The Centre for Australian Weather and Climate Research
A partnership between CSIRO and the Bureau of Meteorology

Improving Multiweek Rainfall Forecasts: Experiments with the ACCESS climate models

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Enquiries should be addressed to:

Mei Zhao

The Centre for Australian Weather & Climate Research
GPO Box 1289 Melbourne
Victoria 3001, Australia

m.zhao@bom.gov.au

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ABSTRACT

Multiweek-seasonal climate forecasts are currently provided by the POAMA2 coupled forecast system (Hudson et al. 2013). This system, while providing skilful and useful predictions of many aspects of the climate, has many limitations for application to water resource management, including relatively low spatial resolution (~250 km grid) and simplistic treatment of the land surface. The POAMA system is in the process of being updated to the ACCESS coupled model, which will be a significant step forward for the POAMA system. The development of a multi-week to seasonal prediction capability based on ACCESS will require significant system development, including a new coupled atmosphere-ocean data assimilation system, appropriate initialization procedures, effective ensemble generation strategies, and optimal configuration of the ACCESS component models. As a contribution to these efforts, the WIRADA project on "Improving Multiweek Rainfall Forecasts" supported the initial experiments for forecasting at multiweek lead times using prototype versions of the ACCESS model. Although the ACCESS model has been extensively tested and tuned for making multi-year climate simulations, its performance and optimal configuration for shorter lead-time, initialized climate predictions has yet to be determined. The multiweek lead time for this project was targeted both because it is a high priority growth area for water resource management but also for economy: much can be learned about the performance of the seasonal prediction system by the performance in the first month and with uncoupled (cheaper) versions of the model.

Multi-week prediction of rainfall (or multi-week prediction of climate) sits in between short timescale NWP and long timescale seasonal prediction. At multi-week lead times, regional rainfall prediction derives from the ability to predict the large-scale, slowly varying circulation that involves both uncoupled atmospheric variability (tropical and extra-tropical) and coupling of the atmosphere with the tropical oceans. Multi-week prediction ultimately will require use of a coupled forecast model, initialized with concomitant ocean initial conditions and also high quality atmospheric initial conditions. However, while the new coupled atmosphere-ocean data assimilation systems are being developed, much can be learned about optimal model configuration and expected performance gains compared to POAMA2 by using uncoupled versions of ACCESS and coupled versions with simplified ocean-atmosphere initialization.

We describe the various versions of the ACCESS uncoupled and coupled models and the initial conditions in Section 2. Comparison of forecast skill for month 1 (days 0-30) between the versions of ACCESS and POAMA M24 is presented in Section 3. Implications and recommendation for POAMA3, which will be based on ACCESS, are provided in Section 4.

1. ACCESS MODEL FEATURES AND INITIAL CONDITIONS

The ACCESS coupled model is based on the UKMO Unified Model (UM) atmospheric model, the MOM4 ocean model, and the CABLE land surface model. For implementation in multiweek-seasonal prediction, the initial effort here employed the configurations of the component models as for the ACCESS 1.3 climate model. Compared to POAMA M24, this includes:

- significant new atmospheric physics, in particular the PC2 cloud scheme (Wilson et al. 2008);
- higher resolution for the atmosphere model (horizontal resolution of 1.25° latitude by 1.875° longitude, and 38 levels in the vertical; referred to as N96L38) compared to POAMA2 (approximately 2.5° by 2.5° for horizontal, L17 for vertical resolution, referred to as T47L17);
- CABLE land surface model consists of a comprehensive description of the surface processes that calculate momentum, heat, water and carbon fluxes (Kowalczyk et al. 2006, Wang et al. 2011). It also has 13 surface tile types (ten vegetated and three non-vegetated tile types). In contrast, POAMA2 uses a simple bucket model;
- higher resolution for the ocean model. The ACCESS ocean model has 360 longitude by 300 latitude points on a logically rectangular matrix with 50 vertical levels (0-6000m). The POAMA2 ocean model has 180 longitude by 196 latitude points and with 25 vertical levels (0-5000m);
- the LANL CICE4.1 sea-ice model (Hunke and Lipscomb 2010) compared to climatology sea-ice represented in POAMA M24.

In this report, the atmosphere-land model used in ACCESS 1.3 uncoupled and coupled models is based on version UM7.3 (or GA1.0) of the UM model and is coupled with the CABLE (version 1.8) land surface model. More details about ACCESS1.3 can be found in Bi et al. (2013), and details of the POAMA M24 can be found in Hudson et al. (2013). In order to explore more recent updates to model physics and to run at higher vertical resolution, we have also made direct use of a preliminary version of the UM uncoupled model (using MOSES rather than CABLE) version GA4.0 (resolution N96L85).

1.1 ACCESS 1.3x Uncoupled Model

The atmosphere-land surface component models for ACCESS1.3 use UM 7.3 (also referred to as GA 1.0 or HadGEM3) together with the CABLE land surface model. We have adopted two changes to the models convection scheme as suggested by Sun et al. (2013). The first is to change the trigger for shallow convection, so that the shallow convection can happen without a vertical velocity restriction. The second is to increase the background entrainment rate for deep convection from 1 to 1.5, which has been found useful for improving the simulation of the MJO. In order to signify these differences with ACCESS1.3 we refer to this version as ACCESS1.3x.

Some of the key physical processes represented in the atmosphere-land surface models that are improvements compared to the BAM3 model used in POAMA2 include:

- atmospheric longwave and shortwave radiation allowing for the effects of clouds, water vapour, ozone, carbon dioxide and a number of trace gases;

- land surface processes represented by a 6-layer soil temperature and moisture prediction scheme;
- a treatment of the form drag due to the sub-grid scale variations in orography;
- improved vertical turbulent transport within the boundary layer;
- large-scale precipitation determined from the water and ice content of cloud;
- the effects of convection through a scheme based on the initial buoyancy flux of a parcel of air, which includes entrainment, detrainment and the evaporation of falling precipitation;
- an interactive modelling of the effects of aerosols, such as sulphates, fossil fuel soot, mineral dust and biomass smoke as well as sea salt, with their transport, mixing deposition and radiative effects being represented;
- time varying ozone, aerosols, and CO_2 , which are updated daily in the model.

(source from: UM user guide
http://solar/~access/umdoc_system_7.3/UM_docs/papers/html/000/index.html).

1.2 UM GA4.0 Atmosphere-MOSES Land Model

We also investigate the impact on forecast skill by using increased vertical resolution of the atmospheric model. Unfortunately, a version of ACCESS1.3x at N96L85 resolution has not been well tunning in the tropsphere. So, we have had to resort to directly using the UM version GA4.0 at N96L85 that uses the MOSES land surface model. In addition to increased vertical resolution, GA4.0 incorporates recent improvements to model physics (described in Walters et al. 2013). A major change is coupling structure of the land surface model compared to UM7.3 (or GA1.0). It used the interface to coupled atmosphere and land surface model rather than put the land surface model into the atmosphere model. It will be much easier and quicker for upgrading the UM model in the coupled system in the future.

1.3 ACCESS 1.3x Coupled Model

For our experimentation with the ACCESS coupled model, we use a version also based on ACCESS1.3 coupled version but with the following changes:

In the atmosphere model:

- coastal ice albedo bug fixed;
- new cloud overlap scheme with cloud standard deviation set to 0.8

In the ocean model:

- use the MA (Morel and Antonie, 1994) shortwave penetration schemes with maximum attenuation depth 300 m.
- SeaWiFS chlorophyll concentration;

The standard features of the ACCESS1.3 model are described in Bi et al. (2013).

1.4 Initial Conditions

In order to make experimental forecasts we need to initialize the atmosphere-land surface (and for the coupled experiments, the ocean). For good sampling of internal variability, we generate forecasts from the first of each month for the period 1980-2011. Because the initialization system for multiweek-seasonal prediction with ACCESS has yet to be developed, we have had to devise a simple scheme to initialize the models for the experimentation in this project. For uncoupled model forecasts, we have developed a method to directly initialize the atmosphere from the ERA-Interim reanalyse (Dee et al. 2011). We interpolate the ERA-interim model level data (0.75 degree resolution, 60 vertical levels) to the grid of the UM atmosphere model (N96L38). In order to initialize the land surface (CABLE), which we can not do directly from the ERA-Interim reanalyses, we devise a scheme based on a parallel AMIP run of the atmosphere-land model. We output the restart file from the AMIP run for the specific day that we wish to initialize (thus providing the land surface initial state) and we initialise the atmosphere model by using U, V, T and Q fields directly from ERA-Interim.

In order to generate perturbed initial condition for ensemble hindcasts, we integrate forward from successively 6-hour earlier start times to 00Z on 1st of each month, thus creating a lagged ensemble. Because the dump file from the AMIP run is only available at 00Z on the 1st of each month, we then reinitialize the land surface with the 00Z values from the initial condition file. In so doing, we obtain a 10-member ensemble initial condition from 00Z on the 1st of each month. Although this method of initialization avoids shock in the atmosphere, we acknowledge that the lack of perturbation in the land surface is a potential shortcoming.

For coupled model, a simple coupled initialization is developed. We run the coupled model continuously for the period we require initial conditions, during which we strongly relax the SST to the same SST as in the AMIP run and we constrain the atmosphere to the ERA-Interim reanalyses as in the POAMA2 system (daily nudging with a 0.8 weight). In so doing, we produce atmospheric initial conditions that are very similar to those used for the uncoupled model and we make an improved initialization of the land surface because the land surface model sees surface fluxes that are tightly constrained to ERA-Interim rather than being determined as the atmospheric model’s response to observed SST. The SST is initialized very close to the observed SST. There is no observed subsurface ocean data used in this initialization, but the ocean is initialized in balance with the atmospheric surface forcing that is highly constrained by the ERA-Interim reanalyses.

1.5 Prescribed SST

In order to run the uncoupled model in forecast mode, we had to develop a scheme to update the SST during the forecast. We tried two different approaches. In the first, we damped the initial SST anomaly back to climatology with an e-folding decay time of 90 days (representative of the observed decorrelation time of tropical SST in the Pacific). In the second, we prescribed the SST during the forecast to follow the observed monthly mean SST. While this second method means that our results do not represent a true forecast (i.e., because we are using future information during the forecast), we find that the results are systematically better than for damping the observed SST anomaly. By comparison with the SST forecasts from POAMA, we can see that damping the observed anomalies to climatology is a less skilful forecast of future SST than what we can currently achieve with POAMA (Figure not shown). So, we decided to concentrate on forecasts using SST that is prescribed to be observed, acknowledging that we might be overestimating forecast skill when we switch to the fully coupled system.

2. COMPARISON OF RESULTS

Forecast quality and mean state bias from the ACCESS 1.3x uncoupled, coupled climate model and POAMA M24 model (POAMA2) are discussed in this Section. The aim of the comparison between the ACCESS 1.3x uncoupled and coupled models is to identify any potential benefits of coupling at short lead times (i.e., lead times to 1 month). We also want to compare the ACCESS 1.3x model to the POAMA M24 model because this will provide the benchmark for our expected performance gains when the POAMA system switches to ACCESS (POAMA3). We will also flag particular model errors that will help direct future development of the ACCESS model and the POAMA3 system.

Both uncoupled and coupled hindcast runs with ACCESS are 10-member ensemble runs from the first of each month for 1982 to 2010. The results shown in this report are based on 10-member ensemble means. POAMA M24 results are based on 33-member ensemble means. For comparison to the POAMA M24 forecasts, all verification and output from the ACCESS models are interpolated to the standard 144x73 grid (2.5 deg) used by POAMA M24.

2.1 Model Mean State Biases

We first look at the model mean state biases. For precipitation, we compare with both the GPCP (Global Precipitation Climatology Project) and CMAP (CPC Merged Analysis of Precipitation). Figure 1 displays the ACCESS1.3x uncoupled, 1.3x coupled model, and POAMA M24 model mean biases of precipitation for the first month of the forecasts from 1982 to 2007 (limited to 2007 because of availability of observed data). Both ACCESS models have significant larger mean biases over the Indian Ocean and Maritime Continent than POAMA M24, with a prominent wet bias in the western Indian Ocean and dry bias over the Maritime Continent ocean areas. Coupling appears to alleviate some of the bias, although the ACCESS model versions are slightly different so we can’t be sure that this reduction is solely due to coupling. These large biases are consistent with the recent UKMO report (Johns et al. 2012) and represent a longstanding problem in the UM model. These biases may play a primary role in the poor simulation of the MJO in this region using the UM. In contrast, over the western Pacific, the ACCESS models generally have better performance than POAMA M24, especially in the representation of the ITCZ's. POAMA M24 has a particularly erroneous depiction of a double ITCZ, and some bias in the Maritime Continent.

