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# Contributions of carbon cycle uncertainty to future climate projection spread

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ABSTRACT

We have characterized the relative contributions to uncertainty in predictions of global warming amount by year 2100 in the C4MIP model ensemble (Friedlingstein et al., 2006) due to both carbon cycle process uncertainty and uncertainty in the physical climate properties of the Earth system. We find carbon cycle uncertainty to be important. On average the spread in transient climate response is around 40% of that due to the more frequently debated uncertainties in equilibrium climate sensitivity and global heat capacity.

This result is derived by characterizing the influence of different parameters in a global climate-carbon cycle 'box' model that has been calibrated against the 11 General Circulation models (GCMs) and Earth system Models of Intermediate Complexity (EMICs) in the C4MIP ensemble; a collection of current state-of-the-art climate models that include an explicit representation of the global carbon cycle.

## 1. Introduction

Climate sensitivity, $\Delta T_{2\times CO2}$ (K), is the amount of globally averaged near-surface equilibrium warming that would occur for a doubling of atmospheric $CO_2$ concentrations. In complex physical climate models, General Circulation Models (GCMs), the climate sensitivity is an emergent property rather than a parameter that is set a priori. In the simpler energy balance models of climate, the climate sensitivity is actually specified directly. Simple models are often used by policymakers to link particular concentration pathways to warming levels (Stern, 2007); so, credible estimates for the range of $\Delta T_{2\times CO2}$ are essential. Knowledge of $\Delta T_{2\times CO2}$ allows translation of these possible future temperature increases to levels of stabilized $CO_2$ concentrations (Meinshausen, 2006).

Unfortunately, there remains significant uncertainty in the value of climate sensitivity. Current estimates come from a range of sources, including GCMs alone, observation of warming and radiative forcing changes (Gregory et al., 2002) and combined climate model/observational constraint studies (e.g. Forest et al., 2000, 2002; Frame et al., 2005). Current estimates from the GCMs used in the recent IPCC 4th assessment are in the range 2.1–4.4 K, with a mean value of 3.2 K (Randall et al., 2007; table 8.2). However, much larger values are possible and cannot, at present, be ruled out. This is partly a consequence of the nonlinear relation between climate sensitivity and positive feedbacks in the climate system (see Roe and Baker, 2007).

Temperature in the near future will not have reached an equilibrium because radiative forcing is still changing, and the climate response to a given change in radiative forcing will take at least a few decades to be fully realized (Meehl et al., 2005). Hence models of contemporary climatic change need to also represent the thermal inertia of the system, which is dominated by the ocean heat uptake. Complex GCMs do this by explicitly describing ocean dynamics with three-dimensional ocean models. However, in the simple energy balance representation of climate, it is again specified a priori, frequently as a model parameter called effective heat capacity, $C$ (J m$^{-2}$ K$^{-1}$). Like climate sensitivity, the effective heat capacity of the Earth system is uncertain.

For many policy applications, it is desirable to go further and model the functional linkage between emissions pathways and the concentration/radiative forcing pathways mentioned above. This latter stage requires gas cycle models to be used,

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for instance, to convert carbon emissions into $CO_2$ concentrations. During the last decade, there have been major advances towards the implementation of full global carbon cycle representations in GCMs, and such modelling includes the derivation of land–atmosphere and ocean–atmosphere $CO_2$ exchanges in a changing climate. These models make possible calculations of the amount by which natural components of the Earth system may mitigate—or add to—anthropogenic emissions caused by the burning of fossil fuels. Since the first coupled climate-carbon cycle GCM simulations (Cox et al., 2000), other GCM modelling groups (and groups with climate models of intermediate complexity) have implemented global carbon cycles in their models, cumulating in 11 models taking part in the Coupled Climate-Carbon Cycle Model Intercomparison Project (C4MIP; Friedlingstein et al., 2006). It is noticeable in this intercomparison that significant differences exist in how the carbon cycle is modelled. Such model differences are in substantial part due to remaining unknowns in ecological processes affecting land–atmosphere $CO_2$ fluxes (e.g. Meir et al., 2006). However, common to all models is that climate-carbon cycle feedbacks are positive, that is, the effect of warming on the land surface and oceans is such that it reduces the ability to 'drawdown' extra $CO_2$ from the atmosphere compared with if these natural components were responding to increased $CO_2$ only (i.e. purely a "fertilization effect") plus a modelled climate that is both invariant and representative of that of the pre-industrial period. Some models predict this feedback to become sufficiently strong that the land surface eventually becomes a net source of $CO_2$. This modelled positive feedback, as defined above, varies significantly between the C4MIP runs, leaving between 20 and 200 ppmv of extra $CO_2$ in the atmosphere for simulations forced with the SRES A2 (Nakićenović and Swart, 2000) emissions of $CO_2$.

