A Technique for Dynamically Downscaling Daily-Averaged GCM Datasets Using the Conformal Cubic Atmospheric Model

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ABSTRACT

In this paper the authors dynamically downscale daily-averaged general circulation model (GCM) datasets over Australia using the Conformal Cubic Atmospheric Model (CCAM). The technique can take advantage of the wider range of Coupled Model Intercomparison Project phase 3 (CMIP3) daily-averaged GCM datasets than is available using 3-hourly datasets. The daily-averaged host GCM atmospheric data are fitted to a time interpolation formula and then differentiated in time to produce a first-order estimate of the atmosphere at 0000 UTC on each simulation day. The processed GCM data are forced into CCAM using a scale-selective filter with an 18\degree\ radius. Since this procedure is unable to account for the diurnal cycle, the forcing data are only applied to winds and air temperatures once per day between 800 and 100 hPa. Lateral boundary conditions are not required since CCAM employs a variable-resolution global grid. The technique is evaluated by downscaling daily-averaged 2.5\degree NCEP reanalyses over Australia at 60-km resolution from 1971 to 2000 and comparing the results to downscaling the 6-hourly reanalyses and to simulating with sea surface temperature (SST)-only forcing. The results show that the daily-averaged downscaling technique can simulate average seasonal maximum and minimum screen temperatures and rainfall similar to those obtained downscaling 6-hourly reanalyses. Some implications for regional climate projections are considered by downscaling four daily-averaged GCM datasets from the twentieth-century climate in coupled models (20C3M) experiment over Australia.

1. Introduction

Regional climate models (RCMs) are commonly used for the dynamical downscaling of coupled ocean–atmosphere general circulation models (GCMs). In this way, RCMs can be used to estimate changes to the climate at regional length scales that are also consistent with the global scale predictions of GCMs for different Intergovernmental Panel on Climate Change (IPCC) emission scenarios. For example, the resolution of GCM output is generally 2\degree–4\degree, whereas RCMs typically operate at a resolution of 60 km or finer. RCMs simulate atmospheric dynamics and physics using modeling techniques similar to those used in GCMs, but with enhancements for modeling mesoscale and local-scale meteorology. In addition, RCMs use high-resolution orography and land-use datasets to account for regional surface forcings that are not resolved by GCMs since these surface forcings can have a significant influence on the atmosphere within the planetary boundary layer. It is also necessary for RCMs to account for the influence of the synoptic-scale circulations simulated by the host GCM, but which are outside the region over which the RCM is being applied. The “assimilation” or forcing of large-scale weather patterns into the RCM can be achieved by a variety of techniques including Davies (1976) boundary conditions, relaxation techniques, and spectral filters (Kida et al. 1991; Waldron et al. 1996; von Storch et al. 2000). By accounting for both the regional-scale influences and the synoptic-scale behavior of the host GCM, it is possible to estimate how a region’s climate may change under different global climate projections.

A significant issue for RCMs is estimating the uncertainty in the regional climate projections. The uncertainty in atmospheric climate model output is typically assessed by considering an ensemble of models, with an important example being the Coupled Model Intercomparison Project phase 3 (CMIP3) of GCMs (Meehl et al. 2007). There are also RCM intercomparisons (e.g., Takle et al. 1999; Fu et al. 2005; Fox-Rabinovitz et al. 2006; Christensen et al. 2007, 2008; Fowler and Ekstrom 2009), where different RCMs are nested in a common host dataset. However, it is

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also necessary to account for uncertainty in the host forcings (i.e., from the GCM) since these forcings can have a strong influence on the regional climate projection (Deque et al. 2007). For this reason, ensembles of RCMs using multiple GCM forcings have also been constructed (e.g., Fowler and Ekstrom 2009).

Instead of the more usual approach of nesting the regional model in 6-hourly output from the GCM host model, in this paper we downscale daily-averaged GCM output over Australia from 1971–2000, using the Conformal Cubic Atmospheric Model (CCAM) (McGregor 2005; McGregor and Dix 2008). This is done by calculating the time integral of the GCM atmospheric fields using the daily-averaged dataset and then fitting the result with a piecewise-cubic Bessel function. The fitted result can then be differentiated in time to provide a first-order estimate of the atmosphere at 0000 UTC on each simulation day. Since this approximation does not account for the diurnal cycle, we choose to force the atmospheric fields into the model between 800 and 100 hPa. We use a Gaussian low-bandpass, scale-selective digital filter to perturb the atmosphere of the regional model once per day at a length scale radius of 18° (Thatcher and McGregor 2009). Since the atmosphere is only perturbed once per day using the scale-selective digital filter, there is no need to further temporally interpolate the 0000 UTC estimate of the atmosphere derived from the daily-averaged GCM output. Lateral boundary conditions (LBCs) are also not required as CCAM employs a variable-resolution global grid.

A possible application of the daily-averaged downscaling technique described in this paper is that it allows us greater flexibility in choosing host models from CMIP3 since there is a larger number of models providing daily-averaged output compared to 3-hourly output. However, we first need to assess the extent that the regional simulation is influenced by the daily-averaging forcing data. This is done by comparing the results of CCAM 60-km resolution simulations after downscaling 6-hourly National Centers for Environmental Prediction (NCEP) reanalyses, with downscaling daily-averaged NCEP reanalyses and with only sea surface temperature forcing (i.e., no other atmospheric forcing). The daily-average downscaling method can be expected to partially force systematic biases from the GCM into the CCAM regional simulation (see section 4), and any such biases can affect the accuracy of the regional simulation. A similar issue has been raised by Kanamaru and Kanamitsu (2007) in the context of numerical weather prediction (NWP). Therefore, when downscaling the regional climate using the daily-average downscaling approach, it is important to choose host GCMs that have produced a reasonable simulation of the Australian climate during the twentieth century (so as to minimize the introduction of biases). To gain some understanding of the implications of GCM biases when applying the daily-average downscaling technique, we also downscale four daily-averaged GCM datasets over Australia from the CMIP3 20C3M experiment (1971–2000) and compare the results to the original host GCMs.

