GA6 Transpose-AMIP: Procedure and preliminary comparison with ACCESS 1.3

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Introduction

This paper documents the setup procedure for GA6 Transpose AMIP II experiments along with initial results which are compared to similar ACCESS 1.3 experiments. The Transpose-AMIP II experimental procedure is one where climate models are run in Numerical Weather Prediction (NWP) mode. The following sections will introduce the experiment and the GA6 and ACCESS models, the setup procedure for the GA6 model and then the run procedure and results.

Transpose-AMIP II

Transpose-AMIP II is a procedure designed to run climate models in weather forecast (hindcast) mode with the aim of examining biases from fast process in a more timely manner.

More details are on the Transpose-AMIP II website (http://hadobs.metoffice.com/tamip/), but the basic experiment consists of 64 global 5-day hindcasts consisting of 4 sets of 16 hindcasts at 30 hour intervals starting at 00UTC on the 15th of October 2008, January 2009, April 2009 and July 2009. This ensures sampling throughout the annual and diurnal cycles and these periods have been chosen to tie in with the Year of Tropical Convection (YOTC[1]). We will refer to this experimental design as T-AMIP for convenience. Note that the same procedures could be applied to other periods in the ERA-40 and ERA-Interim re-analyses or indeed any analysis/re-analysis data sets.

GA6 and ACCESS 1.3 models

GA6 (Global Atmosphere 6.0) is the current U.K.

Met Office global atmospheric model configuration and is the atmospheric component of the GC2 (Global Coupled configuration 2) climate model configuration. The configuration here is based on the vn8.5 code with Met Office GA6.0 patches for both the Unified Model (UM) and the Joint UK Land Environment Simulator (JULES).

The Australian Community Climate and Earth System Simulator (ACCESS) is a coupled model (Bi *et al*., 2013) using the Ocean Atmosphere Sea Ice Soil (OASIS) coupler (Valcke, 2006) to link the atmosphere with land surface, ocean and sea ice components (Puri, 2005). We will compare T-AMIP results from the atmosphere only version of this coupled model, ACCESS 1.3.

GA6 T-AMIP Setup procedure

The following steps, covering those listed in the T-AMIP experimental design, were taken to set up the GA6 T-AMIP procedure. Similar steps taken to set up the ACCESS 1.3 T-AMIP experiment are covered in more detail in Roff (2014), called R14 for convenience below. The location of all the scripts, jobs and datasets used in this procedure are described in the Conclusions section.

(1) Model state variables initialization.

The UM User Interface (UMUI) submits UM jobs which can be used to: build a UM model executable; run a reconfiguration executable to convert an input dump file into a configuration suitable for the UM model executable; run a UM executable; or all these steps in sequence. Here we use the same YOTC grib files as created in R14 as input "start dump", or initial conditions, for the GA6 UM reconfiguration run job (*vacee* on the NCI *raijin* computer) to produce an

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[1]See http://yotc.ucar.edu/ for details.

N96L85[2] um-formatted initial condition file. Note: GA6 uses the JULES land surface model (LSM) and is run on the "endgame" grid, which is different from the older ACCESS 1.3 N96 "new physics" grid.

> (2) Atmospheric composition, solar forcing and land use.

As in R14 the atmospheric mixing ratios of CO2, CH4, N2O, CFC11, CFC12, CFC113, HCFC22, HFC125 and HFC134A, as well as the solar forcing and the volcanic forcing for the T-AMIP period have been set in the reconfiguration step *vacee* to the same values as used in the ACCESS 1.3 AR5 RCP4.5[3] experiment.

> (3) Sea Surface Temperatures (SSTs) from ECMWF YOTC should be used in the hindcasts.

The 0.75° resolution SST and Seaice YOTC fields were downloaded and processed in the same manner as R14.

> (4) Land surface model initialisation.