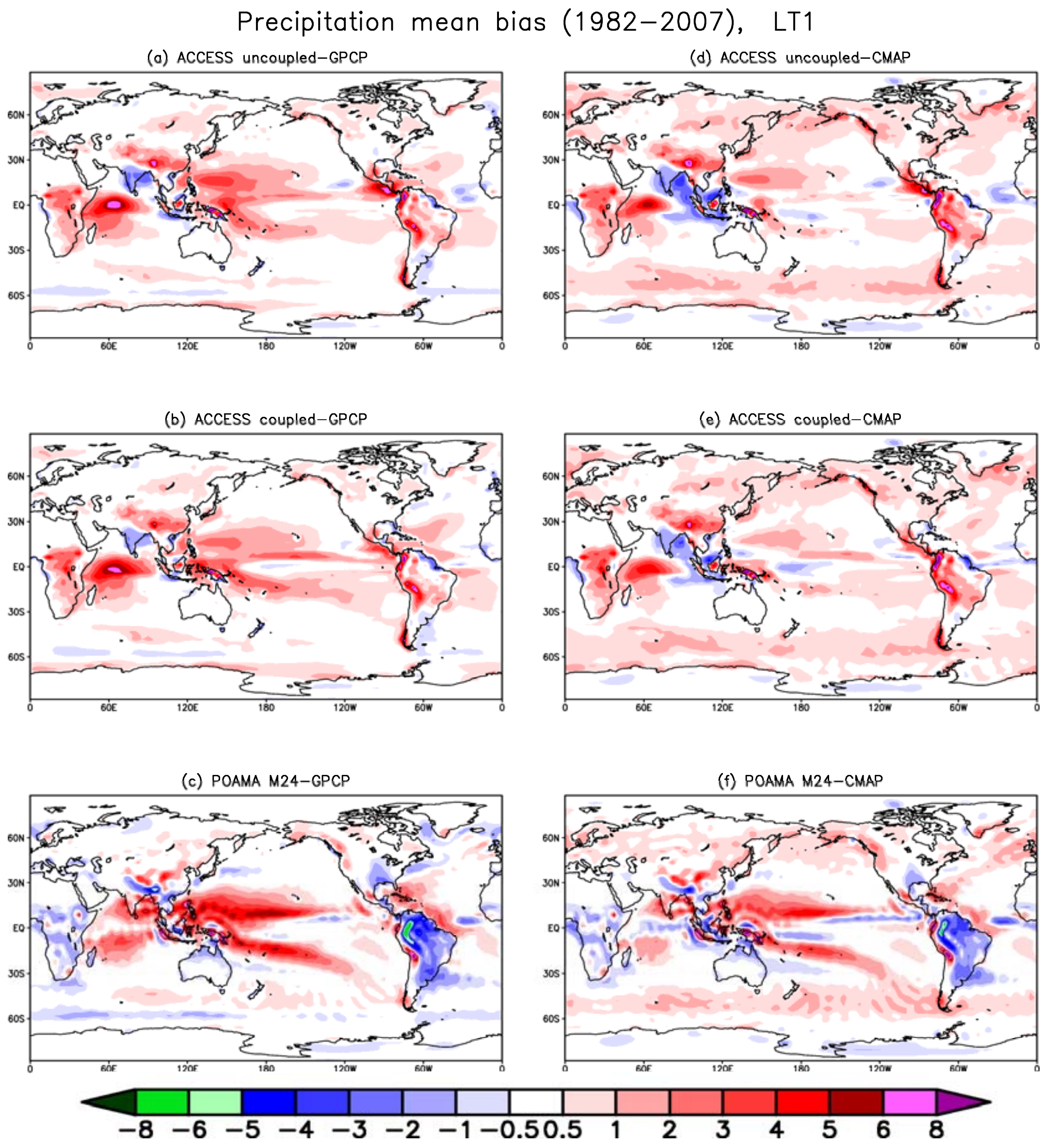

Fig. 1 Mean state biases of precipitation at the lead time 1 month for (a) and (d) ACCESS uncoupled model, (b) and (e) ACCESS coupled model, (c) and (f) POAMA M24 compared to GPCP (left panel) or CMAP (right panel) data for all start months from 1982 to 2007 (model results minus observation data). Units are mm/day.

Concentrating on biases over Australia in the first month, which is difficult to surmise in Fig. 1, we show detailed maps for biases of precipitation (PREC), maximum temperature (TMAX), minimum temperature (TMIN) (Fig. 2). Here we verify temperature and precipitation using the AWAP (Australia Water Availability Project) analyses for a common period 1982 to 2010. Generally, over Australia, there is not too much difference in biases between ACCESS uncoupled and coupled models. However, compared to the well-known dry bias over Australia in POAMA M24, the ACCESS models have a noteworthy wet bias over the central east (Fig. 2). The largest bias occurs in DJF season for both ACCESS and POAMA models (Fig. A.1). Consistent with the wet bias in ACCESS, TMAX in ACCESS is too cold and TMIN is too warm (enhanced cloudiness associated with increased rainfall lowers day time temperature and reduces cooling at night). In Fig. 2, both ACCESS and POAMA have much less diurnal range compared to observation. These biases based on initialized forecasts are also very similar to the biases from the long AMIP climate runs. The bias in TMAX in ACCESS especially needs attention because of the key role that daytime temperature plays for local evaporation. Figures for the biases of PREC, TMAX and TMIN in each season can be seen in Appendix A.

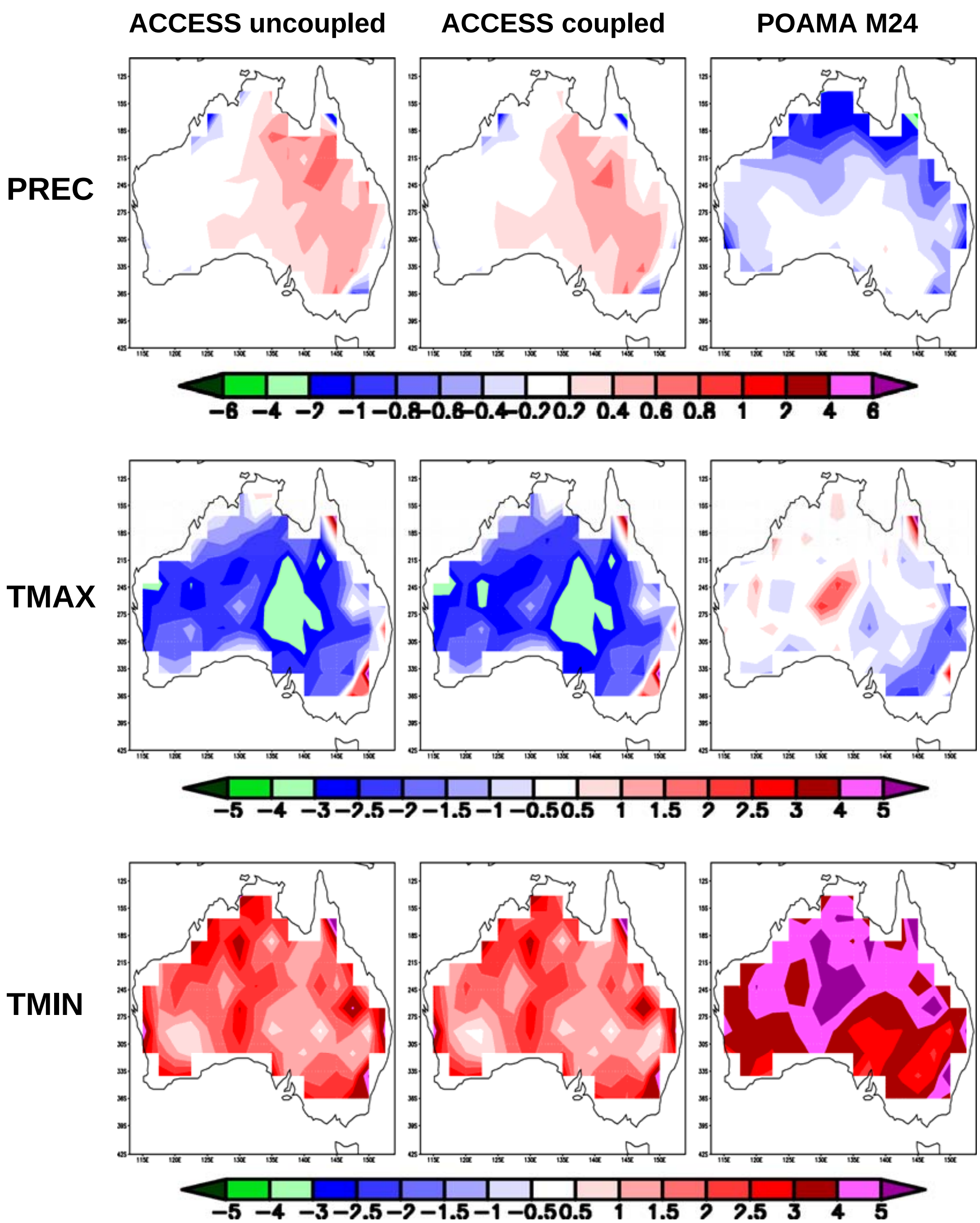

Fig. 2 Mean state biases of precipitation (PREC), maximum temperature (TMAX), minimum mperature (TMIN) at the lead time 1 month over Australia for ACCESS uncoupled model (left panel), ACCESS coupled model (middle panel), and POAMA M24 model (right panel) compared to AWAP observation data for all start months from 1982 to 2010 (model results minus AWAP data). Units are mm/day for PREC, and °C for TMAX and TMIN.

We next look at the bias in the large-scale circulation (Fig. 3), which will play a key role in how the SAM and the teleconnections of ENSO and the IOD affect Australian climate, hence affecting the capability to make regional forecasts of rainfall and temperature. We examine the bias in Geopotential Height at 500 hPa compared to NCEP reanalysis data at day 1, day 5 and day 10 of the forecast (the bias after day 10 is very similar to day 10). Because POAMA M24 only outputs instantaneous heights rather than daily means as for ACCESS, we have to verify ACCESS model data with the daily mean NCEP data, but verify POAMA M24 with the instantaneous analyses at 00Z. The instantaneous data has more noise compared to the daily mean data so this needs to be taken into account in this comparison. Nevertheless, the ACCESS models clearly have a reduced circulation bias compared to POAMA M24, especially at high-latitudes. However, there are noticeable biases in the Australian sector in ACCESS (e.g. positive heights over the east of the continent, which would be expected to interfere with the west-east progression of midlatitude weather systems). This height bias is hypothesized to stem from the dry bias in the Maritime Continent region, which is expressed as a Rossby wave train emanating from the eastern Indian Ocean as during a positive Indian Ocean Dipole episode. Hence, the dry bias in the eastern Indian Ocean in the ACCESS models will affect not only the climate in the tropics but also the capability to predict climate in the subtropics.

The development of these biases is a very fast process. The major bias patterns immediately show up at day 1 and are almost identical in pattern as in the long climate run, especially for ACCESS model. This implies that we do not need long climate runs in order to identify the ACCESS model biases. In fact, our experimental forecasts, whereby we have initialized the ACCESS climate model, is essentially what is required for participation in the Transpose-AMIP project, which aims to tackle systematic climate model bias by utilizing suites of short range forecasts. Hence, an unexpected outcome of this project has been the development of the Transpose AMIP protocol for the ACCESS model.

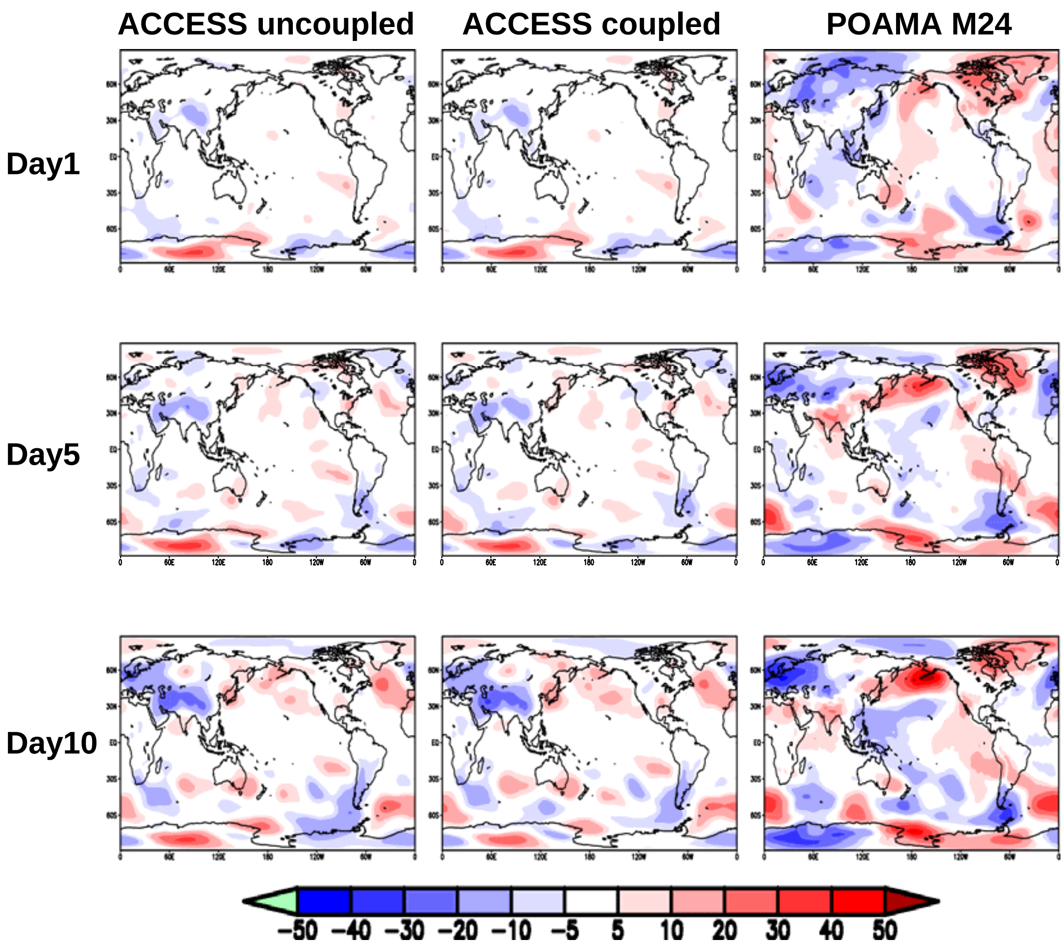

Fig. 3 Mean state biases of Geopotential Height at 500 hPa at day 1, day 5, and day 10 for ACCESS1.3x uncoupled model (left panel), ACCESS1.3x coupled model (middle panel), and POAMA M24 model (right panel) compared to NCEP reanalysis data for all start months from 1982 to 2010 (model results minus NCEP data). Note: the ACCESS model verifies with daily mean NCEP data and POAMA M24 verifies with instantaneous 00Z NCEP data.