The methodology for downscaling daily-averaged datasets is discussed in section 2, including a technical description of CCAM. The downscaling technique is evaluated by comparing the simulated climate after nesting CCAM in 6-hourly NCEP reanalyses, daily-averaged NCEP reanalyses, and SST-only forcing from the reanalyses in section 3. An application of the technique is described in section 4, where we use the methodology to dynamically downscale the daily-averaged Commonwealth Scientific and Industrial Research Organisation Mark version 3.5 (CSIRO Mk3.5), Geophysical Fluid Dynamics Laboratory Climate Model version 2.1 (GFDL CM2.1), National Institute for Environmental Studies (NIES) Model for Interdisciplinary Research on Climate 3.2 (MIROC3.2), and Max Planck Institute ECHAM5 output for the twentieth-century climate in coupled models (20C3M) experiments. The downscaled climate from these experiments is compared to the host GCMs, so as to quantify the potential implications of applying the daily-averaged downscaling technique. The results of the paper are summarized in section 5.

2. Methodology for downscaling daily-averaged GCM output

In this section, we describe a methodology for using CCAM to dynamically downscale daily-averaged GCM data over Australia. CCAM is a semi-implicit, semi-Lagrangian atmospheric climate model based on the conformal cubic grid (McGregor 2005; McGregor and Dix 2008). In addition to functioning as an atmospheric general circulation model (AGCM), CCAM can also be employed for regional climate simulations since CCAM supports a variable-resolution global grid. To explain the variable-resolution grid, we first define the conformal cubic coordinates \(A\), \(B\), and \(C\) by relating them to the Cartesian coordinates \(X'\), \(Y'\), and \(Z'\) by

\[
(X', Y', Z') = \frac{(A, B, C)}{(A^2 + B^2 + C^2)^{1/2}} R, \tag{1}
\]

where \(R\) is the radius of the spherical surface. A regional focus can be applied to the grid by using a Schmidt transformation (Schmidt 1977):

\[
X = \frac{2S X'}{S^2 + 1 + (S^2 - 1)Z'/R}, \tag{2}
\]

\[
Y = \frac{2S Y'}{S^2 + 1 + (S^2 - 1)Z'/R}. \tag{3}
\]
in which $S$ is the Schmidt factor. Setting the Schmidt factor $S > 1$ has the effect of focusing grid points over a particular area. Larger values of $S$ result in finer grid spacing in the high-resolution region. However, as the total number of grid points in the model remains the same, the high-resolution grid points over the target region are achieved at the expense of a corresponding region of low-resolution grid points on the opposite side of the globe. For example, in the case of a C72 grid (i.e., $72 \times 72$ horizontal grid points on each of the six cubic panels), $S = 2.22$ results in a grid with 60-km resolution in the regional focus, 310-km resolution on the opposite side of the globe, and an average resolution of approximately 140 km (see Fig. 1). Since CCAM employs a variable-resolution global grid, then dynamical downscaling with CCAM does not require LBC data.

CCAM includes a prognostic cloud scheme (Rotstayn 1997) and a land surface scheme that has six levels of soil temperature and moisture as well as three layers of snow (Kowalczyk et al. 1994). The gravity wave drag scheme is implemented following Chouinard et al. (1986). CCAM employs a stability-dependent boundary layer scheme (McGregor et al. 1993) with nonlocal vertical mixing (Holtslag and Boville 1993) and enhanced mixing of cloudy boundary layer air (Smith 1990). Convection is implemented using the approach described by McGregor (2003). CCAM uses the Lacis and Hansen (1974) and Schwarzkopf and Fels (1991) schemes for shortwave and longwave radiation, respectively. For this paper we employ 18 vertical levels (ranging from 40 m to 35 km), which is typically used for climate studies, although 27 level and 35 level configurations of CCAM are also employed. Further details on the design of CCAM can be obtained from McGregor (2005).

CCAM supports a variety of methods for assimilating large-scale atmospheric forcings from GCM datasets, including far-field nudging (Wang et al. 2004), relaxation methods, scale-selective digital filters (Thatcher and McGregor 2009), as well as SST-only forcing. Far-field nudging is analogous to Davies (1976)–style boundary conditions, but adapted to the variable-resolution global grid. Global nudging uses a relaxation technique to perturb the atmosphere toward the interpolated host data with some $e$-folding time (e.g., 24 h) by including tendency terms in the prognostic equations for winds, pressure, and temperature (e.g., Jeuken et al. 1996). The scale-selective filter is analogous to spectral nudging (e.g., Kida et al. 1991; Waldron et al. 1996; von Storch et al. 2000; Kanamaru and Kanamitsu 2007), where large spatial wavelengths are perturbed toward the host model while small spatial wavelengths are left unperturbed. In the case of SST-only forcing, there is no nudging of the atmospheric fields and CCAM operates as an AGCM. For large values of the Schmidt factor $S$, the coarse region of the stretched conformal cubic grid can become sufficiently sparse that synoptic-scale atmospheric processes are not sufficiently resolved. In these cases, some perturbation from the host dataset is required over the coarse-resolution region using one of the atmospheric forcing methods listed above, which results in the coarse-resolution region being perturbed to follow the host dataset. In the case of the C72, $S = 2.22$ grid used in this paper, CCAM can be run without any atmospheric perturbation from the host dataset without generating unphysical atmospheric behavior.