We initialize the JULES LSM snow amount, soil moisture and temperature fields from the GA6 AMIP climatology. These fields are then collected into a netcdf monthly mean LSM file which is then used to initialize the T-AMIP runs.

> (5) Aerosol concentration initialisation.

We take the aerosol concentrations from the ancillary files that were used for the ACCESS 1.3 CMIP5 and AR5 RCP4.5 experiments.

> (6) Initialisation of non-state variable prognostics which spin-up quickly (such as cloud fraction).

In the reconfiguration step *vacee* we initialize all the cloud fields to zero.

GA6 T-AMIP Run procedure
On the NCI *accessdev* platform the GA6 T-AMIP jobs are:

- *vacea*: a GA6 build job

- *vaceb*: a GA6 N96L85 run job
- *vacee*: a reconfig job, based on *vaceb*

The vacea build job creates both the reconfiguration and model executables used in the vacee and vaceb jobs. These are vacea.recon and vacea.exe, respectively, and can be found on the raijin platform in directory */short/dp9/glr548/UM_ROUTDIR/glr548/vacea/bin.*

The run job *vaceb* is initialized from the dump file created by the reconfiguration job *vacee* as in (1) and both have: atmospheric composition and forcing changes from (2); use the SST and Seaice ancillaries from (3); point to the GA6 AMIP climatology LSM fields discussed in (4); use the aerosol ancillaries created in (5); and have all the cloud fields zeroed as discussed in (6).

This run job *vaceb* can then be submitted to raijin via the accessdev UMUI, or we can use automated *raijin* job scripts *run_tamipGA6_recon* and *run_tamipGA6* to submit several reconfiguration or run dates in series. The run job operates on 256 processors and takes ~4 minutes to complete a single 5 day hindcast, so ~4 hours for a full T-AMIP run over all 64 dates. Note that this run time is the same as for N96L38 ACCESS 1.3 using 64 processors.

The following sections compare the T-AMIP simulations from GA6 and ACCESS 1.3 using traditional climate and numerical weather prediction diagnostics. For convenience we will refer to the ACCESS 1.3 model as A13 below; though these are actually hindcasts, we refer to them below as forecasts for convenience.

T-AMIP GA6 / A13 comparison: Climate
Here we compare the GA6 T-AMIP run against its corresponding AMIP simulation.

Figure 1 shows the AMIP climatology and T-AMIP mean 5-day forecast surface air temperature (SAT) bias (K), relative to ERA-Interim reanalysis 1979-2008 data. Note that similar biases (not shown) were seen when compared to ERA-Interim re-analyses just for 2008-2009.

The T-AMIP and AMIP biases are very similar: small over the oceans, due to pre-scribed SST and Seaice; warm biases over equatorial Africa and South America and India; cold biases over North Africa and the

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[2] N96L85 indicates the resolution of the GA6 run with: N96 indicating a horizontal resolution of ~130km with 2x96=192 longitudinal grid points and 1.5x96=144 latitudinal grid points; and L85 indicating 85 model levels in the vertical.
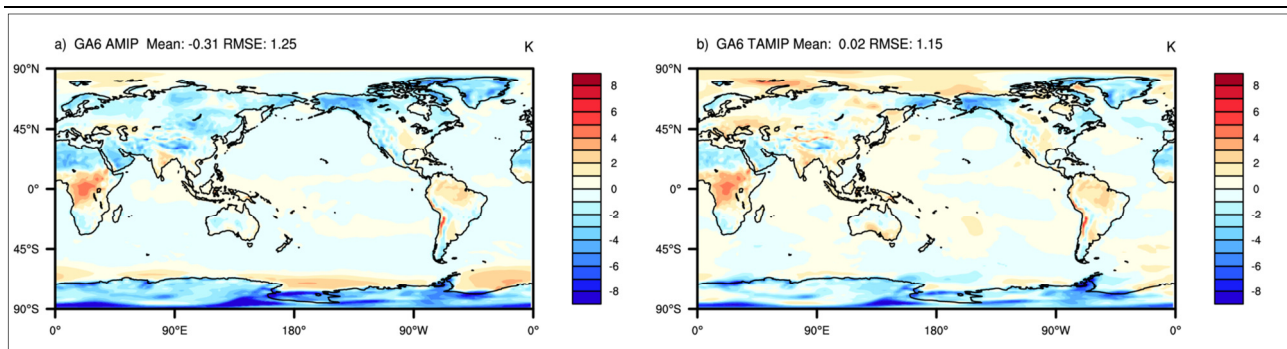
[3] See http://cmip-pcmdi.llnl.gov/cmip5