Hence the linkage between prescribed emissions of $CO_2$ and temperature increases must take account of two causes of uncertainty. First, uncertainty in the physical climate properties (climate sensitivity and heat capacity) of the Earth system in response to realized changes in atmospheric $CO_2$ concentrations must be included. Second, uncertainty in the modelled global carbon cycle and its interaction with climate must be considered, as this will have a major bearing on $CO_2$ pathways for prescribed emissions trajectories. In this paper, we seek to characterize the relative sizes of these uncertainties in the C4MIP ensemble. We see this as an important quantity to evaluate, which, besides policy implications, may also provide guidance as to the aspects of climate modelling that still require the most effort in refinement. Our approach in determining a first estimate of the balance of these uncertainties is to use a simple climate model set up to replicate the physical climate uncertainties and carbon cycle uncertainties exhibited in the C4MIP experiments. The C4MIP ensemble represents the coupled carbon cycle models that have contributed to the past two IPCC assessment reports.

## 2. Methods

Jones et al. (2006) present a simple global average model of climate-carbon cycle behaviour and originally calibrate this against the Cox et al. (2000) Hadley Centre GCM simulation with carbon cycle. This simple model (now called the Hadley Centre Simple Climate-Carbon Cycle Model, HadSCCCM1) has now been calibrated against all 11 C4MIP simulations. Besides climate sensitivity and heat capacity, the model tuning procedure includes fitting carbon cycle parameters depicting climate-dependent global terrestrial uptake through photosynthesis, temperature-dependent respiration from plants and soil and $CO_2$-level and temperature-dependent global uptake by oceans. An outline of this fitting procedure is given below.

In the HadSCCCM1 model, the global-mean surface temperature response, $\Delta T(t)$ (K), at time $t$ (s) to radiative forcing $\Delta Q(t)$ ($\mathrm{Wm}^{-2}$) is given by solution of the simple energy balance equation (Andrews and Allen, 2008) $C\mathrm{d}(\Delta T)/\mathrm{d}t + \lambda\Delta T = \Delta Q(t)$, where $C$ is the effective heat capacity (mainly controlled by the oceans) and $\lambda$ ($\mathrm{W\,m^{-2}K^{-1}}$) the climate feedback parameter. Radiative forcing due to increasing concentrations $c_\mathrm{a}(t)$ (ppmv) of atmospheric $CO_2$ is given by $\Delta Q = (\Delta Q/\ln 2) \times \ln(c_\mathrm{a}(t)/c_\mathrm{a}(0))$ $\mathrm{W\,m^{-2}}$. Climate feedback is related to equilibrium climate sensitivity $\Delta T_{2\times\mathrm{CO2}}$ by $\lambda = \Delta Q_{2\times\mathrm{CO2}}/\Delta T_{2\times\mathrm{CO2}}$, where $\Delta Q_{2\times\mathrm{CO2}}$, the radiative forcing for a doubling of $CO_2$ concentration, is 3.74 $\mathrm{W\,m^{-2}}$. Since $CO_2$ concentrations and hence radiative forcing are known for each of the 11 C4MIP simulations, calibration of the physical climate component of HadSCCCM1 requires tuning of the two parameters $\Delta T_{2\times\mathrm{CO2}}$ (or $\lambda$) and $C$. This is attempted by aiming to obtain an optimal fit in projected global temperature changes between the simple model and the corresponding C4MIP member—we define optimal fit as the pair of [$\Delta T_{2\times\mathrm{CO2}}$, $C$] values that minimize the root mean square (rms) errors. However, only in three cases—BERN, CLIMBER and UVIC models—do the surfaces for rms error exhibit a well-defined local minimum. For the other models, global temperature alone is insufficient to constrain [$\Delta T_{2\times\mathrm{CO2}}$, $C$] to give a unique optimal fit, since in these cases, bands of parameter pairs give comparable rms error. Additional information from the GCM simulations, in the form of diagnosed ocean heat uptake, would allow better constraint of [$\Delta T_{2\times\mathrm{CO2}}$, $C$], but unfortunately this diagnostic is not available for the C4MIP ensemble. Hence for the remaining models, we therefore prescribe $\Delta T_{2\times\mathrm{CO2}}$ using published values for the atmospheric component of the C4MIP models, and then minimize the rms error as a function of $C$ only to calibrate HadSCCCM1. In the case of the FRCGC and IPSL models, climate sensitivity was obtained from Cubasch et al. (2001); for CCSM1, HADLEY, LLNL, IPSL-LOOP and MPI models we used Randall et al. (2008); whereas Zeng (personal communication, 2007) provided $\Delta T_{2\times\mathrm{CO2}}$ for UMD.