In this paper, we intend to perturb the regional climate with atmospheric forcings based on daily-averaged GCM datasets. Since more research centers have contributed daily-averaged data to CMIP3 than have contributed 3-hourly datasets, the use of daily-averaged GCM datasets allows us to downscale a larger range of CMIP3 GCMs than would otherwise be the case. For example, in section 3, we downscale GFDL2.1, CSIRO3.5, ECHAM5, and MIROC3.2 medium-resolution version (medres) GCMs of which only two have 3-hourly datasets available in the CMIP3 database. Furthermore, as discussed in section 3, different downscaling techniques can produce different

![Fig. 1. The C72, $S = 2.22$, variable-resolution conformal cubic grid used for the experiments considered in this paper. The grid is stretched using the Schmidt transform so that the grid has a 60-km resolution over Australia.](image-url)
behavior in the RCM, which is useful for understanding the uncertainties associated with different downscaling techniques. Daily-average GCM data in its raw form is not suitable for perturbing the atmospheric fields of the regional climate model. This is because most perturbation schemes assume that the host data represents the instantaneous state of the atmosphere. For example, a typical perturbation scheme resembles the following equation:

$$\frac{du}{dt} = K_P(u^H - u),$$  \hspace{1cm} (5)

where $u$ is some prognostic atmospheric field for the regional climate model, $u^H$ is the equivalent atmospheric field that is spatially interpolated from the host model, and $K_P$ is a constant that is usually a function of the $e$-folding time and the vertical height (i.e., so that the perturbation can be reduced or eliminated within the boundary layer; e.g., von Storch et al. 2000). Although it is possible to include integral and derivative contributions to the perturbation in (5) [e.g., following PID control loop theory; Visioli (2006)], in practice a simple “proportional only” perturbation scheme, as described in (5), is sufficient for most atmospheric modeling applications. In CCAM we employ a scale-selective filter (Thatcher and McGregor 2009) in which the usual perturbation in (5) is revised to become

$$\frac{du}{dt} = K_P(u^H - u) * W,$$  \hspace{1cm} (6)

where $W$ is a scale-selective filter and the asterisk indicates a convolution. In the case of CCAM we use a Gaussian function for the filter $W$ and use a convolution to apply the scale-selective filter since the convolution is easily applied to the conformal cubic coordinate system. Using the convolution theorem, it can be shown that the approach in (6) is equivalent to a scale-selective filter based on a Fourier transform.

The first step in processing the daily-averaged data is to convert the data into a discrete approximation of the integral of each atmospheric field, as described by

$$\int_0^{t=n} u^H(\tau) d\tau = \sum_{i=1}^{n} U^H_i,$$  \hspace{1cm} (7)

where $n$ is an integer $(n = 1, 2, 3, \ldots)$ representing the simulation day, $t$ is the CCAM simulation time in units of days, $U^H_i$ are the discrete daily-average values of $u^H$ from the host GCM dataset, $\tau$ is a variable used for the integration, and $i$ is an integer used for the summation. Equation (7) is only valid at the end of each simulation day (i.e., discrete values of $n$) since the daily-average fields, $U^H_i$, are only saved once per day. Note that we cannot perturb the difference in the daily integrals [e.g., replace (6)] with

$$\frac{du}{dt} = K_P \left\{ \int_0^t [u^H(\tau) - u(\tau)] W \right\} d\tau$$  \hspace{1cm} (8)

since such “integral only” control strategies are known to be unstable owing to the need to continually overshoot and undershoot $u^H$. Instead, we can approximate the instantaneous value of $u^H$ from $U^H_i$ by taking the derivative of (7). In this paper, we estimate the derivative by using the piecewise-cubic Bessel (PWCB) approach to interpolate the discrete values of the integral of $u^H$. The interpolation function for the discrete daily-averaged data at index $n$ is written as a polynomial of the form

$$P_n(t) = A_n + B_n(t-n) + C_n(t-n)^2 + D_n(t-n)^3.$$  \hspace{1cm} (9)

The constants $A_n, B_n, C_n$, and $D_n$ are defined by solving for the polynomial at $t = n - 1, t = n, t = n + 1$, and $t = n + 2$ as described by

$$P_n(n-1) = 0,$$  \hspace{1cm} (10)

$$P_n(n) = U^H_{n-1},$$  \hspace{1cm} (11)

$$P_n(n+1) = P_n(n) + U^H_n,$$  \hspace{1cm} (12)

and

$$P_n(n+2) = P_n(n+1) + U^H_{n+1}.$$  \hspace{1cm} (13)

The expressions for determining $A_n, B_n, C_n$, and $D_n$ can then be written as

$$A_n = P_n(n),$$  \hspace{1cm} (14)

$$B_n = \frac{[P_n(n+1) - P_n(n-1)]}{2},$$  \hspace{1cm} (15)

$$C_n = Y_n/2,$$  \hspace{1cm} (16)

$$D_n = X_n/2,$$  \hspace{1cm} (17)

$$X_n = P_n(n+2) - P_n(n-1) + 3[P_n(n) - P_n(n+1)],$$  \hspace{1cm} (18)

and

$$Y_n = P_n(n-1) - 2P_n(n) + P_n(n+1) - X_n,$$  \hspace{1cm} (19)

where $X_n$ and $Y_n$ are constants for a given value of $n$. Note that, since we only intend to use the derivative of $P_n(t)$, that is,
\[ Q_n(t) = \frac{dP_n(t)}{dt} = B_n + 2C_n(t - n) + 3D_n(t - n)^2, \quad (20) \]

we can set \( P_n(n - 1) = 0 \) without any loss of generality. Furthermore, the PWCB interpolation satisfies the relationship

\[ Q_n(t = n) = Q_{n+1}(t = n) \quad (21) \]

so that the estimate for \( u^H \) is consistent at time \( t \) with the interpolation used for time \( t - 1 \) (i.e., for the previous day). We can then approximate \( u^H \) by

\[ u^H(t) \approx H(t) = \begin{cases} Q_1(t), & 0 \leq t \leq 1 \\ Q_2(t), & 1 < t \leq 2 \\ \vdots & \vdots \end{cases} \quad (22) \]

Note that after substituting (10)–(19) into (20), the function \( H(t) \) at the end of each simulation day (i.e., 0000 UTC) can be written as

\[ H(t = n) = (U^H_{n-1} + U^H_n)/2. \quad (23) \]

In this way, we use the scale-selective filter to adjust the state of the atmosphere at large length scales to resemble that of the host dataset, \( H(t) \), at the end of each simulation day.