Figure 1 (a) AMIP and (b) T-AMIP SAT biases, see text for details. Units are K.

Arabian Peninsula, Alaska, NE Russia, Greenland and Antarctica. This similarity is expected due to T-AMIP using the AMIP land surface climatology.

Figure 2 shows the GA6 AMIP and T-AMIP annual mean Total cloud radiative forcing (CRF) biases, relative to the ISCCP observations 1983–2007 mean.

In both AMIP and T-AMIP the Total CRF has a strong positive bias in the Southern Ocean as well as off the south-western coasts of Africa and North and South America. From the corresponding short- and long-wave forcing plots (not shown), these are mainly due to the short-wave forcing.

The magnitude of the GA6 SAT and Total CRF biases shown here are less than those for A13 (Figures 4 and 5, R14), but both models indicate that the faster and cheaper T-AMIP experimental procedure is able to simulate the climate biases seen in full AMIP runs.

T-AMIP GA6 / A13 comparison: NWP

Here we compare the NWP aspects of two T-

AMIP runs from GA6, as described in previous section, and A13, as described in R14.

Classic NWP diagnostics consist of biases, Root Mean Square Errors (RMSE), anomaly correlations and Brier skill scores (Wilks, 1995). These have been computed for MSLP (hPa) and T2m (K) for both T-AMIP runs and expressed as global diagnostics below. In all cases errors have been calculated relative to the corresponding analysis fields from the six hourly YOTC dataset, which we treat as "observational truth".

The bias (or mean error) is calculated via

$$\text{BIAS}(\tau) = \frac{1}{N_\varphi N_\theta N_\delta} \sum_\varphi \sum_\theta \sum_\delta \{m(\varphi, \theta, \delta, \tau) - a(\varphi, \theta, \delta, \tau)\} w(\theta)$$

where: m and a are the model and analysis values, respectively; φ is longitude; θ is latitude; δ is start date; N_φ is the number of longitudes (192); N_θ is the number of latitudes (144); N_δ is the number of start dates (64); w is cosine θ grid-box area weighting; and, $\tau = 1$, N_τ is forecast time with $N_\tau = 20$ corresponding to every 6 hours for the five-day forecasts.