2.2 Forecast Skill

We now assess aspects of forecast skill for the first month of the forecasts. We focus on the SON and DJF seasons since SON is the peak season for impacts of ENSO and the IOD, and DJF is the peak season for the MJO. Results for other seasons are provided in Appendix B.

2.2.1 Skill for Rainfall and Temperature

We calculate the temporal anomaly correlation coefficient (ACC) between AWAP analyses and model forecasts for precipitation, maximum temperature, and minimum temperature over Australia from 1982 to 2010 for the monthly means over the first month of each forecast (Figs.

4 and 5). The results for the JJA and MAM seasons can be seen in Appendix B. For precipitation, the forecast skill in SON is generally high over southern and eastern Australia, reflecting the predictable impacts of ENSO and the IOD. Encouragingly, both ACCESS models outperform and the coupled ACCESS model is better than the uncoupled model although the gains are modest. The biggest increase in skill relative to M24 is over northeast Australia. The reason for these differences will be explained in the next Section. Unfortunately, we do not see much improvement for the DJF season, reflecting the challenge of predicting precipitation during summer months.

For maximum temperature, ACCESS 1.3 coupled model is better than the uncoupled model and better than POAMA M24, consistent with the improvements in rainfall predictions. For minimum temperature, the differences in forecast skill between models appear to be slight. However, as we will address in the next section, the estimates of forecast skill from ACCESS should be considered on the low side due to sub-optimal ensemble generation and initialization.

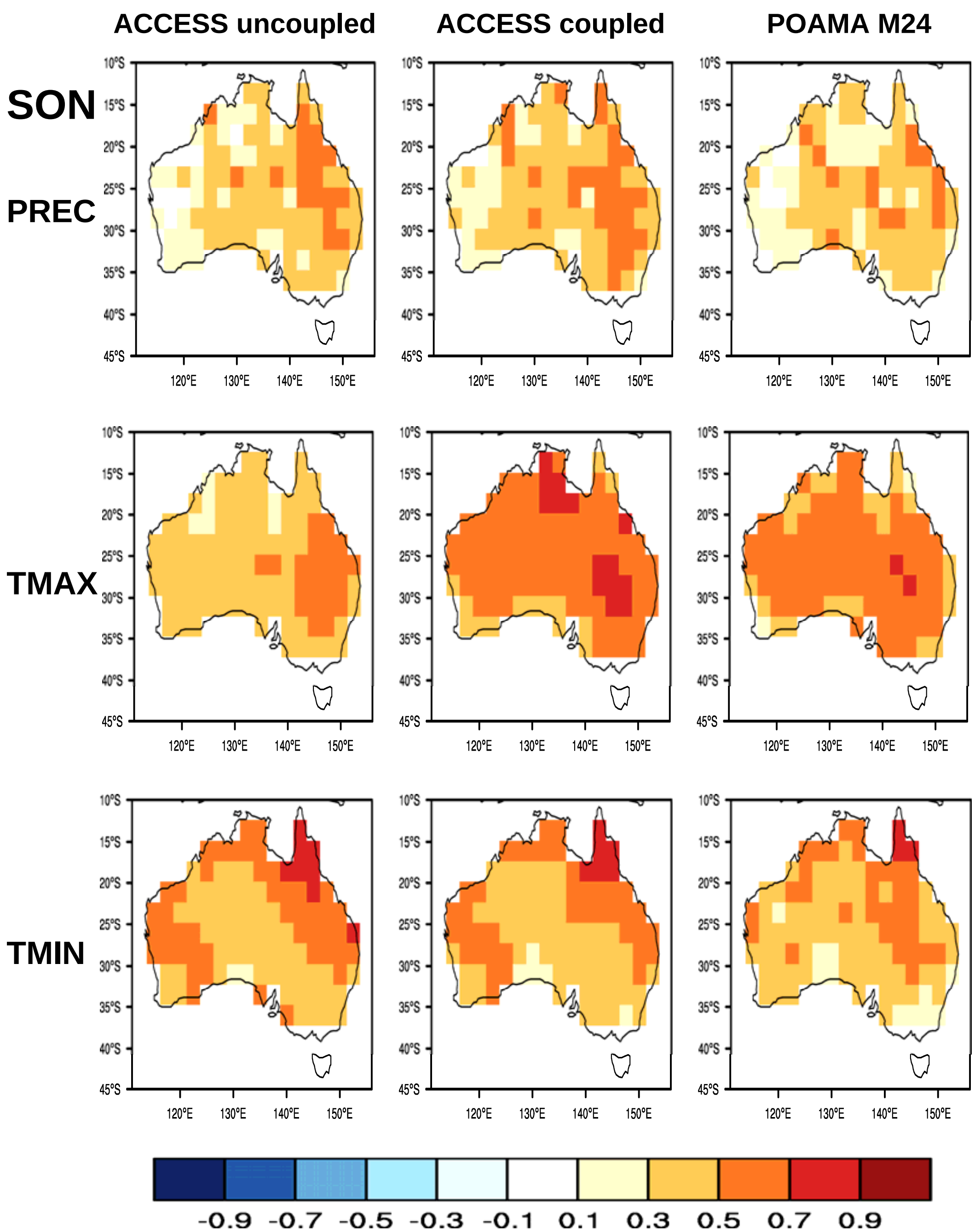

Fig. 4 Temporal anomaly correlation coefficient (ACC) between AWAP observation data and ensemble mean precipitation (PREC), maximum temperature (TMAX) and minimum temperature (TMIN) over Australia for ACCESS uncoupled model (left panel), ACCESS coupled model (middle panel), and POAMA M24 model (right panel) in SON season from 1982 to 2010.

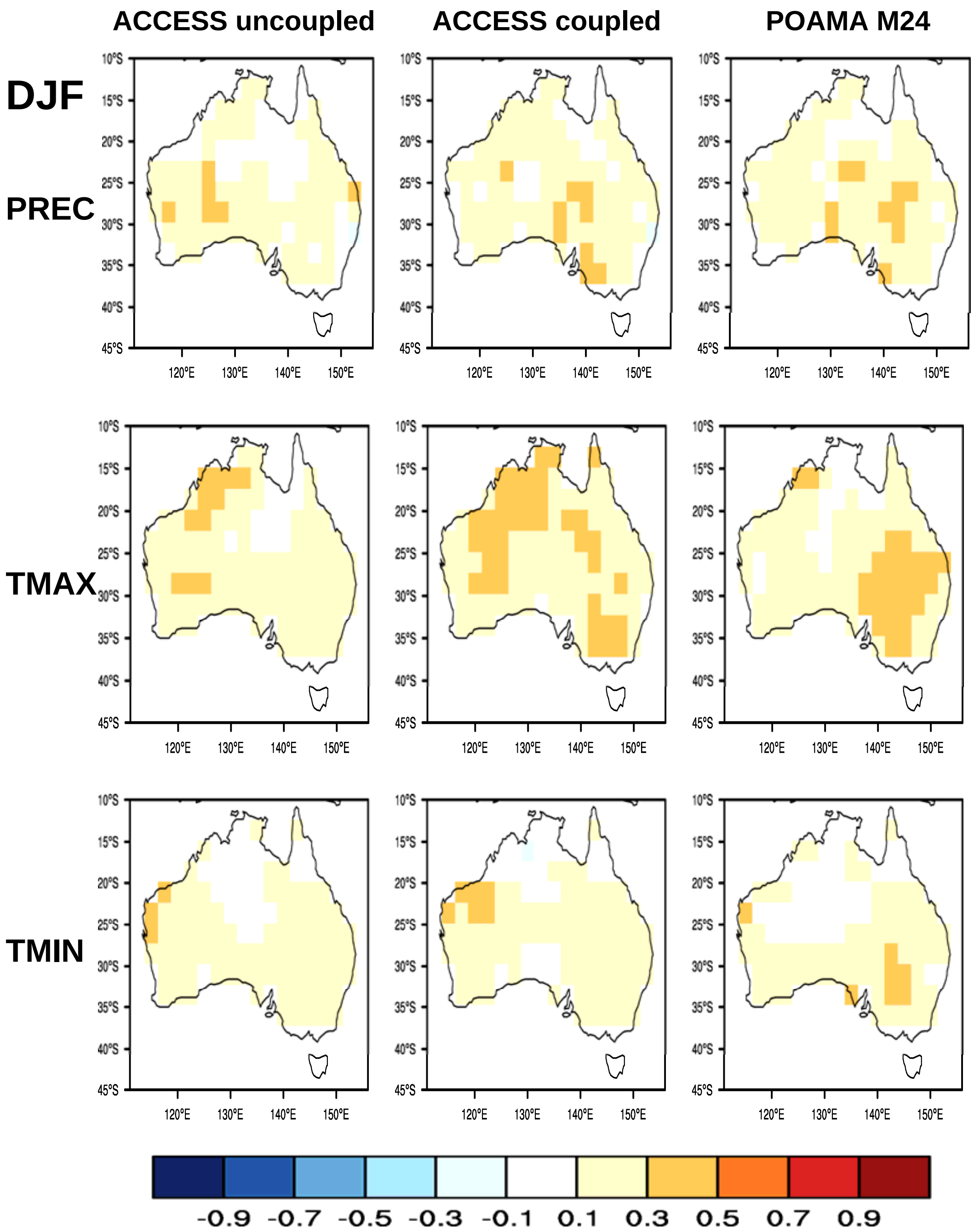

Fig. 5 The same as Fig.4, but in DJF season.

2.2.2 Skill for Geopotential Height

We now step back from the Australian focus and assess the performance of the ACCESS model from a hemispheric perspective. We first explore the "weather" forecasting capability of the systems by scoring forecasts of 500 hPa geopotential height anomalies over the southern hemisphere extratropics. Because the ACCESS model has higher resolution than POAMA M24 and it is initialized with presumably improved atmosphere initial conditions (ERA-Interim for

ACCESS as compared to ERA-40 for POAMA M24), we would expect that the ACCESS model should provide an improved deterministic prediction of midlatitude "weather" (i.e., days 1-10) even though the model set up targets climate scales. We display in Fig. 6 the spatial anomaly correlation averaged over the mid-latitudes (left) and over the polar cap (right) as a function of forecast lead time for forecast starts from 1st Sep, 1st Oct, and 1st Nov. Both ACCESS models provide significantly improved "weather" forecasts, with the improvement equating to about 1.5 days (i.e., forecast skill for POAMA at day 2 is achieved by ACCESS at day 3.5). To quantify the possible impact of improved initial conditions, we also provide the correlation of the respective initial conditions from each model with NCEP (crosses on X axis). At least for the mid-latitude region, the quality of the initial condition for POAMA M24 appears to be similar to the quality for ACCESS, so we cannot attribute the differences seen in Fig. 6 to the initial conditions. The other likely explanation is that the high skill in ACCESS stems from model improvements compared to POAMA M24. However, because we are verifying instantaneous output from POAMA M24 (more noisy) and daily mean output from ACCESS (less noisy) some of the improvement in ACCESS seen in Fig. 6 may actually stem from the effective smoothing of the ACCESS forecasts. More insight into the actual improvement for ACCESS will be assessed in Section 3.4.1 and 3.4.2 where we make use of the available daily mean output from POAMA and we use spatial smoothing for verification of the MJO and SAM indices. We do not see any notable difference in the performance of "weather" forecasts between the ACCESS1.3x coupled and uncoupled models within the first 10 days. This implies that the atmosphere initial condition and the model configuration are the dominant factors for improving weather forecast skill.