The absence of a diurnal cycle in the 0000 UTC approximation, \( H(t) \), is a source of error in our daily-average downscaling technique. To estimate the size of this error and the likely implications for the downscaled regional climate simulations, we have compared the NCEP 0000 UTC reanalyses with the atmosphere estimated using the interpolation \( H(t) \) for winds and air temperature. This comparison was carried out by estimating the daily-average values of the NCEP 2.5° reanalyses for the year 2000 (i.e., averaging 6-hourly reanalyses using the trapezoidal formula) and then applying the methodology described in (9) to (22) so as to produce an estimate of the instantaneous 0000 UTC fields (i.e., constructing 365 samples for the error analysis). Since the regional simulation is only perturbed by the host model at large length scales, we also need to apply the scale-selective filter to the error, \( H(t) - u(t) \), at 0000 UTC. For this experiment, we have chosen to use a scale-selective filter length scale of 18° (i.e., approximately half the width of the high-resolution panel) as this was found to be reasonably optimum when downsampling NCEP analyses to 60-km resolution (Thatcher and McGregor 2009).

Figure 2 plots the root-mean-square error (RMSE) between the estimated and actual 0000 UTC NCEP reanalyses as a function of pressure, with the 18° scale-selective filter centered on 27°S, 135°E (i.e., centered over Australia). In particular, Fig. 2 shows that the errors in the
estimated 0000 UTC reanalyses, after scale-selective filtering, grow rapidly when the pressure exceeds 800 hPa or the pressure is less than 100 hPa (i.e., where a strong diurnal cycle is present in the atmospheric fields). Note that the wind RMSEs show a local peak around 300 hPa (e.g., RMSE of 0.9 and 1.2 m s\(^{-1}\) for \(U\) and \(V\), respectively), although there is a corresponding peak in the root-mean-square (RMS) wind speed at this level (e.g., RMS wind speed of 40 and 15 m s\(^{-1}\) for \(U\) and \(V\), respectively). We find the proportional error in winds to be less than 20% over the 100- to 800-hPa range. As discussed in sections 3 and 4, this error does not invalidate the simulation of the regional climate.

Based on the results of Fig. 2, we only apply the estimated 0000 UTC reanalyses using (24) between 100 and 800 hPa, after applying a scale-selective filter with 18° radius length scale. We then define \(K_P\) from (24) as

\[
K_P = \begin{cases} 1, & 100 \leq p \leq 800 \text{ hPa} \\ 0, & \text{elsewhere}, \end{cases}
\]  

\[\frac{du}{dt} = \left\{ \begin{aligned} & K_P [H(t) - u(t)] + K_I \sum_{i=1}^{t} U^H_i - \int_{0}^{t} u(\tau) d\tau \right\} * W, \quad t = \text{int}(t) \\ & 0, \quad t \neq \text{int}(t) \end{aligned} \]  

(26)

and \(K_I\) is a constant. The advantage with (26) is that it reduces the dependence of the perturbation on the proportional term and therefore reduces errors arising from neglecting the diurnal cycle in the PWCB interpolation. Proportional-integral schemes are typically used in engineering applications (e.g., Visioli 2006) as they avoid the “steady-state error” associated with proportional-only perturbation strategies. However, in this paper we concentrate our analysis on the proportional-only perturbation approach (24) owing to its simplicity and compatibility with existing perturbation approaches in atmospheric models.

In this section we have proposed a method for forcing daily-average GCM datasets into the CCAM regional climate model. In particular, the downscaling method is designed to interface with existing approaches to perturbing the atmosphere (e.g., the scale-selective filter) that are numerically stable and computationally efficient. The method proposed here is appropriate for a global atmospheric model, such as CCAM with its variable-resolution global grid; the methodology does not provide LBCs for a limited-area RCM. In the next section, we evaluate the size of the simulation errors arising from the daily-average downscaling approach when simulating the regional climate over Australia with forcing from NCEP reanalyses.

where \(p\) is the pressure of the atmospheric level in the simulation. Only winds and air temperature fields are perturbed in the daily-average downscaling technique. The surface pressure exhibits a clear diurnal signal and therefore should not be perturbed by using the technique in (9) to (22). We also avoid perturbing the regional model’s moisture, as perturbing the moisture can lead to unphysical behavior (e.g., excessive rainfall from moisture that has precipitated out of the atmosphere being replaced by the perturbation scheme, or vice versa). SSTs are used either directly from the NCEP reanalyses (section 3) or interpolated from monthly mean values and converted to instantaneous daily values using the PWCB approach but applied to monthly fields (so that the average of the interpolated SSTs matches the original monthly average data set). As discussed in section 4, we do not attempt any bias correction of SST or atmospheric fields from the GCM.

In principle the downscaling method could be improved by replacing the proportional perturbation with a proportional-integral approach, where (24) is replaced with

3. Downscaling results using daily-averaged NCEP reanalyses

The method for downscaling daily-averaged GCM datasets outlined in section 2 is designed to be numerically stable and computationally efficient. However, limitations to the method were seen arising from neglecting a diurnal cycle in the atmospheric fields when estimating the state of the atmosphere at 0000 UTC. In this section, we compare the simulated climate between three different downscaling methods: downscaling NCEP reanalyses using the scale-selective filter 6-hourly, downscaling daily-averaged NCEP reanalyses using the method in section 2, and downscaling using SST-only forcings (i.e., no nudging of the atmospheric fields). Daily-averaged NCEP reanalyses are approximated by averaging 6-hourly reanalyses using the trapezoidal formula. For both 6-hourly and daily-averaged experiments, atmospheric forcing of temperature and winds is applied between 800 and 100 hPa (see section 2) with no forcing of the surface pressure. The downscaling experiments are conducted over Australia from 1971 to 2000 at 60-km resolution, using a C72 grid with a Schmidt factor of \(S = 2.22\) (i.e., 31 104 horizontal grid points per level). Note that using a variable-resolution grid will exacerbate the differences in the results between the different downscaling techniques since the downscaling
methods will need to compensate for errors arising from the coarse-resolution region of the simulation (i.e., where the grid is stretched on the opposite side of the globe from the region of interest). All simulations were performed on an SGI Altix NUMA ia64 using 12 Itanium 1.67-GHz processors per simulation. The model was able to generate approximately 3.4 simulation years per day with the C72, $S = 2.22$ conformal cubic grid using 18 vertical levels.