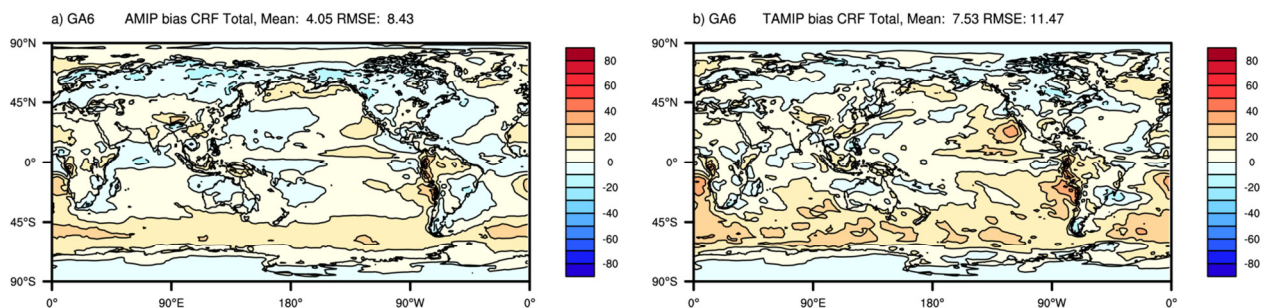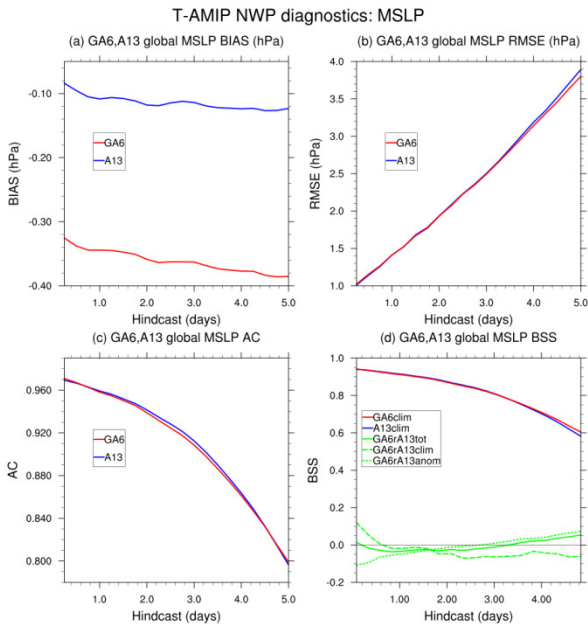**Figure 2 (a) AMIP and (b) T-AMIP mean Total CRF biases, see text for details. Units are W m–2.**

Figure 3 MSLP (hPa) T-AMIP GA6 and A13 NWP diagnostics: (a) bias (hPa); (b) RMSE (Pa); (c) anomaly correlation (AC); and (d) Brier Skill-score (BSS). See text for details.

The MSLP bias for GA6 is much larger than A13, as seen in Figure 3(a), with means(standard deviations) -0.36(0.01) hPa and -0.11(0.02) hPa, respectively. The biases both develop by dropping quickly in the first day and then descend more slowly, though A13 shows signs of levelling out near day five whereas GA6 does not. These biases indicate that while both models under-forecast the MSLP, A13 has a much smaller absolute bias.

The T2m biases (Figure 4a) also show this rapid adjustment in the first day but then settle to more steady values around -0.06 K and 0.17 K for GA6 and A13, respectively, though both show a slight trend to diverge from zero.

The rapid initial bias changes seen in both variables indicates that the models adjust to the YOTC initial conditions within one day, while the following slow trending suggest a more gradual drift in the models with GA6 and A13 both under-forecasting MSLP and under-/over-forecasting T2m, respectively.

While the above bias gives the overall sign of
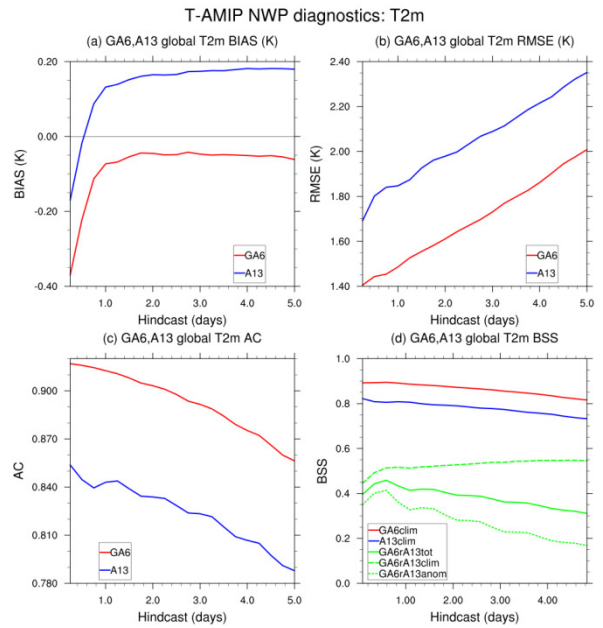
Figure 4 As in Figure 3 but for the temperature at 2 metres (K).