The terrestrial carbon cycle model has vegetation and soil component stores.

The vegetation carbon content is a balance between global average net primary productivity (parametrized as a function of atmospheric $CO_2$ that asymptotes to a maximum value, and which is also modulated by a function of temperature rise capturing the effect of climate change) and turnover. The vegetation carbon turnover time, which controls the rate at which vegetation carbon is lost to the soil in the form of litter, is a function of vegetation carbon. Modelled soil carbon is a balance between the litter supply and respiration loss, the latter parametrized as having a '$Q_{10}$' dependence on temperature and a dependence on soil carbon content. The ocean carbon cycle model consists of two parts, following Joos et al. (1996). The first is a diffusive flux of carbon into the ocean mixed layer, depending on the difference in concentration of $CO_2$ between the atmosphere and the ocean mixed layer. The second component is then the removal of dissolved inorganic carbon (a temperature-dependent function of mean surface oceanic $CO_2$ concentration) from the mixed layer into the deep ocean and is estimated using a linear impulse response function with multiple time modes.

The terrestrial carbon fluxes are calibrated against simultaneous diagnostics from the C4MIP simulations, these being net primary productivity, soil respiration and vegetation and carbon stores. The only parameter we alter in the ocean carbon cycle (again through comparison against the C4MIP simulations) is the depth of the mixed layer as seen by the carbon cycle. Table 1 lists predictions from HadSCCCM1 for $CO_2$ concentration and temperature for the year 2100 using the calibrations outlined above. The agreement with the C4MIP models is good.

A key assumption is made at this point that each GCM modelling centre taking part in the C4MIP study has built their representation of the global carbon cycle independent of any initial model development describing expected temperature responses to increasing but prescribed atmospheric greenhouse gas concentrations. Using this assumption that there are no particular linkages between the calibration of the physical climate properties of a GCM and subsequent chosen parametrization of the global carbon cycle, we suggest that these components, as captured by the simple climate-carbon cycle model, can be varied independently to assess the impact of the two sources of uncertainty. The two sets of parametrizations do, however, interact in their projections of future temperature change. So, for instance, in a global carbon cycle modelled with plant or soil respiration as having strong temperature dependence, the impact of this on atmospheric $CO_2$ concentration will be more pronounced in a GCM that also has a high climate sensitivity and low thermal capacity and thus warms faster (In the future, it might be possible to use emerging observational constraints to eliminate some climate-carbon cycle combinations).

More specifically, we use predicted global temperature increase by the year 2100, $\Delta T_{2100}$ (K), for a common emissions profile, as our metric to compare the two influences of model uncertainty. The emissions profile for $CO_2$, as used by the C4MIP simulations and now prescribed to the 'box'-model, is SRES A2 (see Nakićenović and Swart, 2000 for economic storyline for this scenario). Other non-$CO_2$ greenhouse gases are not considered, nor radiation loadings due to sulphate aerosols (as is also the case for the C4MIP simulations.) Then for each of the 11 versions of the HadSCCCM1 model (i.e. with parameters fitted against each simulation in the C4MIP study), we then individually replace the two physical climate parameters with those appropriate to the other GCMs and models of intermediate complexity (keeping the carbon cycle parameters fixed). Then, in a second set of simulations and again for each C4MIP model emulated, we replace the carbon cycle parameters with those appropriate to the other GCMs and models of intermediate complexity (and now keep the two physical climate parameters fixed). The spread of predicted values of $\Delta T_{2100}$ (K) then provides insight into the relative importance of the two sources of uncertainty.