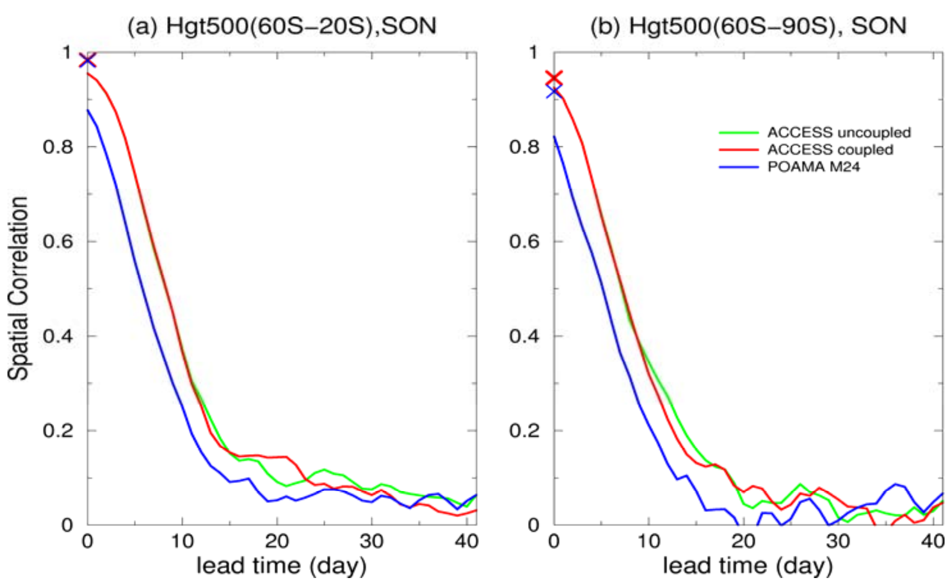

Fig. 6 The spatial correlation (SCOR) between NCEP reanalysis data and model forecasts for Geopotential Height anomalies at 500 hPa over (a) 60°S-20°S and (b) 60°S-90°S in SON as a function of lead time (days). The green line is ACCESS uncoupled model, the red line is ACCESS coupled model, and the blue line is POAMA M24 model. The blue X is the SCOR between POAMA M24 (based on ERA-40) initial condition and NCEP 00Z analyses, and the red X is the SCOR between ACCESS (based on ERA-interim) initial condition and NCEP 00Z analyses.

2.3 Teleconnection Pattern of ENSO and IOD

Regional climate predictability, especially for rainfall, is primarily contributed to by slow coupled atmosphere ocean variations due to ENSO and the IOD, but also by slow internal variations of the atmosphere associated with the MJO and the SAM. The representation of these modes and their remote impacts over Australia is critical for good forecast performance. We now assess these modes in the ACCESS models and compare to POAMA M24.

We begin by looking at ENSO and the IOD. We determine the teleconnection by regression of the equivalent monthly mean Niño3.4 and IOD indices respectively onto the precipitation (PREC), TMAX and TMIN anomalies (averaged over days 1-30 of the forecasts) for the SON and DJF seasons (Figs. 7, 8 and 9).

For precipitation in SON (Fig.7), the observed relationship for both Niño3.4 and the IOD is primarily dry in the east, i.e., dry during El Nino plus positive IOD events. There are stronger dry anomalies in the south when using the IOD index (cf Cai et al., 2012). Both of the ACCESS models outperform POAMA M24, especially in the north east. However, all the models show weaker teleconnection for both ENSO and IOD indices over the south-east Australia than observed, which probably stems from biases in the rainfall in the Maritime Continent region (bias is weaker in POAMA and so teleconnection is slightly better). For DJF, the ACCESS models are better than POAMA M24 over northern Australia, which probably reflects greater sensitivity to ENSO due to a reduction in the dry bias in ACCESS compared to POAMA. However, the ACCESS coupled model shows the worst performance over north-west Australia for the IOD, which again flags the dry bias in the Maritime Continent region as being at fault.

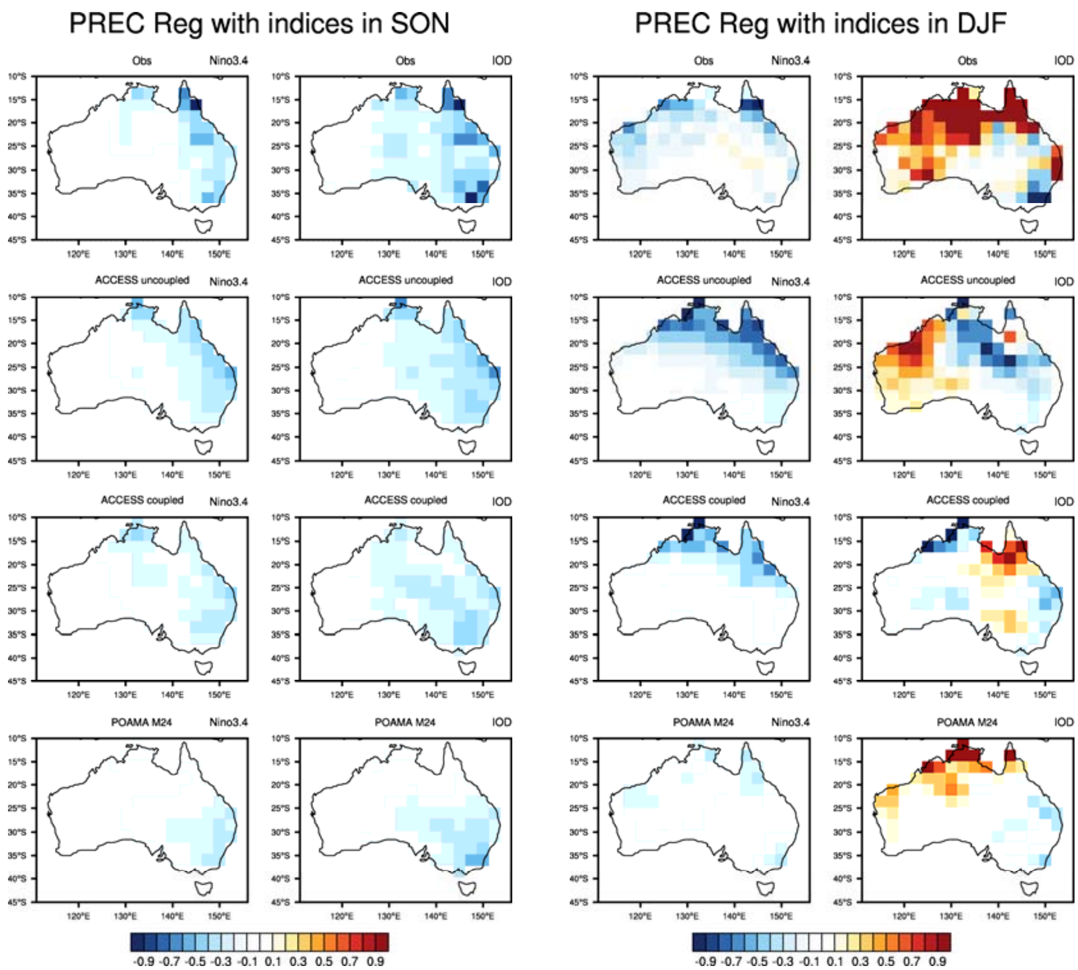

Fig. 7 Regression of Niño3.4 and IOD indices onto precipitation anomalies over Australia in SON and DJF seasons for Observation, ACCESS uncoupled model, ACCESS coupled model and POMAM M24 (from top to the bottom panel). Units are mm/day.

For TMAX in SON (Fig. 8), both teleconnections for ENSO and IOD in the ACCESS models are too weak compared to observations and to POAMA M24, especially the teleconnection of the IOD over south-east Australia. The ACCESS coupled model has a slightly stronger response than the ACCESS uncoupled model, which might explain why the coupled prediction skill of TMAX is higher than the uncoupled skill (see the results in Section 3.2.1). However, the accurate amplitude of the teleconnection for climate drivers may not be the only necessary reason to have better prediction skill. For example, in DJF, although the teleconnection pattern of TMAX in ACCESS coupled model over the north-west is the weakest, the prediction skill of TMAX is the highest over that region.

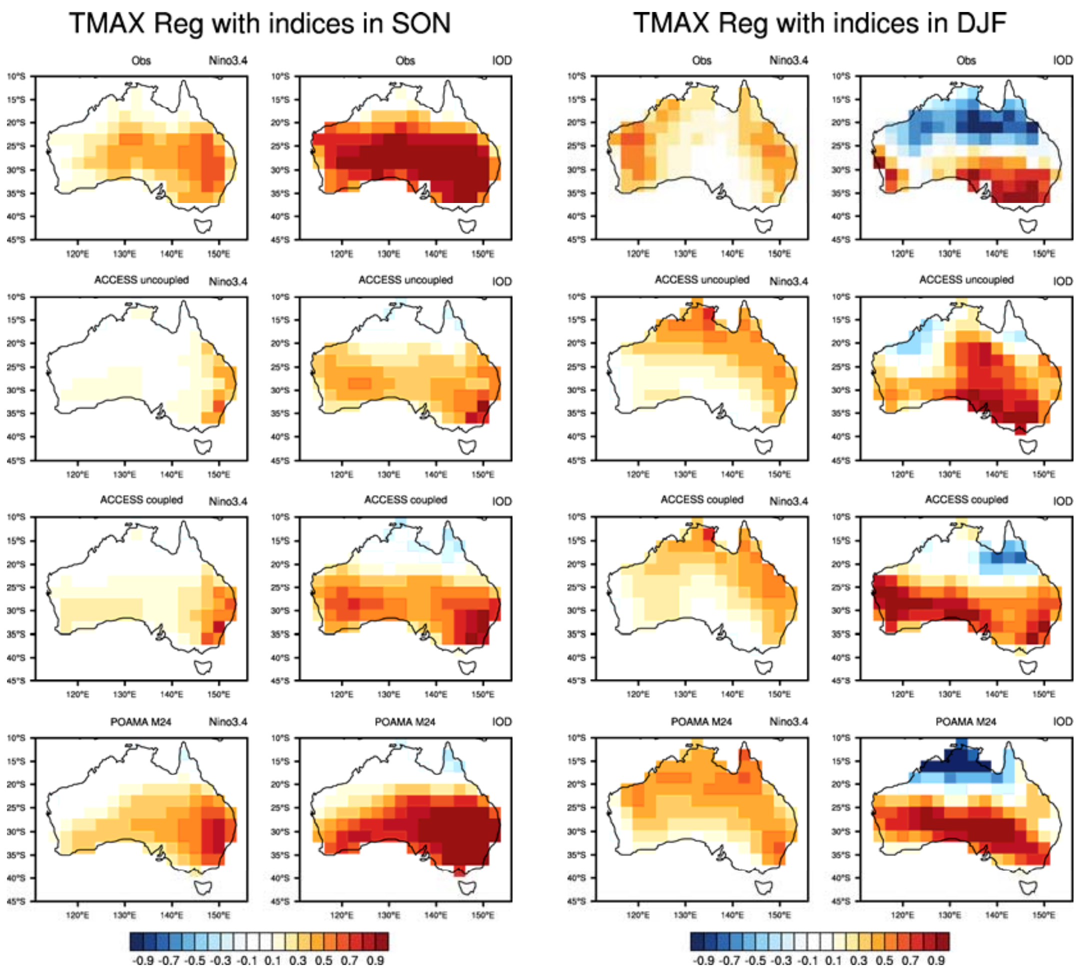

Fig. 8 The same as Fig.7, but for maximum temperature anomalies. Units are °C.

For TMIN in SON (Fig. 9), the teleconnection is even weaker in the ACCESS models especially for the IOD over southern Australia. The ACCESS models have relatively higher skill over western Australia, but this is evidently not having improved ability to capture ENSO and IOD teleconnection. In DJF, all the models show stronger teleconnection with ENSO over northern Australia than observed. Both coupled models teleconnections with the IOD are too strong over south-western Australia.

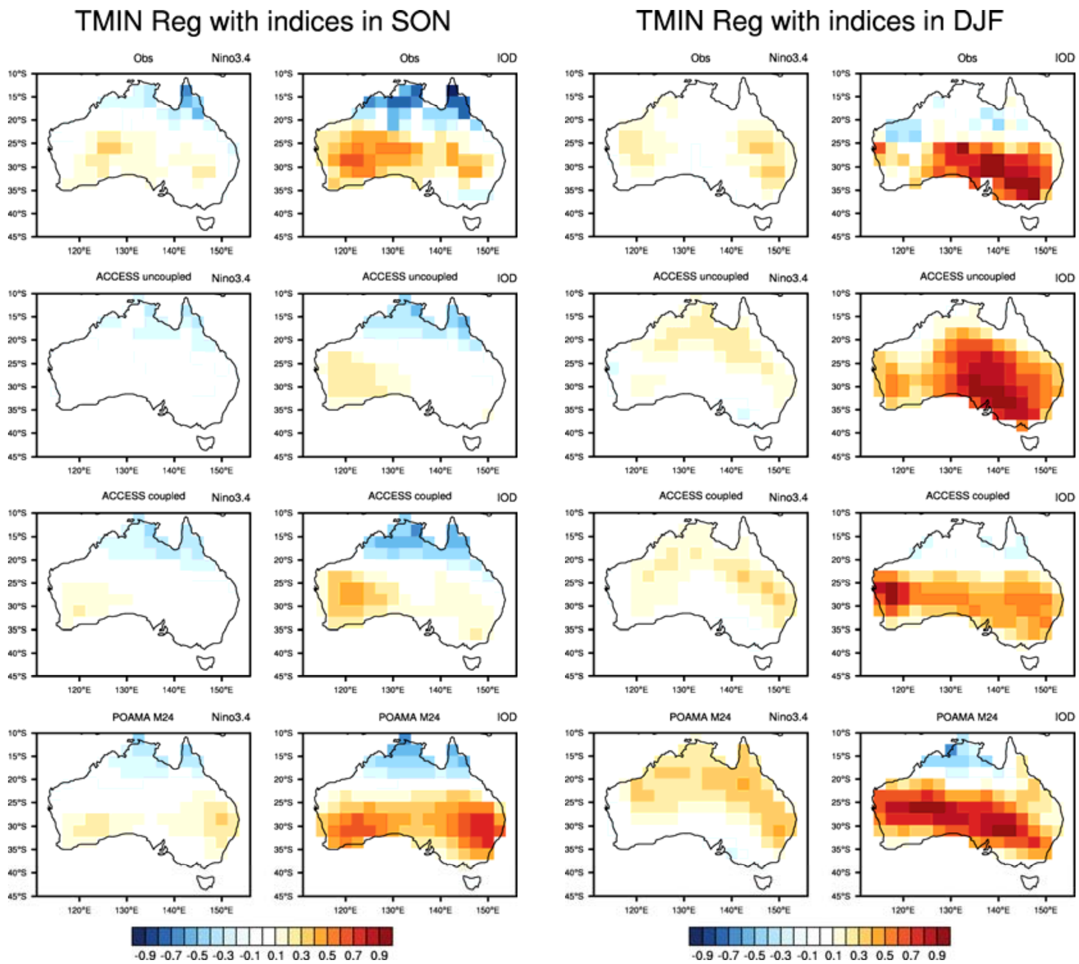

Fig. 9 The same as Fig.7, but for minimum temperature anomalies.