the forecast errors it does not measure their magnitude. To look at this we consider the RMSE and it is calculated via

$$\text{RMSE}(\tau) = \sqrt{\frac{1}{N_\varphi N_\theta N_\delta} \sum_\varphi \sum_\theta \sum_\delta \{m(\varphi,\theta,\delta,\tau) - a(\varphi,\theta,\delta,\tau)\}^2 w(\theta)}$$

The MSLP RMSE (Figure 3b) shows GA6 and A13 are similar with both approximately linearly increasing from ~1 to ~3.7 hPa over the five days with GA6 showing a slight but growing advantage after day three. However for T2m RMSE (Figure 4b) while both show a steady increase with time, ~0.1 K/day, A13 is consistently larger by ~0.35 K, with some of this coming from the bias differences.

The anomaly correlation detects similarities in the patterns of departures (ie anomalies) from the observed climatology mean field, which in this case is taken as the observed field averaged over all T-AMIP dates and forecast times. The anomaly correlation is calculated via

$$\text{AC}(\tau) = \frac{\frac{1}{N_\varphi N_\theta N_\delta} \Sigma_\varphi \Sigma_\theta \Sigma_\delta \{ma(\varphi,\theta,\delta,\tau) * aa(\varphi,\theta,\delta,\tau)\} w(\theta)}{\sqrt{\left\{\frac{1}{N_\varphi N_\theta N_\delta} \Sigma_\varphi \Sigma_\theta \Sigma_\delta ma(\varphi,\theta,\delta,\tau)^2 w(\theta)\right\}\left\{\frac{1}{N_\varphi N_\theta N_\delta} \Sigma_\varphi \Sigma_\theta \Sigma_\delta aa(\varphi,\theta,\delta,\tau)^2 w(\theta)\right\}}}$$

where the model and observation anomalies are given by

and
$$ma(\varphi,\theta,\delta,\tau)=m(\varphi,\theta,\delta,\tau)\text{ - }c(\varphi,\theta)$$

$$aa(\varphi,\theta,\delta,\tau)=a(\varphi,\theta,\delta,\tau)\text{ - }c(\varphi,\theta)$$

respectively, and the climatology is given by

$$c(\varphi,\theta)=\frac{1}{N_\delta N_\tau}\sum_\delta\sum_\tau oa(\varphi,\theta,\delta,\tau)$$

The MSLP anomaly correlation (Figure 3c) is very similar for GA6 and A13 dropping from 0.97 to 0.8 in five days but with A13 being slightly better for days one to four. The T2m anomaly correlation (Figure 4c) also shows a decrease with time but, as with the RMSE, there is a large separation between GA6 and A13 with the latter consistently worse.

The Brier skill score (Wilks, 1995) measures the relative accuracy of a forecast (*M*) over a reference forecast (*ref*) and the relative accuracy measure we use here is the Mean Square Error (MSE). The skill score is then calculated via

$$BSS_{Mref}=\frac{MSE_M-MSE_{ref}}{MSE_{perf}-MSE_{ref}}=1-\frac{MSE_M}{MSE_{ref}}$$

where we assume a perfect forecast has $MSE_{perf}=0$ and the skill score BSS_{Mref} has a maximum of one for a perfect model forecast and a value greater than zero if the model is better than the reference forecast. MSE can be split into

$$MSE=MSE^{tot}=MSE^{clim}+MSE^{anom}$$

where: MSE^{tot} is just the square of the RMSE calculated above; MSE^{clim} is the same but replaces *m* and *a* with their date averaged means and so represents systematic error in the climatological mean state of the model; and MSE^{anom} is the same but replaces *m* and *a* with their difference from their date averaged means and so represents the model's ability to forecast the evolution of the flow.

