Impact of Land-surface Initialization on ACCESS-S1 and Comparison with POAMA

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ABSTRACT

Land surface conditions are one of the key sources of climate predictability in sub-seasonal to seasonal time scales. The next generation coupled seasonal forecast system in the Bureau, known as ACCESS-S1, is based on GC2 configuration from the UK Met Office. It is due to become operational in 2017. While the atmosphere and ocean models of this system are initialised with high quality observed conditions, its land-surface model is initialised with climatological soil moisture in generating its hindcasts.

In this study we have conducted sensitivity experiments to explore the impact of such land-surface initialization on its forecast skill. Firstly, we force its land surface model JULES by ERA-interim 3-hourly atmospheric data, with precipitation further adjusted by monthly GPCP data. This produces 23-year soil moisture and soil temperature data which we deem as “realistic” corresponding to “observational” meteorological forcing. We then use them to initialize a suite of ACCESS-S1 seasonal hindcasts on 1st May for the 23-yr period of 1991-2012. Skill assessment on the experimental hindcasts shows significant improvements on the prediction skill of surface maximum temperature (Tmax) and latent heat flux, with moderate improvements on surface minimum temperature (Tmin) and precipitation (Prec) from sub-seasonal to seasonal time scales over Australia, particularly over the north-eastern part of the continent. While the gain of its precipitation forecast skill is relatively small, the impacts on forecasting surface air temperature and its diurnal range are significant. In addition, we find the impacts on precipitation biases over Indian Ocean and Maritime Continent.

Furthermore, we have compared the ACCESS-S1 forecast skill with “realistic” land-surface initial conditions to that from the current operational seasonal forecast system POAMA. Our analysis suggests that there is potential for improved performance in ACCESS-S2 (the next version of the ACCESS-S system) with advanced land-surface data assimilation. At the same time, results from this sensitivity study will be further examined to provide more insightful understanding of impacts of land-surface initial conditions on ACCESS-S1 seasonal forecasts, such as the asymmetric impacts of wet and dry soil moisture initialization as well as the impacts during different ENSO years or IPO periods.
1. INTRODUCTION

In the last two decades, significant improvements have been made in coupled seasonal forecast at a lead time (LT) of one season or longer. Much of the notable skill gain comes from improved predictions of tropical sea surface temperature (SST) variations which have profound influence on regional and global weather and climate (Trenberth et al. 1998). The climate drivers for Australia climate such as IOD and ENSO have strong phase lock characteristics, with high predictive skill in austral spring and summer when IOD and ENSO peak, respectively. However, austral autumn and winter seasons are a critical period for the most of the agriculture activities in Australia. This is also the time of year when land surface can have utmost impacts on weather and climate since land surface is largely coupled from the atmosphere due to weakened influences of tropical ocean anomalies (Dirmeyer 2003). Therefore, in-depth research is needed to investigate the impacts of land-surface conditions on the performance of coupled seasonal forecasts in the austral cool seasons.

Many modelling studies have shown that land surface conditions, especially soil moisture, can influence the variability and predictability of precipitation and surface temperature from subseasonal to seasonal time scales. For example, two phases of the global land–atmosphere coupling experiment (GLACE) intercomparison project (http://gmao.gsfc.nasa.gov/research/GLACE) showed regions where soil moisture has significant impact on surface temperature and precipitation and further assessed the impact of improved soil moisture initialization on forecast skill using a multi-model approach (Koster et al. 2004, 2011). It is well understood that soil moisture directly affects surface temperature through its impact on partitioning surface radiative energy into latent and sensible heat fluxes. In contrast, how soil moisture affects precipitation is more complex since it involves both energy and water cycles in the system and contains a range of positive and negative feedbacks, including effects on the growth of atmospheric boundary layer and large-scale circulation (Cook et al. 2006). Thus, it can even affect precipitation in remote regions (Douville 2002; Zhang and Frederiksen 2003). Most of these studies were focused on the impacts in the Northern Hemisphere. In this report, we investigate the predictability associated with soil moisture from sub-seasonal to seasonal time scales on Australia.