*Table 1.* A comparison, for each GCM and model of intermediate complexity in the C4MIP ensemble, between their emulation by HadSCCCM1 and the simulations themselves. The comparison is of future predicted atmospheric $CO_2$ concentration, $c_a$ (ppmv) and of global warming since pre-industrial period. For this table, all values are for the average period 2090–2099

| 2100 | $CO_2$ concentration (ppmv) | | Temperature increase (K) | |
|---|---|---|---|---|
| | HadSCCCM1 | C4MIP | HadSCCCM1 | C4MIP |
| IPSL-LOOP | 757 | 764 | 3.91 | 3.78 |
| CLIMBER | 829 | 817 | 2.95 | 2.87 |
| BERN | 741 | 743 | 2.12 | 2.18 |
| UMD | 870 | 910 | 3.06 | 3.46 |
| UVIC | 830 | 869 | 3.56 | 3.75 |
| FRCGC | 832 | 844 | 3.44 | 3.50 |
| CCSMI | 805 | 744 | 2.00 | 1.75 |
| LLNL | 701 | 694 | 3.06 | 2.92 |
| MPI | 794 | 793 | 3.82 | 3.87 |
| IPSL-CM2 | 728 | 731 | 3.09 | 2.96 |
| HADLEY | 963 | 943 | 4.33 | 4.08 |

## 3. Results and discussion

For each model in the C4MIP ensemble replicated by HadSCCCM1 (see left-hand column in Fig. 1 for model names), predictions of global temperature increase by year 2100 are given by the thick vertical light blue line. Then, for each C4MIP model emulated, a perturbation to HadSCCCM1 is made by adopting the physical climate response parameters from each of the other GCMs. This is represented by the vertical red lines. Similarly, for each emulation, the carbon cycle parameters from the other GCMs are adopted, and this is given by the vertical green lines. Thus, for each C4MIP model, a comparison of the spread of the green lines compared with the spread of the red lines provides an indication of the relative impact on our chosen warming metric, $\Delta T_{2100}$, of carbon cycle modelling uncertainty versus physical