The skill score can be calculated from any/all of these MSE quantities and against various reference forecasts. We first assess the forecast skill of each model relative to the observed climatological forecast. So we compute

$$BSS_{M/clim}^{anom}=1-\frac{MSE_M^{anom}}{MSE_{clim}^{anom}}$$

where M is either model GA6 or A13 and MSE_{clim}^{anom} is the variance of the observations. Note that the BSS calculated using MSE^{tot} has similar results (not shown) while the BSS calculated using MSE^{clim} is undefined since the reference MSE_{clim}^{clim} is zero.

The skill score $BSS_{GA6/clim}^{anom}$ and $BSS_{A13/clim}^{anom}$ for MSLP are seen in the red and blue curves, respectively, in Figure 3(d). Both start with high skill relative to climatology but have dropped to below 0.7 by day five, with A13 dropping slightly faster. The corresponding T2m skill score curves are seen in Figure 4d and indicate a lower initial skill which decreases more slowly but with GA6 consistently better than A13 by ~10%.

We can also use the skill score to compare the two model forecasts with each other and so compare GA6 with A13 by using the latter as the reference forecast scheme e.g. for the anomalies we have

$$BSS_{GA6/A13}^{anom}=1-\frac{MSE_{GA6}^{anom}}{MSE_{A13}^{anom}}$$

We calculate this for all three MSE quantities and Figure 3(d) shows $BSS_{GA6/A13}^{tot}$, $BSS_{GA6/A13}^{clim}$ and $BSS_{GA6/A13}^{anom}$ for MSLP as the solid, dashed and dotted green curves, respectively.

The climatology skill score $BSS_{GA6/A13}^{clim}$ (dashed) starts positive but quickly drops below zero and remains approximately constant, indicating that the GA6 climatological forecast mean state is less skilful than A13.

The anomaly skill score $BSS_{GA6/A13}^{anom}$ (dotted) starts negative but steadily increases and becomes positive by day 4. This indicates that A13 forecasts the evolution of the flow better than GA6 out to day 3 but then GA6 overtakes it.

The total skill score $BSS_{GA6/A13}^{tot}$ (solid) is dominated by the climatology component in the first day and then parallels, but is consistently less, than the anomaly skill score - remaining below zero till day 4 when GA6 becomes the

more skilful. In all of these curves, the difference in skill between the two models is small.

The difference in skill between the two models is much larger in Figure 4(d) which shows corresponding T2m $BSS_{GA6/A13}^{tot}$, $BSS_{GA6/A13}^{clim}$ and $BSS_{GA6/A13}^{anom}$ curves.

Here all curves are greater than zero, indicating that GA6 has much larger relative forecast skill for T2m than A13. Again the skill from the climatological MSE component plateaus after about one day while the MSE anomaly component descends with time and the total mimics this. We note that while the T2m GA6 skill is much larger than A13 it does decrease with forecast time while the MSLP skill has a slowly increasing skill. This result dovetails nicely with the SAT bias results from the previous section.

The strong similarity in skill in the MSLP diagnostics for the two models contrasts sharply with the large differences seen in the T2m diagnostics. This suggests that MSLP is a robust field while T2m is more sensitive to the model characteristics.

Potential characteristics that may explain the T2m skill difference are: GA6 is based on the newer and more complex physics in UM vn8.5 while A13 is based on an earlier and simpler physics in UM vn7.3; GA6 has the JULES land surface scheme while A13 uses the Australian developed CSIRO Atmosphere Biosphere Land Exchange (CABLE) scheme (Kowalczyk et al., 2006); A13 has 38 vertical levels whereas GA6 has 85, with many of the extra levels in the boundary layer (*e.g.* Figure 1, Roff *et al.*, 2012).

Conclusions and Future work
This paper has extended the Transpose-AMIP experimental procedure for ACCESS 1.3, discussed in Roff (2014), to the GA6 model. Descriptions of the run procedure for setting up and carrying out this experiment have been presented. Both of these T-AMIP experiments take approximately ~4min for each of the 64 T-AMIP dates but the higher

vertical resolution and more complex GA6 model uses 256 processors while ACCESS 1.3 only uses 64.