The teleconnections from ENSO and the IOD to Australian climate are ultimately driven by the tropical rainfall response to each of these phenomena. In order to assess the realism of the tropical rainfall responses during ENSO and the IOD, we plot the regression of Niño3.4 and IOD indices onto precipitation anomalies over the tropical Indian and Pacific Ocean region (30°N-30°S, 35°E-70°W) in Fig. 10. For the regression onto Niño3.4, the pattern, amplitude and location of the maximum centres in the ACCESS models are more close to the observation than POAMA M24. For instance, the ACCESS models pick up the negative anomaly in the Bay of Bengal. Over the western Pacific Ocean, the negative precipitation anomalies in the ACCESS models are relatively weaker over the South China Sea and the East China Sea than observation and POAMA M24. In contrast, POAMA M24 shows too strong negative precipitation anomalies in the region of Indonesia and the Coral Sea. For positive precipitation anomalies in the central Pacific, both the ACCESS and POAMA coupled models have the common issue of erroneous extension westward compared with observation and the uncoupled model. The rainfall anomalies in the central Pacific in POAMA M24 are too broad compared with observation and the ACCESS models, which has important implications for longer lead forecasts of ENSO. In addition, in the eastern Pacific along the equator, the ACCESS models performance appears better than POAMA M24.

For the IOD index over the Indian Ocean, the ACCESS models have slightly better performance in the western Indian Ocean. POAMA M24's precipitation response in the western Indian Ocean is too strong. Although the ACCESS models have much larger mean biases of precipitation over the Indian Ocean, it seems not to have an overly strong impact on the anomalies and the teleconnection.

In summary, both ACCESS models and POAMA M24 depict the key teleconnections of ENSO and the IOD reasonably well, with the ACCESS models generally showing slightly improved performance over POAMA M24. This improved depiction of the teleconnections is reflected in the modest improvement of regional forecast skill using the ACCESS models.

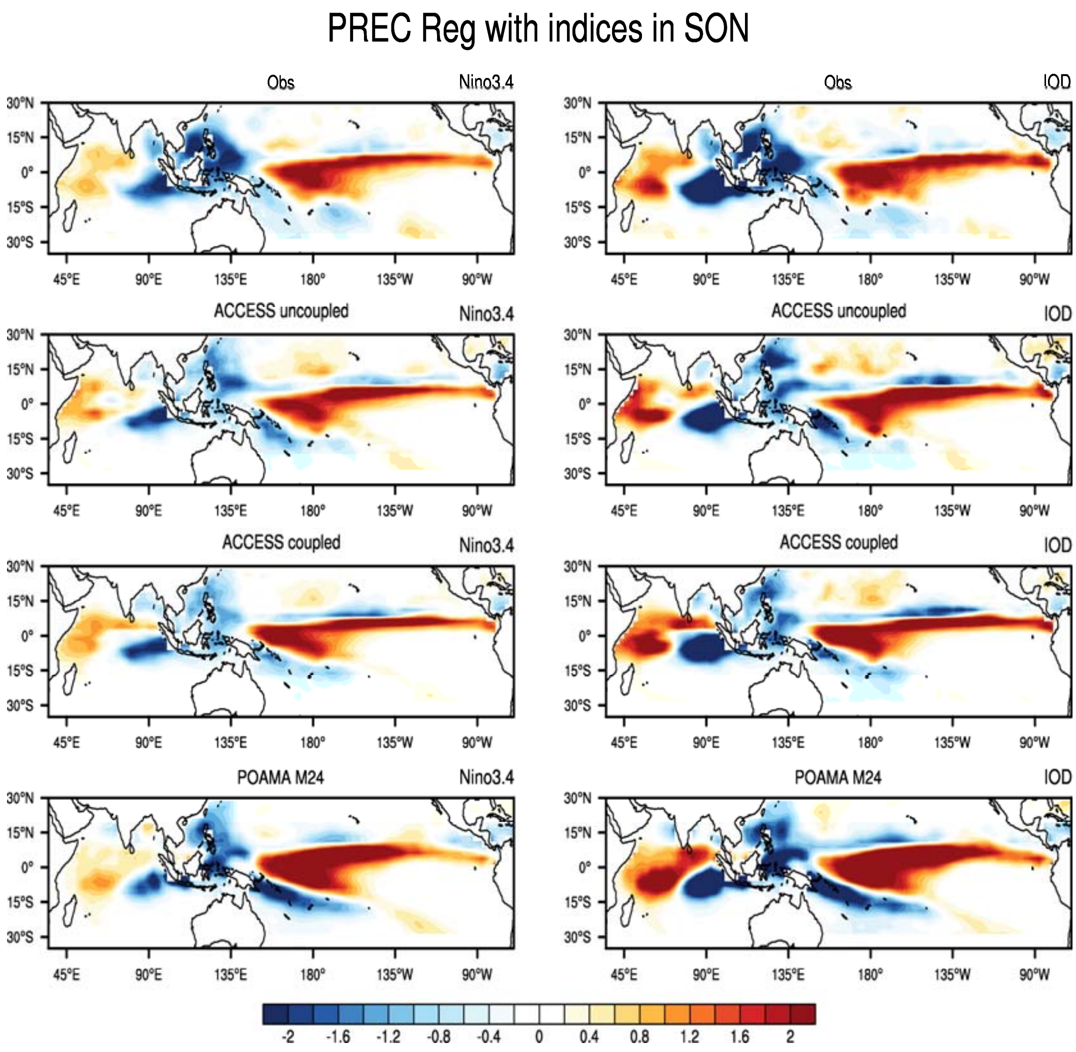

Fig. 10 The same as Fig.7, but over the tropical Indian and Pacific ocean region (30°N-30°S, 35°E-70°W). Units are mm/day.

2.4 Forecast Skills for MJO and SAM Indices

Multi-week predictability is also contributed to by slow internal variations of the atmosphere. Here we assess the performance of predicting and simulating two key modes: the MJO and the SAM.

2.4.1 Skill for MJO Index

We assess the forecast skill (temporal correction) for the MJO in DJF (the season when the MJO is strongest) and all start months in Figs. 11 and 12 using the bivariate correlation of the MJO index (Rashid et al. 2009). The skill for the other seasons is shown in Appendix B (Fig. B.3). In DJF, POAMA M24 forecasts maintain skill longer than the ACCESS model, with a correlation of 0.5 achieved out to 24-days lead time. Disappointingly, the ACCESS coupled model falls to 0.5 at 20-days lead and the uncoupled model only achieves 16-days lead. Notably, during the first 10-days, the skill of the ACCESS models is slightly higher than POAMA M24 model, which suggests that the initial conditions in ACCESS are better than POAMA, but the representation of the MJO is poorer in ACCESS so that after day 10 the skill is worse in ACCESS. Importantly, the ACCESS coupled model outperforms the uncoupled model.

Because of the poorer performance of the ACCESS model for predicting the MJO in the peak season of the MJO compared to POAMA, we explored the impact of some modifications of the convection scheme in the UM that are targeted for improving the representation of the MJO (discussed in Sec. 2). However, using the uncoupled model we could discern no difference in forecast performance with and without these changes. We note that the ACCESS1.3x coupled model did not use these changes to the convection scheme, but it does show better skill for the MJO compared to the uncoupled model with the changes. However, forecast performance is still lower than POAMA M24 during the peak season (DJF) for the MJO. The reason for improvement in the coupled model needs to be determined, because it could stem from improved air-sea interaction due to coupling or reduced mean state biases in the Maritime Continent that then allow a better representation of the MJO through this reason. Discerning this cause will help guide future model improvements.

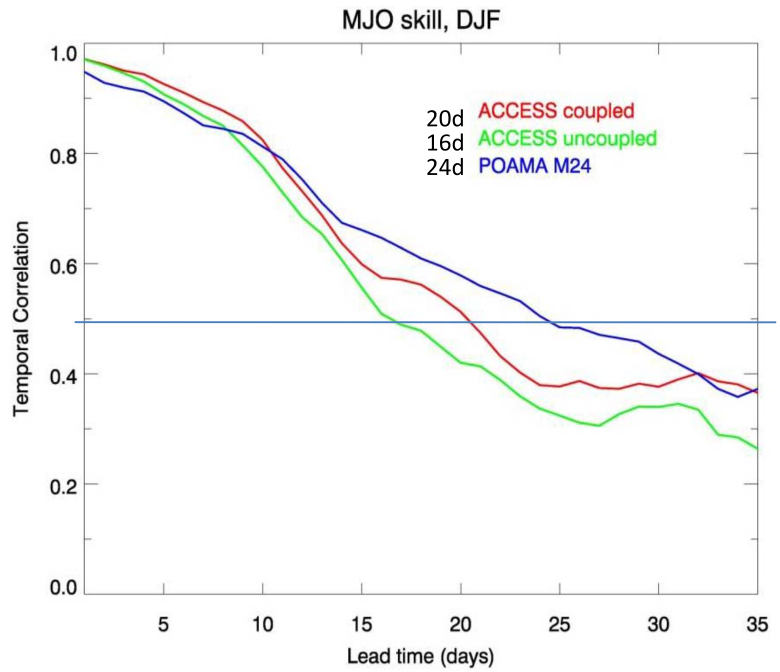

Fig. 11 Bivariate correlation for RMM MJO indices as a function of lead time (days) for ACCESS uncoupled (green line), ACCESS coupled (red line), and POAMA M24 (blue line) models in DJF.

When all start months are considered together (Fig. 12a), the performance of the ACCESS coupled model is clearly superior to POAMA M24 and the uncoupled model. We attribute this improvement over POAMA M24 to the reduction in mean state bias in the ACCESS coupled model for the non summer seasons, although more work is required to prove this. We also consider the bivariate root mean square error (RMSE) and ensemble spread (Fig. 12b). Although the RMSE for the two coupled models are similar, the forecast spread for the ACCESS model is much less than for POAMA. This reflects the sophisticated breeding technique used to generate ensemble perturbation in POAMA and the simplistic approach of using lagged initial conditions for ACCESS. We therefore expect substantial gains in performance (both skill and reliability) from ACCESS once the breeding technique is implemented.

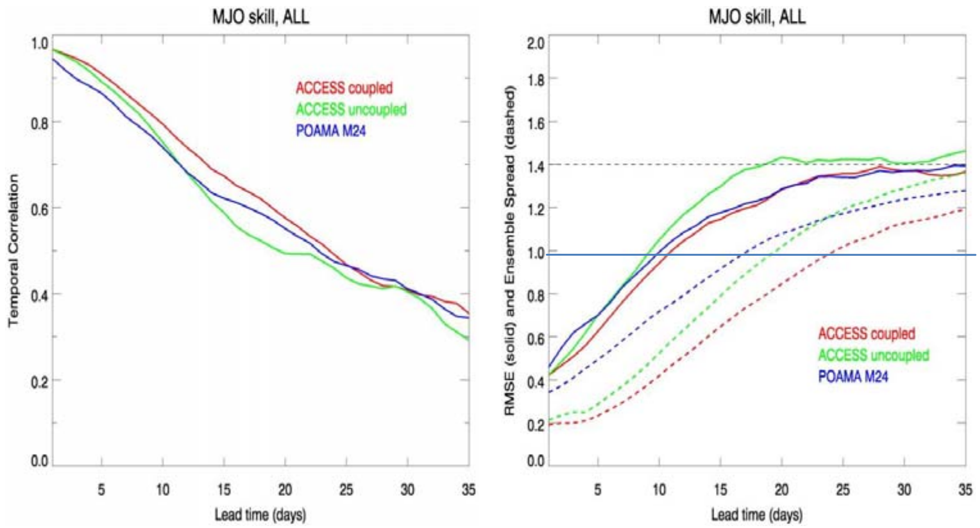

Fig. 12 Bivariate correlation skill of the RMM MJO index (left) and bivariate root mean square error (RMSE, solid line) and ensemble spread (dash line) (right plot), as a function of lead time (days) for ACCESS uncoupled (green line), ACCESS coupled (red line), and POAMA M24 (blue line) models by using all start months data (right plot).