We first evaluate the different downscaling techniques at the 500-hPa pressure level, which is near the middle of the 800- to 100-hPa range for which the winds and air temperature are perturbed. Table 1 shows the performance of the different downscaling techniques for simulating the average 500-hPa $U$ wind (zonal) speed, $V$ wind (meridional) speed, (air) temperature, and geopotential height with respect to NCEP 2.5\degree reanalysis from 1971 to 2000. The maximum 95\% confidence interval for the biases at a grid point is approximately $0.04$ m s$^{-1}$ for winds, $0.01$\degreeCelsius for temperature, and $0.4$ m for geopotential height, suggesting that there are statistically significant differences between the results of the downscaling methods. The results in Table 1 suggest that the daily-averaged downscaling method is producing a reasonable representation of the atmosphere at 500 hPa, with RMSEs within $1.9$ m s$^{-1}$ for $U$ wind, $1.1$ m s$^{-1}$ for $V$ wind, and $0.6$\degreeCelsius for temperature. Pattern correlations, RMSEs, and biases for the daily-averaged experiment typically lie between the results of the 6-hourly and SST-only experiments, as may be expected from perturbing the atmosphere less frequently than the 6-hourly experiment, but with the daily perturbation still helping to reduce errors that arise when there is no atmospheric forcing on the stretched grid (i.e., the SST-only experiment). Nevertheless, the daily-averaged RMSE and biases for mean 500-hPa $V$ wind, temperature, and geopotential height are generally much closer to the 6-hourly results than the SST-only forcing results. In the case of the mean 500-hPa $U$ wind, the RMSEs for the daily-averaged experiment are similar to the SST-only forcing results, suggesting that the daily-averaged downscaling is less effective at correcting errors in the $U$-wind component at this pressure level. The typical bias in the mean 500-hPa $U$ wind is also larger for the daily-averaged downscaling experiment (i.e., approximately $-1.2$ m s$^{-1}$ on average, compared to a value of $-0.7$ m s$^{-1}$ for the 6-hourly downscaling). It is possible that this error could be reduced (maybe by increasing the number of vertical levels), although these biases are acceptable when compared to those from some GCMs [e.g., $-1.9$ and $-1.2$ m s$^{-1}$ for the CSIRO3.5 and MIROC3.2(medres) models, respectively]. Table 1 also shows that the daily-averaged downscaling does simulate a realistic mean 500-hPa geopotential height, with mostly smaller RMSEs and biases compared to the other downscaling methods.

In addition to considering the average behavior of the 500-hPa winds and temperature, it is worth considering the variance of these variables as shown in Table 2. In this case we are interested in whether there is evidence that the daily-average downscaling technique may be damping the atmosphere and therefore suppressing the variance of

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**Table 1.** Pattern correlation (Corr), RMSE, and biases in average 500-hPa $U$ wind speed (m s$^{-1}$), $V$ wind speed (m s$^{-1}$), temperature (\degreeCelsius), and geopotential height (geopot, m) for the 6-hourly (6-h), daily-average (daily), and SST-only forcing (SST) downscaling experiments from NCEP reanalyses. Errors are calculated with respect to the NCEP reanalyses averaged from 1971 to 2000. Bold values indicate the best-performing model. Seasons are DJF: December–February, MAM: March–May, JJA: June–August, and SON: September–November.

<table>
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<th>Variable</th>
<th>Season</th>
<th>Corr 6-h</th>
<th>Corr day</th>
<th>Corr SST</th>
<th>RMSE 6-h</th>
<th>RMSE day</th>
<th>RMSE SST</th>
<th>Bias 6-h</th>
<th>Bias day</th>
<th>Bias SST</th>
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<tr>
<td></td>
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<tr>
<td>$V$ mean</td>
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<tr>
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Table 2. Corr, RMSE, and biases in the variance (var) of 500-hPa $U$ winds [(m s$^{-1}$)$^2$], $V$ winds [(m s$^{-1}$)$^2$], and temperature (°C$^2$) for the 6-hourly (6-h), daily-average (day), and SST-only forcing (SST) downscaling experiments from NCEP reanalyses. Errors are calculated with respect to the variance of NCEP reanalyses from 1971 to 2000. Values in bold indicate the best-performing model configuration.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Season</th>
<th>Corr 6-h</th>
<th>Corr day</th>
<th>Corr SST</th>
<th>RMSE 6-h</th>
<th>RMSE day</th>
<th>RMSE SST</th>
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Table 3. Daily maximum screen temperature ($T_{\text{max}}$), daily minimum screen temperature ($T_{\text{min}}$), and precipitation ($R_{\text{nd}}$) errors over all Australia (land only) obtained for the 6-hourly (6-h), daily-average (day), and SST-only forcing (SST) downscaling methods after downscaling NCEP reanalyses for 1971 to 2000. Errors are measured in terms of Corr, RMSE, and bias. Temperature RMSEs and biases are in units of °C, and rainfall errors are in units of mm day$^{-1}$. Errors are calculated with respect to the BoM mean climatology dataset at 0.5° resolution. Values in bold indicate the best-performing model configuration.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Season</th>
<th>Corr 6-h</th>
<th>Corr day</th>
<th>Corr SST</th>
<th>RMSE 6-h</th>
<th>RMSE day</th>
<th>RMSE SST</th>
<th>Bias 6-h</th>
<th>Bias day</th>
<th>Bias SST</th>
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<td>0.95</td>
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<td>-0.7</td>
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<tr>
<td></td>
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<td>0.97</td>
<td>0.98</td>
<td>0.97</td>
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<td>0.98</td>
<td>0.98</td>
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<tr>
<td></td>
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<td>0.97</td>
<td>0.98</td>
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<td>$R_{\text{nd}}$</td>
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<tr>
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<tr>
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<td>0.82</td>
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<td>0.6</td>
<td>-0.2</td>
<td>-0.3</td>
<td>-0.5</td>
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</table>