ACCESS-S1 (the seasonal prediction version of the Australian Community Climate and Earth-System Simulator) is planned to be the Bureau of Meteorology's next generation seasonal prediction system, replacing the Bureau’s current operational system POAMA in 2017. ACCESS-S1 is based on the UK Met office (UKMO) GC2 system but with our own initial perturbation scheme in generating atmosphere initial conditions for ensemble runs. Comparing to POAMA system, ACCESS-S1 has higher resolution of the component models (atmosphere and ocean) and state-of-the-art physics parameterisation schemes (for more details see Hudson et al. 2017 in Table 1). The first version of ACCESS-S can be viewed as a "fast-track" option which will not include our coupled data assimilation system being locally developed to provide ocean-atmosphere coupled initial conditions. One of the major issues in ACCESS-S1/GC2 is that it uses soil moisture climatology (with drift correction) rather than realistic soil moisture conditions to initialize the land surface model. Therefore, in this study we assess to what extent such unrealistic soil moisture initialization affects the model hindcast skill with particularly focus on exploring such influence for the austral cool season (May-June-July) when the model forecasting skill is of significant value to agriculture activities as aforementioned.

In this research report, we detail a suite of sensitivity experiments to explore the impact of land-surface initialization on its forecasting skill. Accordingly, it is structured as follows: Section 2
briefly introduces the system ACCESS-S1, how we generated the land initial conditions, and sensitivity experimental design. Section 3 shows the impacts of land-surface initialization on the mean state and forecast skill, and comparison with POAMA. It is then followed by discussion and conclusions in Section 4. In addition, we also report some issues in ACCESS-S1 in Appendix A and the measure of the ensemble performance in Appendix B to be considered for the ACCESS-S2 development.

2. MODELS, LAND DATA, AND EXPERIMENT DESIGN

2.1 The ACCESS-S1 compared to POAMA

Figure 1: The ACCESS-S1 compared to POAMA system.

Figure 1 shows the key components of ACCESS-S1 and POAMA systems. ACCESS-S1 is largely based on the UKMO GC2 configuration. Besides higher resolution of ACCESS-S1 component models (atmosphere and ocean), sea ice model, it has also more advanced physics parameterisation schemes than POAMA. In particular, ACCESS-S1 uses JULES (Joint UK Land Environment Simulator) land surface model version 4.1 (Best et al. 2011; Walters et al. 2015), which has 4 soil layers to represent surface hydrology and fluxes of heat and moisture within the soil column. Land cover heterogeneity is also represented in JULES through sub-grid tiles. In contrast, POAMA uses a much simplified and old bucket land surface model with one layer soil wetness and 4 layers of soil temperature in calculating surface energy and water partitions and no explicit consideration of canopy processes.

2.2 JULES offline model configuration and atmosphere forcing data

As in GC2, ACCESS-S1 hindcast land-surface initialization uses soil moisture climatology derived from a JULES offline run after bias correction to account for the mean differences between averaged soil moisture produced by JULES in its NWP system and its offline averages (personal communication). Assessment of the GC2 and ACCESS-S1 forecast skill over Australia (Shi et al., 2016; Lim et al. 2016) reported degraded forecast skill for temperature compared to POAMA despite its advantages in model resolution and physics. As POAMA uses interannually varying soil moisture to initialize its land model, it is important to understand if
the inferior skill despite using better representation of land surface process model (i.e., JULES vs. simple bucket model) is due to poor land-surface initialisation employed.

In order to perform forecast skill sensitivity assessment, the first key task is to produce “realistic” soil moisture conditions for its land model JULES so we can use them to initialise ACCESS-S1 and compare its forecast skill with/without using these “realistic” soil moisture initial conditions. So far, there is no global scale long-term observational soil moisture dataset readily available for the purpose of our assessment and soil moisture is in fact a conceptual variable which is highly model-dependent. Therefore, land surface model offline simulation with reanalysis-based atmosphere forcing data becomes an attractive alternative to create land-surface data which are close to reality.

In this study, we use the same version of JULES (version 4.1) as used in ACCESS-S1 in our land-surface offline experiments to generate land surface initial condition to be used in our sensitivity study. Full details on JULES are available on http://jules-lsm.github.io/vn4.1/ and in Best et al. (2011) and Clark et al. (2011) and it is only briefly introduced here. It has 4 soil layers of thickness 0.1, 0.25, 0.65 and 2.0 m from top to bottom. JULES views each gridbox as consisting of a number of surface types, and each surface type is represented by a tile with a separate energy balance calculated. The gridbox average energy balance is calculated by weighting the values from each tile. This version of JULES uses 5 vegetation tiles (broadleaf trees, needle-leaved trees, temperate C3 grass, tropical C4 grass and shrubs) and 4 non-vegetated surface types (urban areas, inland water, bare soil and land ice). As used in ACCESS-S1, the fraction of each surface type is prescribed without its dynamical vegetation component. The major differences between online JULES version in ACCESS-S1 and the offline version used in this study is that ACCESS-S1 uses TOPMODEL-like large-scale hydrology model based on Gedney and Cox (2003) and Clark and Gedney (2008) in runoff generation calculation and a river routing scheme as described in Fallon et al (2007) for calculating freshwater flow from the land into the oceans in the coupled forecast system. Both options are not used in the offline JULES runs while we are in the process of evaluating impacts of these processes on model soil moisture and temperature simulations and forecasts.