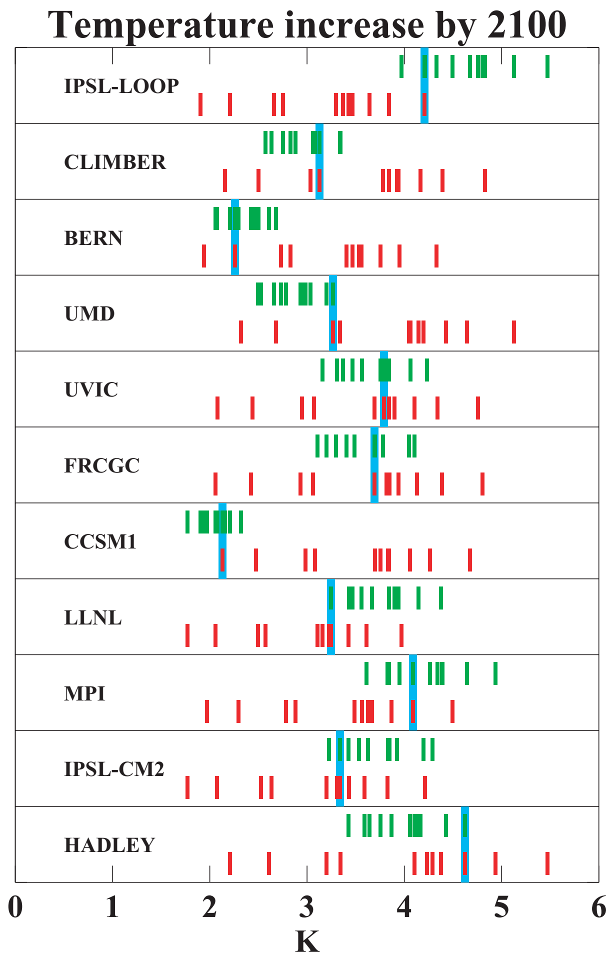


*Fig. 1.* Prediction of global warming by year 2100 since pre-industrial times, $\Delta T_{2100}$ (K), for a range of parametrizations of the simple climate-carbon cycle 'box' model. The thick vertical blue lines represent the predictions when emulating the GCMs and models of intermediate complexity listed on the left-hand side. The vertical red lines then correspond, for each C4MIP model emulated, to altering the physical climate parameters ($\Delta T_{2\times CO2}$ and $C$) to be those found when fitting to the other models. Similarly, the vertical green lines corresponding to adopting parameters describing the carbon cycle from fitting to the other C4MIP models.

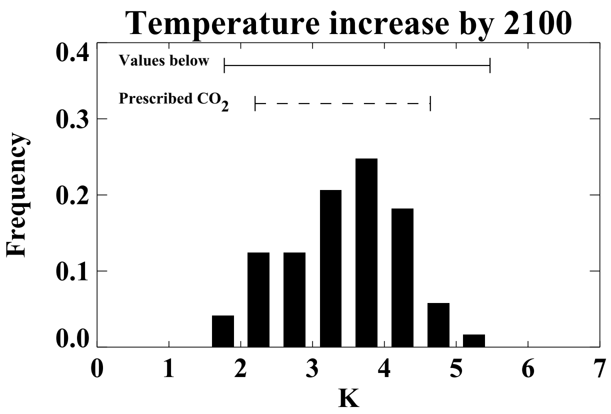


*Fig. 2.* A histogram of $\Delta T_{2100}$ (K) for each combination of physical climate and carbon cycle parameters (121 simulations). Predictions are binned in to regions of 0.5 K, and normalized such that the sum of the histogram bars is equal to unity. The continuous horizontal bar represents the range of these 121 simulations of $\Delta T_{2100}$, whereas the dashed horizontal bar is the range of 11 $\Delta T_{2100}$ values derived for the fixed $CO_2$ pathway described in the earlier footnote.

climate modelling uncertainty. More specifically, we are asking for each C4MIP model that if it had the true carbon cycle parameters, how much uncertainty would remain (in predicting $\Delta T_{2100}$) due to uncertainty in modelling the physical climate properties? We then ask the reciprocal question—if the physical climate behaviour was correctly modelled (for a particular model), how would uncertainty in the carbon cycle parameters manifest itself? It is again important to note that the physical climate and carbon cycle processes do not completely uncouple in this way of assessing the impact of parameter uncertainty—the red vertical lines, even for the same GCM, will correspond to different final atmospheric $CO_2$ concentrations.[1] We also note that there are additional uncertainties when calculating temperature for policy relevant use, in addition to those of the physical climate system and carbon cycle response to $CO_2$ emissions, including the effect of non-$CO_2$ greenhouse gases and the radiative response of atmospheric aerosols.

Figure 2 shows the frequency distribution of $\Delta T_{2100}$ for every combination of carbon cycle and energy balance parameters in Fig. 1, that is, 11 × 11 simulations—'binned' in to 0.5 K ranges, normalized so that bin totals equals unity. The continuous horizontal bar represents the range of these 121 simulations of $\Delta T_{2100}$. The dashed horizontal bar is the range of 11 $\Delta T_{2100}$ values derived for the fixed $CO_2$ pathway described in the earlier footnote.

We estimate the relative importance of the two sources of uncertainty in Fig. 3. We calculate the standard deviation (for each emulated C4MIP model) of the variation due to carbon cycle uncertainty in predictions of $\Delta T_{2100}$ and call this $\sigma_2$ (K; i.e. standard deviation of the vertical green lines in Fig. 1 for each model). Similarly, uncertainty in the energy balance parameters (i.e. $\Delta T_{2\times CO2}$ and $C$) is represented by $\sigma_1$ (K). The ratio of these two ($\sigma_2/\sigma_1$) is given in Fig. 3. They lie in the range of 0.23–0.63, with an average close to 0.4, as given by the dashed horizontal

[1] It is possible to completely uncouple the carbon cycle by prescribing a $CO_2$ pathway to the climate 'box' model and varying just $T_{2\times CO2}$ and $C$ values. As a check, we performed this numerical experiment using the $CO_2$ concentrations given for the Bern-CC model, p. 808 of the 3rd IPCC assessment (IPCC, 2001). The standard deviation of the resultant values of $\Delta T_{2100}$ across the 11 GCMs was 0.74 K, a value similar in magnitude to the standard deviations found (for each GCM) of the vertical red bars in Fig. 1.