These fields. The results in Table 2 indicate that the daily-averaged downscaling method produces RMSEs for the variance of 500-hPa winds and temperature, which typically lie between the results of the 6-hourly and SST-only forcing experiments with the 6-hourly downscaling providing the most accurate simulation of the variance. Again, the daily-averaged RMSEs are usually closer to those obtained from 6-hourly downscaling rather than the SST-only forcing experiment. Table 2 shows that the bias in the variance for the 500-hPa $U$ wind is more negative than that obtained for the other downscaling techniques, although the magnitude of the bias in the variance for 500-hPa $U$ wind, $V$ wind, and temperature using the daily-averaged downscaling technique is considerably smaller on average than that obtained for the SST-only experiment. The daily-averaged downscaling does improve the correlation with the variance of 500-hPa temperature when compared to the SST-only forcing experiment. However, the daily-averaged experiment’s correlation with the variance of the 500-hPa winds is less accurate, with low correlation values for the variance of the 500-hPa $V$ wind in December–February (DJF) and March–May (MAM). This error is predominantly related to CCAM simulating too much variance in the 500-hPa $V$ wind component over northern Australia when using the daily-averaged and SST-only forcing methods, with the daily-averaged experiment reducing this problem to some extent when compared to the SST-only forcing experiment.
(hence the smaller RMSE and biases). In any event, there is no evidence that the daily-averaged downscaling technique is systematically suppressing the variance of the 500-hPa winds and temperature.

With some confidence that plausible winds, temperature, and geopotential height are being simulated by the daily-averaged downscaling experiment, we next consider the performance of the different downscaling techniques in terms of average daily maximum screen temperature ($T_{\text{max}}$), average daily minimum screen temperature ($T_{\text{min}}$), and average precipitation ($R_{\text{nd}}$). Note that these variables are not directly perturbed by the downscaling technique and therefore depend on nonlinear interactions between the atmosphere and the surface scheme. As a consequence, the results can be sensitive to the choice of land-use datasets and model physical parameterizations. Table 3 and Figs. 3–5 compare the performance of the 6-hourly and daily-averaged downscaling techniques with respect to the 1961–2000 Australian climatology as published by the Australian Bureau of Meteorology (BoM). The maximum 95% confidence interval for the biases at a grid point is approximately 0.06°C for $T_{\text{max}}$, 0.03°C for $T_{\text{min}}$, and 0.2 mm day$^{-1}$ for $R_{\text{nd}}$. The daily-averaged downscaling results appear to simulate the mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ with reasonable accuracy when compared to the other downscaling techniques. There is no evidence of significant biases in the daily-averaged experiment, which would invalidate the simulation. As before, the daily-averaged downscaling produces pattern correlations, RMSEs, and biases that generally lie between the results of the 6-hourly and SST-only forcing experiments. The errors for mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ using the daily-averaged technique tend to be closer to those for the 6-hourly data when the difference between the 6-hourly and SST-only forcing results is significant. Since the 6-hourly downscaling is associated with a warm bias in $T_{\text{max}}$ whereas the SST-only forcing experiment is associated with a cold bias, the daily-averaged downscaling produces a relatively small RMSE and bias for $T_{\text{max}}$, compared to the other downscaling methods. Errors in the simulated rainfall are reasonably similar for all three experiments, with no downscaling approach producing systematically better results than the other methods. An example of the simulated rainfall probability density function (PDF) is
shown in Fig. 6 for all three downscaling techniques using a location near Brisbane (27.5°S, 153°E). The results are also compared to observed (gridded 0.25°) rainfall from BoM. All three downscaling methods produce a similar rainfall PDF in Fig. 6, which suggests that there is no artificial suppression in the frequency of higher rainfall events compared to the frequency of lower rainfall events when using the daily-averaged downscaling technique. Note that the probability of rainfall at this location is lower than observed, which is consistent with the dry bias indicated in Table 3. This rainfall bias along the eastern coast is typically improved by further downscaling to 15-km resolution (e.g., Thatcher and McGregor 2007, 2008).

The results of this section indicate that the daily-averaged downscaling technique can be used to produce an acceptable simulation of 500-hPa winds, temperature, and geopotential height, as well as simulating mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$. The daily-averaged downscaling produces errors that typically (but not always) lie between the 6-hourly and SST-only forcing results, although the errors for the daily-averaged downscaling are often closer to those obtained for the 6-hourly experiment than the SST-only forcing experiment. The results also suggest a reasonable similarity between the daily-averaged and 6-hourly downscaling when comparing mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$. It should be noted that the results of this section are partly a consequence of the C72, $S = 2.22$ variable-resolution global grid that was used by CCAM since the simulation errors are partly arising from the 310-km low-resolution region of the simulation. For example, it is possible to further reduce these errors by using a less stretched grid (e.g., a C160 grid with $S = 1$, providing approximately 60-km resolution for the whole globe). Nevertheless, the downscaling results indicate that the daily-averaged downscaling technique can simulate a realistic regional climate, despite the absence of a diurnal cycle in the PCWB interpolation. Therefore, the technique can be useful in situations where 6-hourly host data is not available, such as for the small ensemble of GCMs discussed in the next section.