2.4.2 Skill for SAM Index

We assess the skill of forecasting the SAM by forming an index of daily mean, zonal mean surface pressure at 40°S minus 60°S. High SAM, which reflects a poleward shift of the mid-latitude westerlies, will have lower pressure at 60°S and higher pressure at 40°S and so the index will be positive. We concentrate on the SON season as this is the season when the SAM is most active. The skill of predicting the SAM index for both the coupled and uncoupled ACCESS models beats POAMA M24 by about 3 day lead time. Unlike the MJO, there is no significant difference between ACCESS uncoupled and coupled models. Although we see some small increase in skill at the shortest lead times (which might reflect improved initial conditions and better models), the main gain in skill over M24 does not appear until after 8-9 days. Based on previous work by Roff et al. (2010) with another version of the ACCESS model, this delayed impact of increased skill probably can be attributed to better resolution of the stratosphere in the ACCESS models (L38) over POAMA (L17).

We again see that the ACCESS forecasts are initially under-dispersive (spread is much smaller than RMSE, Fig. 14a), so we can expect further gains in the ACCESS model when the ensemble perturbation strategy is deployed. When taken over all start months, the benefit of ACCESS over POAMA M24 is less obvious (Fig. 14b). Perhaps this is not surprising because the main source of longer lead predictability of the SAM in the other seasons is not the descent of variability from the stratosphere but rather modest forcing by tropical SST variations associated with ENSO (Lim et al. 2013), which are equally well captured in POAMA and ACCESS.

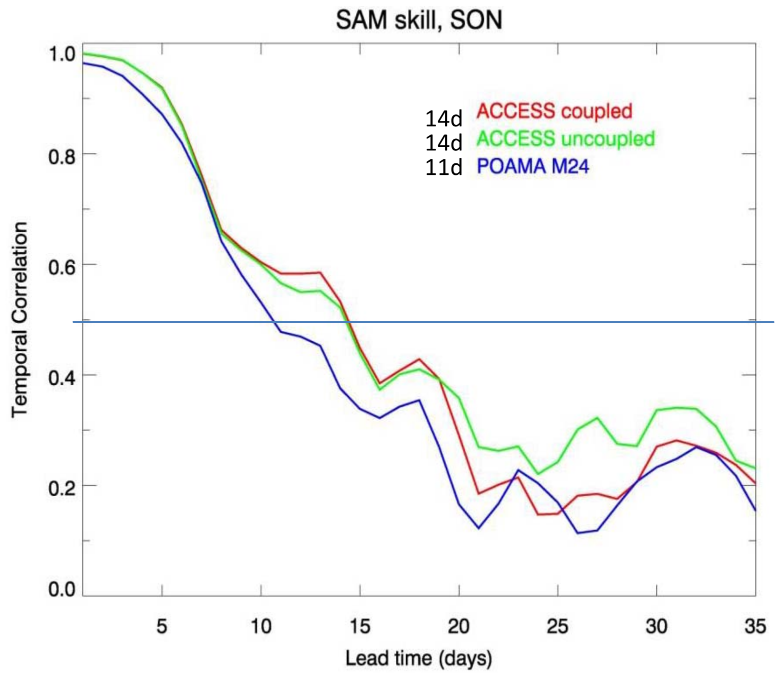

Fig. 13 The same as Fig.11, but for the SAM index.

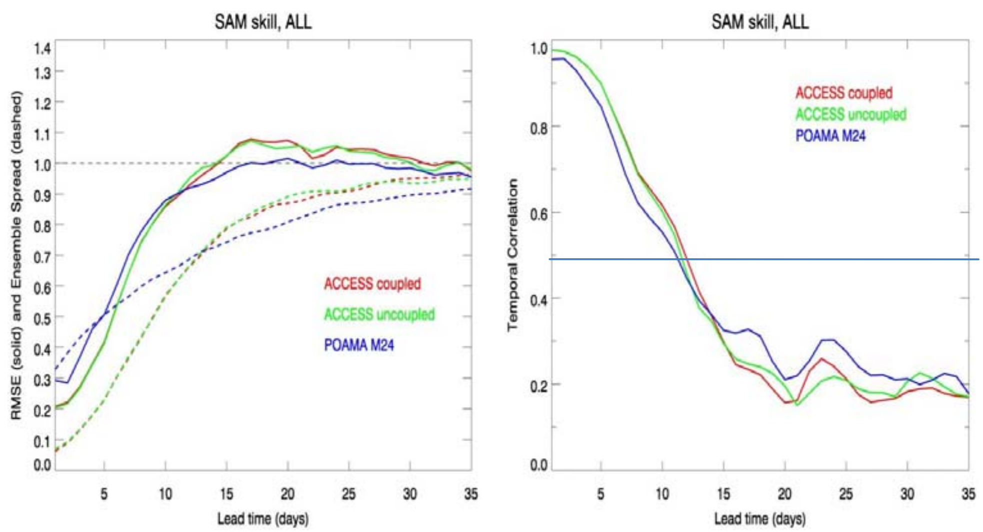

Fig. 14 Same as Fig.12, but for the SAM index.

2.5 Impact of Improved Vertical Resolution

We also investigate the impact on forecast skill by using improved vertical resolution of the uncoupled ACCESS model. We increased the vertical resolution to 85 levels in both the UM7.3

(ACCESS 1.3x) and the newest GA4.0 version of the UM that uses the MOSES land surface scheme. Our main interest in increased resolution is the impact of better resolving the stratosphere which Roff et al. (2011) can be expected to have an impact on tropospheric forecast skill after about 10-15 days lead time. We expect the main impact to be from variability of the polar vortex which affects the SAM during boreal spring. Hence, we focus on forecast skill of the SAM index during the SON season. Unfortunately, we see no indication of improved skill using the L85 model over the L38 model out to the limit of deterministic predictability for the SAM (~15 days). Our interpretation is that there is no more improvement obtainable from L38 over L17 (Fig 15) in going to L85 over L38.

We additionally investigate the forecast skill over the polar cap at each level in the vertical so as to see how the improved skill in predicting the stratosphere afforded by L85 impacts the troposphere. We calculate the spatial correlation of temperature anomalies from 60°S to 90°S at each level and make the skill score (percentage improvement) compared to uncoupled ACCESS 1.3x UM7.3 L38 (Fig. 16). Unfortunately, the UM7.3 L85 version is not well tuned, so the initial skill in the troposphere is worse than L38 (Fig. 16a). Improvement is seen in the stratosphere but the gain over L38 is modest. Furthermore, the L85 version of UM7.3 crashes more than 20% of the time, which necessitates a manual restart in order to complete the forecasts.

In contrast, the GA4.0 L85 version is stable. From Fig. 16b, we see similar forecast skill in the troposphere as ACCESS 1.3 L38 but with a significant improvement in the stratosphere that appears to slowly descend to the tropopause by ~30 day lead time. However, we do not see any extension of this increased skill into the troposphere as was found by Roff et al. (2011). In summary, while we do see a significant improvement in forecast skill in the stratosphere using increased vertical resolution, we do not see any appreciable impact on prediction of the SAM that would then carry over to improved prediction of Australian rainfall.

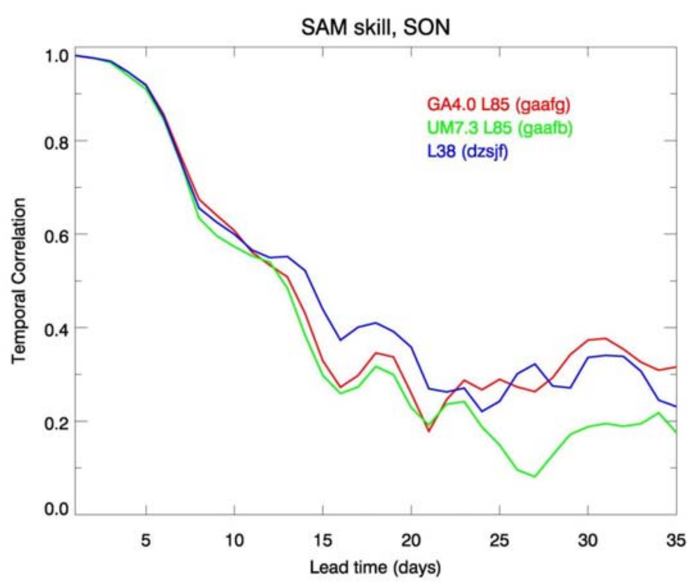

Fig. 15 The skill of SAM index as a function of lead time for GA4.0 L85 (red line), UM7.3 L85 (green line) and ACCESS1.3x uncoupled L38 (blue line).

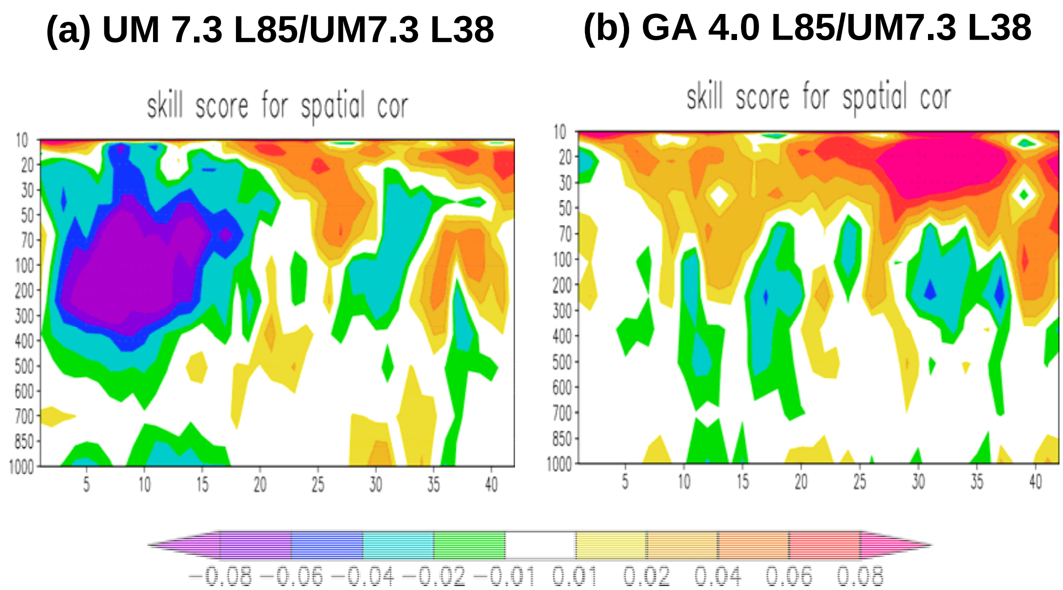

Fig. 16 The skill score of the spatial correlation of temperature anomalies (60°S-90°S) for (a) UM7.3 L85 relative to UM7.3 L38 (i.e., ACCESS1.3x), and (b) GA4.0 L85 relative to UM7.3 L38 (i.e., ACCESS1.3x).

3. SUMMARY AND RECOMMENDATIONS/IMPLICATIONS FOR DEVELOPMENT OF POAMA3

We have compared the mean state biases and forecast skill for 30 day predictions using versions of the ACCESS1.3x uncoupled and coupled models and the POAMA M24 coupled model. Our overall finding is that we can expect a modest gain in forecast skill for regional prediction of rainfall and temperature across Australia at least for the first month of the forecast by using ACCESS compared to POAMA2. We attribute these performance gains to a combination of reduced mean state biases, increased horizontal resolution and improved model physics. However, there are some notable shortcomings of the ACCESS model. This includes degraded prediction performance of the MJO in the season when the MJO is most dominant and has the most impact on Australian climate and increased mean state precipitation bias in the Indian Ocean, which is a critical region for driving Australian climate variability.

Our analysis here recognizes the limitation of the simplistic ensemble generation strategy employed for the ACCESS experiments and so the performance gain expected from using ACCESS should be greater than what we have indicated here.

We further note that we were unable to make use of the most recent upgrades by the UKMO to the UM model because they were not yet made available to us so that we could run in initialized climate mode. Hence, we would anticipate even further gains in performance once the newest versions of ACCESS based on UM GA6.0 are implemented at BoM. Our experimentation with simple modifications to the convective scheme in order to improve prediction of the MJO proved to be futile. However, recent developments at the UKMO suggest improved prediction of the MJO will be achieved with UM GA6.0.

A key finding of this research is that we could see no benefit of increased vertical resolution at least for forecasts out to 30 day lead time. We do not discount that the benefit of increased resolution, especially resolution of the stratosphere, may be felt at longer leads. Importantly, this is a moot point because all future versions of the UM will be based on L85 and so we will necessarily use L85 whether or not there is a demonstrable improvement for regional forecasts of Australian climate.

As a summary, we note some key recommendations for development of POAMA3 based on ACCESS and for future investigation using ACCESS:

1) Considering the modest forecast gains documented here, we recommend further improvements of the atmospheric component for the final configuration of POAMA3, including improvements that may available in the newest version of UM GA6.0. In the overall picture for developing POAMA3, this will probably not cause a delay because the development of the assimilation/initialization scheme for POAMA3 will probably take up to a year, and this can be done using ACCESS1.3x.

2) The initial version of ACCESS based on UM GA6.0 will probably not have the CABLE land surface model. While would make the seasonal prediction version of the model substantially different from the climate version, the use of MOSES would make it consistent with the NWP version. Use of MOSES would be more consistent with the initialisation strategy used in NWP. There is no a priori criterion that clear points to choosing CABLE over MOSES. Therefore the choice of CABLE land surface model for POAMA-3 should be based both on performance and timelines (e.g. of CABLE is not coupled to GA6.0 in time then MOSES should only be considered).

3) The POAMA3 model should be based on the coupled version of ACCESS that can readily use the newest updates to the UM from the UKMO. This will facilitate collaboration with colleagues at the UKMO.

