ocean heat ratio constraint based on SSTs to 700 m OHC also indicate similar settings for K = 0.3–0.8 cm^2 s^{-1}. Changing the ocean parameters requires adjustment of the climate sensitivity based on fitting to the twentieth-century observed global mean surface temperature; reductions in K lead to slightly smaller values for ΔT_{2x}.

These results are not the final answer, but are presented to highlight the discrepancies that exist between observations and existing model results. Further analysis is needed that incorporates aerosol forcing, carbon cycle feedbacks and allows for observational and model uncertainties. This is being investigated using a Monte Carlo Metropolis-Hastings algorithm to combine multiple variables and multiple observational constraints simultaneously.

Neither MAGICC nor the CMIP3 models achieve the large observed ocean temperature change in the top 200 m or so of the ocean (Fig. 1(a)), although with the revised parameter settings (Table 1), MAGICC is able to more closely emulate the CMIP3 model ensemble (with volcanic aerosol forcings included in common). This is a limitation for climate projections and warrants further study, particularly as a slower ocean heat transfer suggests faster transient surface warming than previously expected.

Acknowledgments

The authors thank T. Wigley and M. Meinshausen for providing MAGICC source code and L. Muir for de-trended CMIP3 ocean temperature results. Thanks also for comments by R. Colman. This research was supported by the Australian Research Council through the Discovery Projects funding scheme (project number FF0668679).

References

Andrews, D. G. and Allen, M. R. 2008. Diagnosis of climate models in terms of transient climate response and feedback response time. *Atmospheric Science Letters, 9,* 7–12.

Brohan, P., Kennedy, J. J., Harris, I., Tett, S. F. B. and Jones, P. D. 2006. Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850. *J. Geophys. Res., 111,* doi:10.1029/2005JD006548.

Domingues, C. M., Church, J. A., White, N. J., Gleckler, P. J., Wijffels, S. E., Barker, P. M. and Dunn, J. R. 2008. Improved estimates of upper-ocean warming and multi-decadal sea-level rise. *Nature, 453,* 1090–1093.

Forest, C. E., Stone, P. H. and Sokolov, A. P. 2008. Constraining climate model parameters from observed 20th century changes. *Tellus, 60A,* 911–920.

Frame, D. J., Booth, B. B. B., Kettleborough, J. A., Stainforth, D. A., Gregory, J. M., Collins, M. and Allen, M. R. 2005. Constraining climate forecasts: the role of prior assumptions. *Geophys. Res. Lett., 32,* doi:10.1029/2004GL022241.

Hansen, J. E., Ruedy, R., and Lo, K. 2010. Global Surface Temperature Change. *Rev. Geophys., 48.*

IPCC. 1990. *Climate Change: The IPCC Scientific Assessment*, Cambridge University Press.

IPCC. 2001. *Climate Change 2001: The Scientific Basis.* Contribution of Working Group I of the Third Assessment Report, Cambridge University Press.

IPCC. 2007. *Climate Change 2007: The Physical Science Basis.* Contribution of Working Group I of the Fourth Assessment Report, Cambridge University Press.

Levitus, S., Antonov, J. I., Boyer, T. P., Locarnini, R. A., Garcia, H. E. and Mishonov, A. V. 2009. Global ocean heat content 1955-2008 in light of recently revealed instrumentation problems. *Geophys. Res. Lett., 36,* doi:10.1029/2008GL037155.

Luyten, J. R., Pedlosky, J. and Stommel, H. 1983. The Ventilated Thermocline. *J. Phys. Oceanogr., 13,* 292–309.

Meehl, G.A., et al. 2000. The Coupled Model Intercomparison Project CMIP, *Bull. Am. Meteorol. Soc., 81,* 313–18.

Meehl, G., et al. 2007. The WCRP CMIP3 multi-model dataset: A new era in climate change research, *Bull. Am. Meteorol. Soc., 88,* 1383–94.

Meinshausen, M. 2006. What does a 2 °C target mean for greenhouse gas concentrations? In Schellnhuber H. J., Cramer W., Nakicenovic N., Wigley T. and Yohe G. (Eds.), *Avoiding Dangerous Climate Change*, Cambridge University Press, Cambridge, UK.

Meinshausen, M., Meinshausen, N., Hare, W., Raper, S. C. B., Frieler, K., Knutti, R., Frame, D. J. and Allen, M. R. 2009. Greenhouse-gas emission targets for limiting global warming to 2 °C. *Nature, 458,* 1158–1162.

Meinshausen, M., Raper, S. C. B. and Wigley, T. M. L. 2011. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 - Part 1: Model description and calibration. *Atmos. Chem. Phys., 11,* 1417–1456.

Nakicenovic, N., and Swart, R. 2000. IPCC Special Report on Emissions Scenarios, Cambridge University Press, Cambridge, UK.

Raper, S. C. B., Gregory, J. M. and Osborn, T. J. 2001. Use of an upwelling-diffusion energy balance climate model to simulate and diagnose A/OGCM results. *Clim. Dyn., 17,* 601–613.

Rayner, N. A., Brohan, P., Parker, D. E., Folland, C. K., Kennedy, J. J., Vanicek, M., Ansell, T. and Tett, S. F. B. 2006. Improved analyses of changes and uncertainties in marine temperature measured in situ since the mid-nineteenth century: the HadSST2 dataset. *J. Clim., 19,* 446–469.

Rayner, P. J., Koffi, E., Scholze, M., Kaminski, T. and Dufresne, J.-L. 2010. Constraining predictions of the carbon cycle using data. *Philos. Trans. R. Soc., 2011,* 1955–1966.

Sen Gupta, A., Muir, L., Brown, J., Phipps, S., Durack, P., Monselesan, D. and Wijffels, S. 2012. Climate Drift in the CMIP3 Models. *J. Clim.* doi: 10.1175/JCLI-D-11-00312.1

Smith, T. M., Reynolds, R. W., Peterson, T. C. and Lawrimore, J. 2008. Improvements to NOAA's Historical Merged Land-Ocean Surface Temperature Analysis (1880–2006). *J. Clim., 21,* 2283–2293.

Sutton, R. W., Dong, B. and Gregory, J. M. 2007. Land/sea warming ratio in response to climate change: IPCC AR4 model results and comparison with observations. *Geophys. Res. Lett., 34,* doi:10.1029/2006GL028164.

van Vuuren, D., Lowe, J., Stehfest, E., Gohar, L., Hof, A. F., Hope, C., Warren, R., Meinshausen, M. and Plattner, G-K. 2011. How well do integrated assessment models simulate climate change? *Clim. Change, 104,* 255–285.

Wigley, T. M. L. and Raper, S. C. B. 1990. Natural variability of the climate system and detection of the greenhouse effect. *Nature, 344,* 324–327.

Wigley, T. M. L. and Raper, S. C. B. 2001. Interpretation of high projections for global-mean warming. *Science, 293,* 451–454.

Wijffels, S. E., Willis, J., Domingues, C. M., Barker, P., White, N. J., Gronell, A., Ridgway, K. and Church J.A. 2008. Changing expendable bathythemograph fall rates and their impact on estimates of thermosteric sea level rise. *J.Clim., 21,* 5657–5672.