4. Downscaling results using four CMIP3 GCMs

In this section we show the daily-averaged downscaling technique applied to constructing a small multi-GCM ensemble of regional climate simulations for 1971 to 2000.
using CCAM. In particular, we examine how uncertainty in the choice of GCM forcing can affect the CCAM simulation of the average climate, when using the daily-averaged downscaling technique. For this experiment we dynamically downscale the GFDL2.1, CSIRO3.5, ECHAM5, and MIROC3.2(medres) GCMs for the 20C3M experiment from the Program for Climate Model Diagnosis and Intercomparison (PCMDI) database. These four GCMs were chosen as they have been previously used for climate impact studies over the Australian region (Smith and Chandler 2010). Only two of the four GCMs considered in this section have provided 3-hourly data to CMIP3.

The method for generating suitable atmospheric forcings from daily-average GCM fields has been described in section 2. SSTs were interpolated from monthly-average GCM datasets using the PWCB approach so that the monthly average of the interpolated SSTs matches the original dataset. This is straightforward to implement, as only the previous and following month’s SSTs are required. Note that no bias correction is applied to the SSTs or atmospheric fields. In this way, the RCM can be expected to inherit some of the systematic biases present in the GCM fields, and therefore it is important to select host GCMs that predict a reasonably accurate climate for the Australian region. To inherit less of the GCM regional biases, we adjust the scale-selective filter to force the atmosphere with a 36° radius, employing effectively weaker nudging than used for the experiment downscaling from NCEP reanalyses.

In Tables 4–7 we calculate the pattern correlation, RMSE, and bias from the GCMs (i.e., the “host” GCM output before downscaling) compared to the BoM observed mean climate for $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$. For consistency, the comparisons are made over land points after interpolating to a 0.5° resolution grid between 43.5°S and 10.5°S, and 112.5°E and 153.5°E (i.e., as in Table 3). The host GCM results can be compared to the daily-averaged downscaled regional simulations at 60-km resolution (i.e., CCAM), which are also shown in Tables 4–7. In this way, we can evaluate the relative performance of the host GCM and the downscaled regional climate. It is important to note that the downscaled GCM results can differ from the host dataset due to the nonlinear interactions among the RCM’s surface forcings, physical parameterizations, and

FIG. 5. As in Fig. 3, but showing average annual rainfall (mm day$^{-1}$).
atmospheric forcings (i.e., the regional simulations are not simply an interpolation of the host GCMs). For example, Tables 4–7 show a range of different results for the downscaled climate, depending on the host GCM. When downscaling GFDL2.1 and CSIRO3.5 GCMs (Tables 4 and 5), the daily-averaged downscaling technique was able to generally improve the accuracy of the simulated mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$, by either reducing the RMSEs and biases or improving the pattern correlation. In the case of CSIRO3.5, this involved reducing a noticeable warm bias in the mean $T_{\text{min}}$ that was present in the host GCM. Daily-averaged downscaling also produced a realistic simulation of the regional climate when downscaling the ECHAM5 GCM using the daily-averaged downscaling technique (i.e., the errors are comparable to downscaling from NCEP reanalyses as described in section 2). However, only the mean $T_{\text{min}}$ was significantly improved when downscaling from ECHAM5, with Table 6 showing an increase in the mean $T_{\text{max}}$ and $R_{\text{nd}}$ bias compared to the host GCM. The error in mean $T_{\text{max}}$ significantly increased when using the daily-averaged downscaling technique with MIROC3.2(medres), although the simulation still reduced errors in the mean $T_{\text{min}}$ and reduced the average rainfall bias.

Figures 7–9 compare the mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ in the downscaled present-day climate for different GCM forcings using the daily-average downscaling technique. Noticeable differences in the spatial variation of the mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ can be seen when using the daily-averaged downscaling with different GCMs. A simple estimate of the uncertainty in the regional simulation of mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ arising from uncertainty in the choice of the host GCM can be obtained by calculating the average annual standard deviation between the different ensemble members. For this small ensemble of four downscaled GCMs, we obtain an averaged annual standard deviation of 1.2°C for $T_{\text{max}}$ and 1.1°C for $T_{\text{min}}$. An average annual standard deviation of 0.8 mm day$^{-1}$ is obtained between the GCMs for $R_{\text{nd}}$, but there is also considerable seasonal variation (e.g., a standard deviation between downscaled results of 1.3 mm day$^{-1}$ in summer compared to 0.5 mm day$^{-1}$ in winter). Figures 7–9 show a

![Figure 6](image.png)
tendency to rain too much over western Australia, although this problem is also noticeable to some extent in the host GCMs (not shown). Overall, the daily-averaged downscaling has been able to account for coastal and orographic influences on rainfall, as apparent from the improved representation along the eastern coast and over the Great Dividing Range. The higher rainfall on the western side of Tasmania and lower rainfall on the eastern side of Tasmania is also correctly resolved. To resolve the regional features in greater detail requires multiple nesting (e.g., downscaling to 15-km resolution). However, we do not consider multiple downscaling to higher resolutions in this paper as we wish to focus on developing the daily-averaged downscaling technique and evaluating its basic properties. Some examples of CCAM's ability to downscale the regional climate from 60-km resolution simulations can be obtained from Nunez and McGregor (2007) and Thatcher and McGregor (2007, 2008).

A much more detailed assessment is desired for climate impact studies (e.g., Pearce et al. 2007) than the small ensemble experiment presented here. However, the results are indicative of what can be achieved with the daily-averaged downscaling technique and do reflect some of the implications for downscaling GCMs that contain errors. In particular, CCAM is able to improve the simulation of $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ using the daily-averaged downscaling method for two of the four GCMs considered. Also, CCAM was able to improve the simulation of Tmin for all four GCMs that were downscaled using the daily-averaged technique. However, there are GCMs for which CCAM produced larger errors in $T_{\text{max}}$ than the host model or failed to significantly improve the simulated rainfall.