4) Some key model biases are still present in all versions of the UM-ACCESS that will affect prediction skill of the Australian climate, most notably the rainfall biases across the Indian Ocean and Maritime Continent. Reduction of these biases should be a priority target for ongoing model development, ideally in collaboration with the UKMO.

5) Experience at the UKMO suggests that further increases in horizontal resolution have a beneficial impact on mean state biases and forecast skill. We have yet to be able to experiment using ACCESS at resolutions better than N96. Considering the modest expected performance gains achieved with the N96 version, we further recommend that immediate experimentation with the higher resolution version of ACCESS (e.g. N144 or N216) commence prior to final configuration of POAMA3. To do so will require securing additional staffing and computing resources, but also a sustained effort to properly configure the model. This also includes generation of necessary ancillary files that are required to run the model.

6) One of the most important outcomes of this study was the demonstration of improved prediction of the MJO using the coupled model. This appears to be a robust result and possibly can provide increased insight into the mechanism and predictability of the MJO. The cause of this increased skill should be determined (e.g., reduced mean state bias or a direct benefit of intraseasonal SST variations).

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APPENDIX A – MEAN BIASES

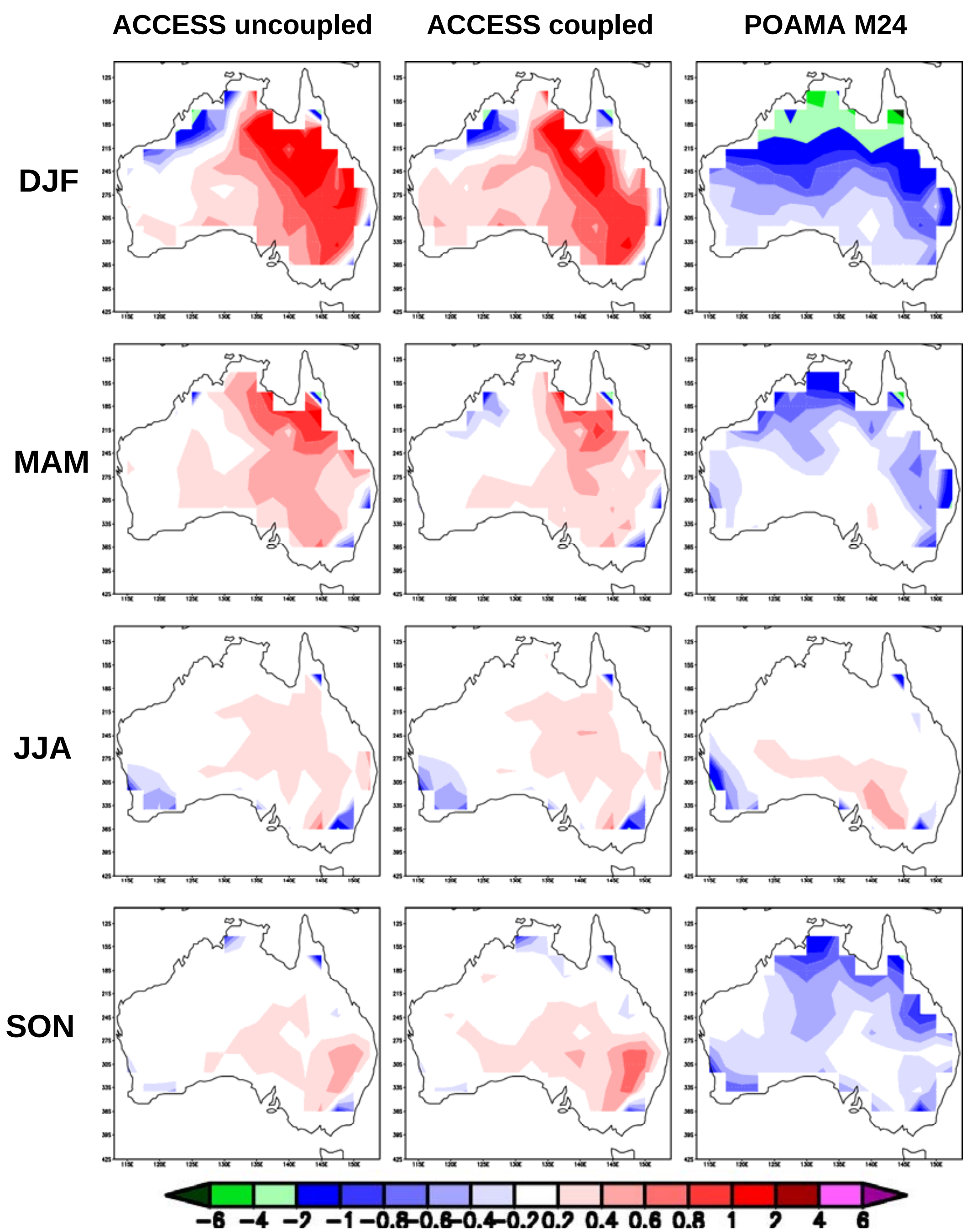

Fig.A. 1 Precipitation mean bias over Australia for ACCESS uncoupled model (left panel), ACCESS coupled model (middle panel), and POAMA M24 model (right panel) compared to AWAP observation data in four seasons from 1982 to 2010 (model results minus AWAP data). Units are mm/day.

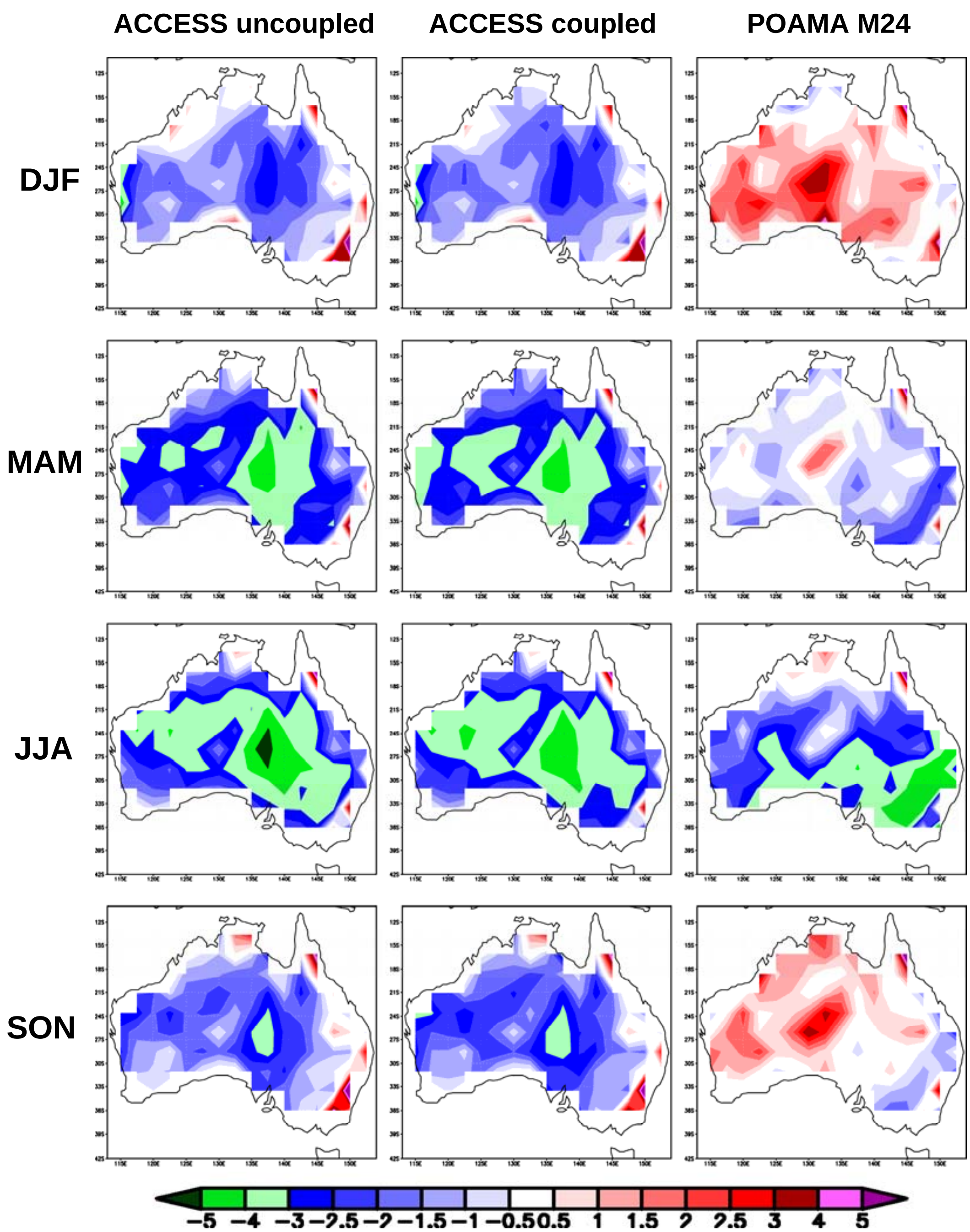

Fig.A. 2 The same as Fig.A.1, but for maximum temperature (TMAX). Units are °C.

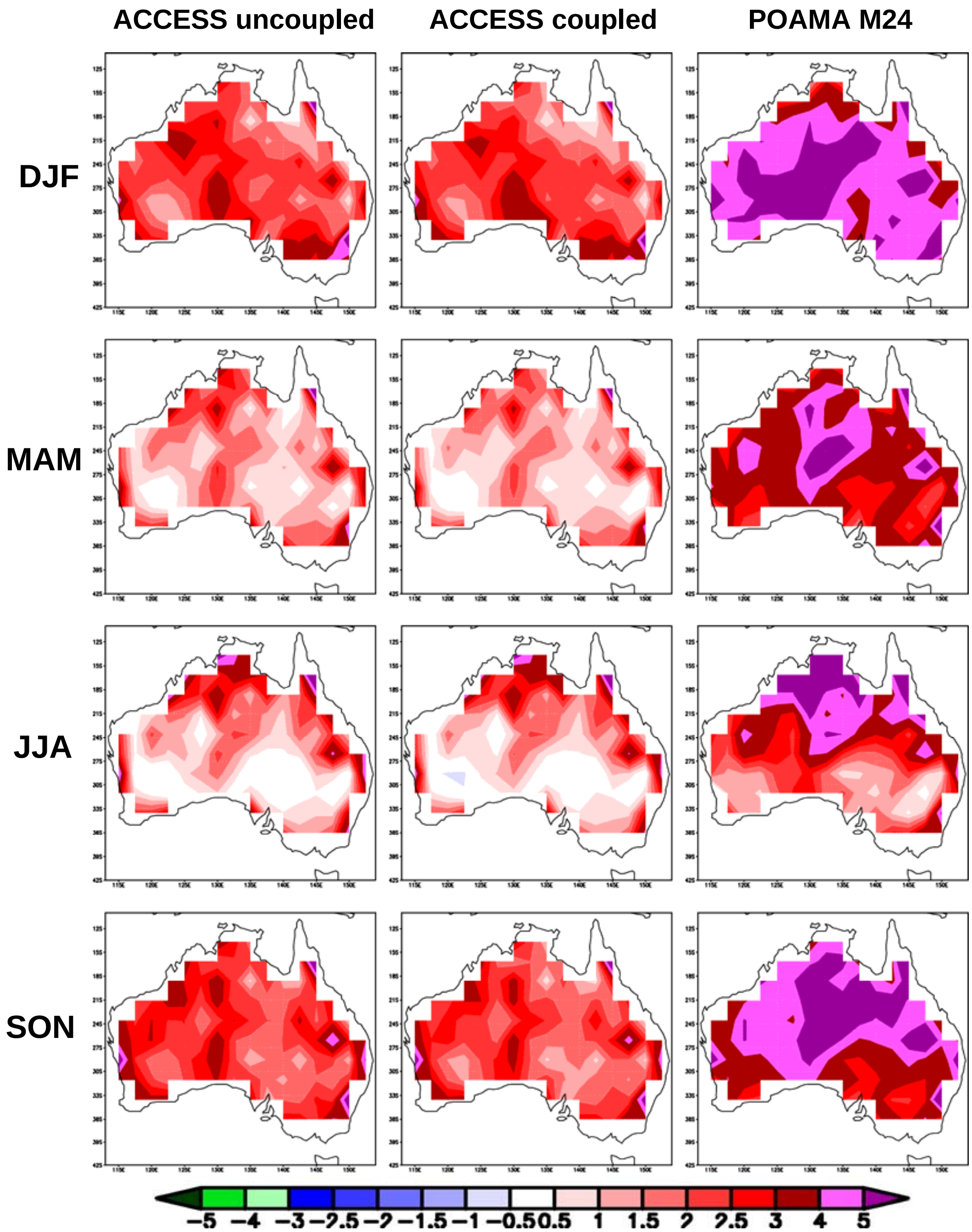

Fig.A. 3 The same as Fig.A.1, but for minimum temperature (TMIN).