University users can access the N96L85 GA6 T-AMIP experimental procedure as it joins that of N96L38 ACCESS 1.3 in the National eResearch Collaboration Tools and Resources (NeCTAR) Climate and Weather Science Laboratory within the ACCESS Model Experimental Library[4] of standard ACCESS experiments and test cases as:

- Transpose-AMIP II configurations¶
    - Introduction to the Transpose-AMIP II experimental design for ACCESS (GregRoff)
    - ACCESS 1.3 Transpose-AMIP II procedure (GregRoff)
    - GA6 Transpose-AMIP II procedure (GregRoff)

As well as this, the input datasets, scripts, example outputs and a README file which explains the GA6 setup and run procedures in greater detail, can be found on the Bureau's SAM-FS system in the directory */samcrc/gen/glr/2014/tamip/ga6* and also on the National Computational Infrastructure (NCI) supercomputer *raijin* in */g/data/p66/glr548/tamip_sam/ga6*.

The GA6 T-AMIP simulation means of surface air temperature (SAT) and cloud radiative forcing (CRF) have been compared with corresponding AMIP outputs. These biases have been shown to be similar, indicating that long-term GA6 biases can manifest themselves in the much cheaper T-AMIP short-term NWP type runs, as was found for ACCESS 1.3 (Roff, 2014).

This ability to use the GA6 climate model in NWP mode has been further demonstrated by calculating typical global average NWP diagnostics of biases, RMSE, anomaly

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See the following URL (requires NCI login):[4]
https://trac.nci.org.au/trac/access/wiki/AccessModelExperimentLibrary#Transpose-AMIPIIconfigurations

correlations and skill scores using the YOTC analyses as "truth". Comparison of these diagnostics with equivalent outputs from ACCESS 1.3 T-AMIP runs show little difference between the two models for MSLP. However the diagnostics clearly demonstrate that GA6 provides better forecasting skill for T2m than A13.

Possible reasons for the increased skill found in the GA6 T2m field will be examined in future studies using the T-AMIP procedure to compare ACCESS 1.3 and GA6 configurations where modifications have been made to the physics parameterisations and vertical resolution.

Future work will also be to: examine the impact of higher resolution by extending the GA6 T-AMIP procedure to the N216L85 configuration with ~60 km horizontal resolution, the same resolution as that proposed for ACCESS seasonal forecasting.

Acknowledgements

References

Bi et al., 2013: The ACCESS coupled model: description, control climate and evaluation, Australian Meteorological and Oceanographic Journal 63:1 March 2013

Kowalczyk, E.A., Y.P. Wang, R.M. Law, H.L. Davies, J.L. McGregor and G. Abramowitz, 2006: The CSIRO Atmosphere Biosphere Land Exchange (CABLE) model for use in climate models and as an offline model,
http://www.cmar.csiro.au/eprint/open//kowalczykea_2006a.pdf

Puri, K, 2005: Project plan for ACCESS, 2005, available at http://www.accessimulator.org.au/report/index.html.

Roff, G. (2014), ACCESS Transpose-AMIP: Experimental Procedure and Preliminary Results, CAWCR Res. Let., (accepted October 2014)

Roff, G., T. Green, M. Dix, and M. Naughton (2012), Initializing ACCESS from ERA-Interim data, CAWCR Res. Let., 8, August 2012, http://cawcr.gov.au/publications/researchletters/CAWCR_Research_Letters_7.pdf

Valcke, S.: OASIS3 User Guide (prism 2-5). PRISM Support Initiative No 3, 68 pp., 2006

Wilks, D. S. (1995), Statistical Methods in the Atmospheric Sciences: An Introduction, Int. Geophys. Ser, vol. 59, 467 pp., Academic, San Diego, Calif.