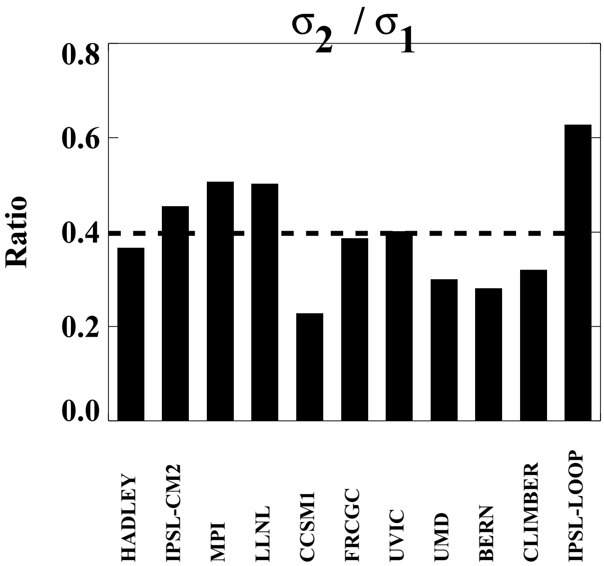


*Fig. 3.* Ratio of the standard deviations (*SD*) in $\Delta T_{2100}$ (K) for each baseline C4MIP model replicated by HadSCCCM1, due to variations in carbon cycle parameters ($\sigma_2$, i.e. *SD* of green values for each model in Fig. 1) and variations in physical climate parameters ($\sigma_1$, i.e. *SD* of red values for each model in Fig. 1). The horizontal dashed line is the mean value of these ratios.

line in Fig. 3. That is, on average, the spread in transient response is around 40% of that due to the more frequently debated uncertainties in equilibrium climate sensitivity and global heat capacity.

We observe from Fig. 1 that the model with largest physical climate response is IPSL-LOOP (blue line overlays highest red line for that model), and the model with the largest carbon cycle response is HADLEY (blue line overlays highest green line for that model). In accordance with this, the highest temperature increase across all model combinations represented in Fig. 1 is the combination of IPSL-LOOP physical climate response and HADLEY carbon cycle response. Conversely, the least warming occurs for the combination of CCSM1 physical climate response and LLNL carbon cycle response.

It is expected that the spread of uncertainty in warming that corresponds to the altered carbon cycle parameters is larger for GCMs with the higher temperature sensitivities (i.e. the spread of green bars is larger in Fig. 1 for warmer models). This has two components. First, temporarily neglecting climate-carbon cycle feedbacks so that $CO_2$ pathways do not depend explicitly on temperature, for higher climate sensitivities, the spread of temperature changes in response to the range of alternative carbon cycle representations will be larger. A second component of the total spread comes from the climate-carbon cycle feedback, where increased temperatures reduce the natural ability to 'drawdown' $CO_2$ from the atmosphere. In this instance, high climate sensitivities lead to warmer temperatures, which, in turn, will lead to an even higher level of atmospheric $CO_2$ concentrations. This effect tends to elevate the upper part of the uncertainty range more than it does the lower part, increasing the spread.

## 4. Conclusions

We conclude, based on uncertainty represented in the C4MIP simulations, that the spread of $\Delta T_{2100}$ (K) due to the current range of carbon cycle parameters is around 40% of that due to uncertainty in the climate sensitivity and thermal inertia. Uncertainties in both the energy balance properties of the Earth system and the global carbon cycle are significant. Although there is a considerable body of literature that seeks to address climate sensitivity uncertainty, there is, in some ways, much less information to date regarding properties of the global carbon cycle. The scientific community is already applying constraints to the physical climate system (e.g. Murphy et al., 2004). However, with carbon cycle uncertainty estimated to be around 40% of that of the physical climate properties (and potentially as high as 63%), our results suggest that constraining the carbon cycle component of the C4MIP ensemble is also vital.

## 5. Acknowledgments

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