APPENDIX B – SKILLS

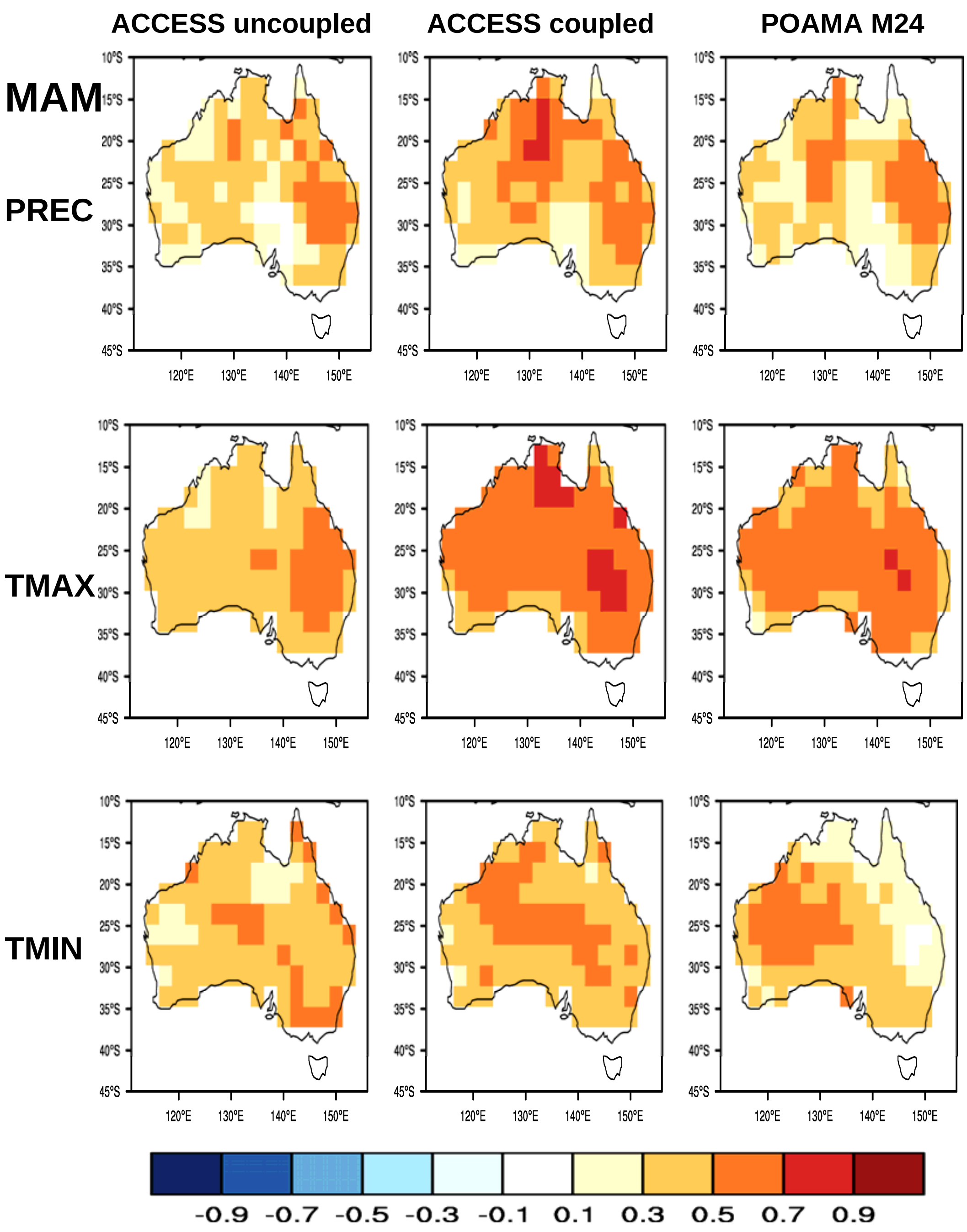

Fig.B. 1 Temporal anomaly correlation coefficient (ACC) between AWAP observation data and ensemble mean precipitation (PREC), maximum temperature (TMAX) and minimum temperature (TMIN) over Australia for ACCESS uncoupled model (left panel), ACCESS coupled model (middle panel), and POAMA M24 model (right panel) in MAM season from 1982 to 2010.

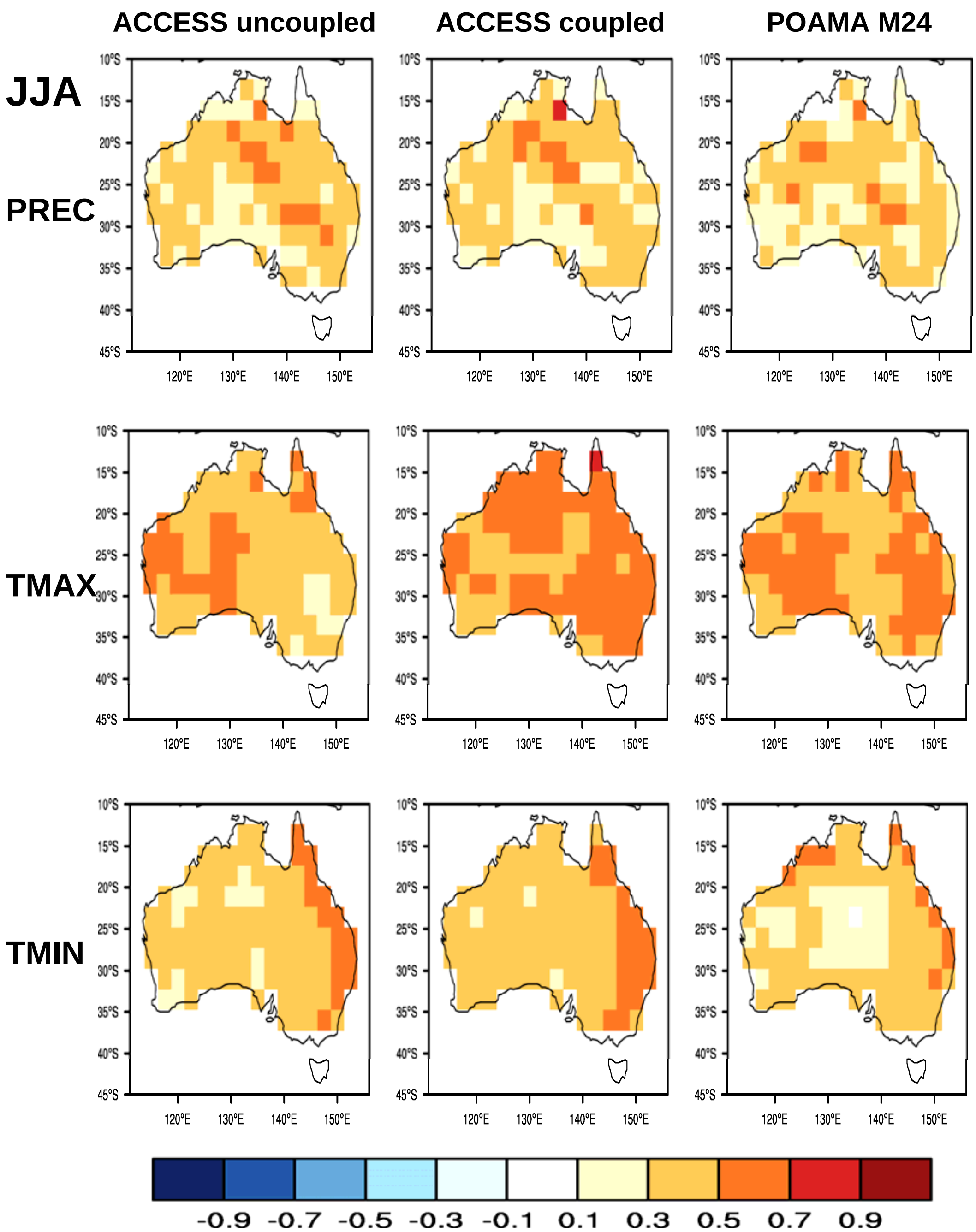

Fig.B. 2 The same as Fig.B.1, but in JJA season.

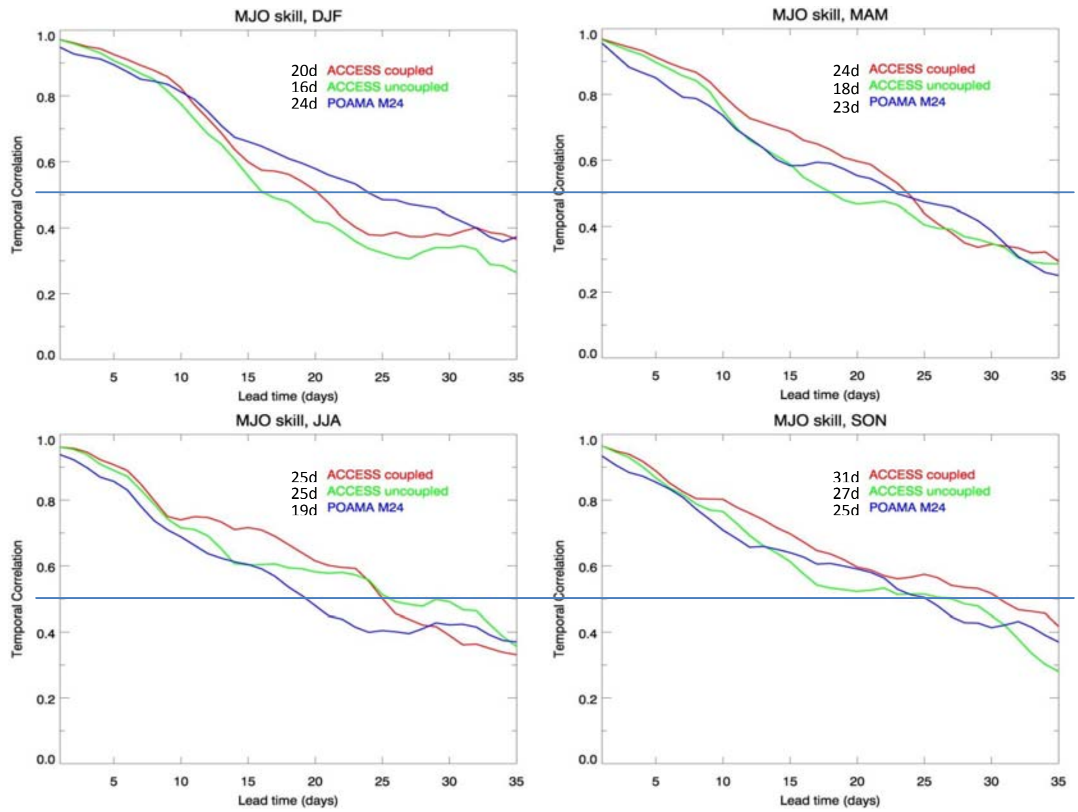

Fig.B. 3 The skill of predicting the MJO bivariate index (temporal correlation) in the four seasons.

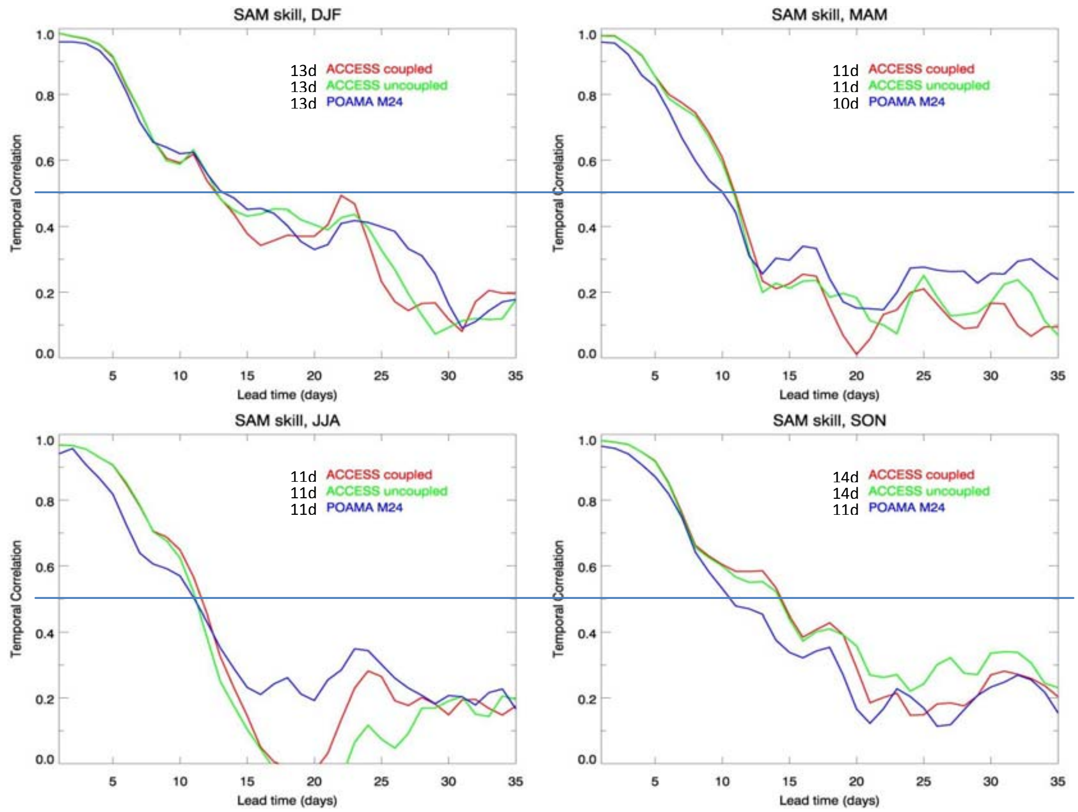

Fig.B. 4 The skill of predicting the SAM index (temporal correlation) in the four seasons.

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