### 5. Conclusions

In this paper we have considered a technique for dynamically downscaling daily-averaged GCM datasets using the CCAM variable-resolution climate model. The technique is intended to take advantage of the greater range of daily-averaged GCM datasets available in the PCMDI CMIP3 database (i.e., compared to 3-hourly datasets). Daily-averaged downscaling may also be of interest in understanding how the regional climate simulation responds to different forcing methods (e.g., daily-averaged downscaling, 6-hourly downscaling, 3-hourly downscaling). The daily-averaging downscaling technique is based on a PWCB interpolation of the time integral of GCM atmospheric fields, which provides an estimate of the state of the atmosphere at 0000 UTC on each simulation day. Because the diurnal cycle is neglected from the interpolation, the resulting daily-averaged downscaling dataset is only applied to the atmospheric model between 800 and 100 hPa, where the diurnal behavior is less significant. Lateral boundary conditions are not required owing to CCAM's variable-resolution global grid. Instead,

### Table 5. As in Table 4, but for the CSIRO3.5 GCM.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Season</th>
<th>Corr</th>
<th>RMSE</th>
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### Table 6. As in Table 4, but for the ECHAM5 GCM.

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### Table 7. As in Table 4, but for the MIROC3.2(medres) GCM.

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<tr>
<td>$R_{\text{nd}}$</td>
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we use a scale-selective filter to assimilate the 0000 UTC estimate of the atmosphere into the regional model. We apply the scale-selective filter only once per simulation day, which avoids the need to temporally interpolate the host forcing dataset.

To test the downscaling of daily-average atmospheric datasets, we have compared the results of downscaling 6-hourly, daily-average, and SST-only forcing with NCEP 2.5° reanalyses and the BoM 1961–2000 gridded climatology for $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$. A scale-selective filter was used to perturb the winds and air temperature of CCAM during the simulation at a radius greater than 18°. For the stretched C72, S = 2.22 grid used in these experiments, we found that the daily-averaged downscaling technique generally produces errors that lie between the results of the 6-hourly and SST-only forcing experiments. The daily-averaged downscaling results were often closer to the 6-hourly downscaling results with the exception of the mean 500-hPa $U$ wind component. The resultant $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$ simulated by the daily-averaged downscaling method were found to be similar to those obtained using the more conventional 6-hourly downscaling approach (i.e., relative to the SST-only forcing experiment). The daily-averaged downscaling technique also produces a realistic simulation of mean $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$, with $T_{\text{max}}$ and $T_{\text{min}}$ having smaller RMSEs and biases than the 6-hourly downscaling for the configuration of CCAM used in this paper. The results then suggest that errors arising from neglecting the diurnal cycle in the PWCB interpolation do not invalidate the downscaling results and that a plausible simulation of the regional climate can be obtained using the daily-averaged downscaling method.

An example of how the daily-average downscaling method can be used to produce a multi-GCM forcing ensemble of regional simulations was provided by downscaling from GFDL2.1, CSIRO3.5, ECHAM5, and MIRCO3.2(mres) GCMs of CMIP3. Since only two of these GCMs supplied 3-hourly data to PCMDI, this provides a practical application of the daily-averaged downscaling technique. The GCMs were downscaled to 60-km resolution over Australia during the 20C3M experiment (1971–2000) and compared to the mean climatology for $T_{\text{max}}$, $T_{\text{min}}$, and $R_{\text{nd}}$. To mitigate the effect of errors in the GCM atmospheric fields, we employed
a scale-selective filter radius of 36° for these downscaling experiments. With this configuration, the daily-averaged downscaling reduced rainfall errors when downscaling GFDL2.1 and CSIRO3.5 and produced similar rainfall errors to the host when downscaling ECHAM5 and MIROC3.2(medres). Simulation errors in $T_{\text{min}}$ were improved when using the daily-averaged downscaling for all four GCMs, and simulation errors for $T_{\text{max}}$ were generally improved in the case of GFDL2.1 and CSIRO3.5. However, simulation errors in $T_{\text{max}}$ increased when downscaling ECHAM5 and MIROC3.2(medres). The 20C3M downscaling results demonstrate the different possible regional climate projections that can be obtained when using different host GCMs, and the small ensemble considered in this paper found a standard deviation between ensemble members of approximately 1°C in screen temperature and 0.8 mm day$^{-1}$ in rainfall on average.

This paper has described an alternative downscaling technique using daily-average GCM datasets, which can be used for constructing multi-GCM ensembles of regional climate simulations when atmospheric forcing is required and 6-hourly GCM datasets are not available. The method is principally intended for CMIP3 GCM datasets, as CMIP5 plans to include 6-hourly datasets of all GCMs which are suitable for dynamical downscaling. The technique also makes it possible to compare a downscaled multi-GCM ensemble from CMIP3 with a multi-GCM ensemble from CMIP5 or to provide an augmented ensemble. There are several avenues for future work, including the need to multiply nest the results to higher resolutions (e.g., 15 km) so the regional implications of different GCM forcings can be understood in detail. Such further downscaling would help develop a rigorous assessment of the regional climate variability (e.g., extremes, probability distribution functions). Work is underway investigating ways to reduce the temperature and rainfall biases (e.g., changes to the land surface scheme, improved land surface datasets, etc.). Finally, a careful assessment of SST-only forcing and daily-average downscaling is required in order to assess how much of the simulated climate variability arises from the SST forcings compared to the atmospheric forcing.

Fig. 8. As in Fig. 7, but comparing the average annual daily minimum screen temperatures (°C).
Acknowledgments. The authors wish to thank Jack Katzfey, Debbie Abbs, Craig Heady, and Kim Nguyen for their constructive comments during the writing of this paper. The authors also appreciate the constructive comments of two anonymous reviewers. We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI), and the WCRP’s Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multimodel dataset.

REFERENCES