The forcing data required for driving offline JULES include 2-meter air temperature, humidity, 10-meter wind, precipitation, surface radiation components, and surface pressure. In this study, we use the 3-hourly ERA-Interim (Dee et al. 2011) reanalysis as atmosphere forcing data to drive the JULES offline model for the period of 1990-2012. The offline simulation covers the period of 1990 to 2014, with a 10-year spin-up period starting in January 1980. There have been a number of studies showed the importance of correcting precipitation errors in these reanalysis products as precipitation is a chief driving force for the land-surface processes and the numerical model products often do not have the desirable quality for this variable (Zhao and Dirmeyer 2003). Therefore, in preparing JULES offline forcing data, we have paid particular attention to correct the ERA-interim precipitation data with observational monthly GPCP (Global Precipitation Climatology Project) v2.2 data (Adler et al. 2003, Huffman et al. 2009). In such a hybridization process, the reanalysis systematic errors are removed via a scaling factor that is based on the ratio of observed monthly precipitation to reanalysis estimates, rather than by subtraction of the mean error:

\[
[P]_{Y,M,D,T} = \frac{[P_{OBS}]_{M}}{[P_{ERA}]_{M}} [P_{ERA}]_{Y,M,D,T}
\]  

(1)
To adjust precipitation forcing data, the value at a grid box for a given year ($Y$), month ($M$), day ($D$) and 3-hour time interval ($T$) is scaled by the ratio of the monthly mean observed precipitation to the corresponding mean value from the reanalysis for that month. This approach avoids problems of negative values for positive definite quantities and provides attainable improvement in the reanalysis estimates given the lack of a long-term sub-monthly global observationally-based dataset (Zhao and Dirmeyer 2003).

To evaluate the quality of soil moisture and soil temperature data from this offline setup, we have verified them with another independent soil moisture dataset from AWAP (Australian Water Availability Project; Jones et al. 2009) in which observed rainfall data and other forcing data over the Australian continent were used in driving a water balance model to monitor its surface water storage. The correlation for normalized soil moisture between our JULES offline and AWAP soil moisture exceeds 0.95. This adds to our confidence that the JULES offline soil moisture and soil temperature have reasonable quality to be viewed as “realistic” surface conditions to be used in initialising ACCESS-S1 hindcasts.

### 2.3 ACCESS-S1 hindcast experimental design

Due to limited resources, we decided to conduct a set of 11 member ensemble hindcasts starting on 1st May for 1990-2012 for a three-month integration. We have discussed in the introduction section that we target the assessment for the austral cool seasons because it is a critical period for the most of the agriculture activities in Australia and a period when land surface can have utmost impacts on weather and climate in the absence of strong influences of tropical ocean anomalies (Dirmeyer 2003). Studies from POAMA (personal communication with Eun-Pa Lim) also showed that land surface makes large contributions to Tmax prediction skill from March to June over Australia. In the analysis, results of this experiment are compared to the ACCESS-S1 and POAMA E24a hindcasts for the same period with the same start dates. In this report, we focus on the comparisons between CTL, LIC and E24a runs:

- **CTL**: standard ACCESS-S1 configuration in which a climatological soil moisture but interannual time varying soil temperature from ERA-Interim are used to initialise JULES;
- **LIC**: using interannually time varying soil moisture and soil temperature generated from our JULES offline run;
- **LICC**: climatological soil moisture from our JULES offline run but interannual time varying JULES offline soil temperature. This is to be more comparable with CTL setup. Comparing CTL, LIC and LICC allows us to assess if the impacts are due to the use of “wrong” soil moisture climatology (with the drift correction) or due to the use of varying soil moisture initial conditions which vary year to year;
- **E24a**: POAMA system which uses ALI coupled initialisation method (coupled breeding scheme) with interannually time varying soil moisture and soil temperature.

### 3. IMPACT ON THE MEAN STATE AND FORECAST SKILL

We calculate anomaly correlation coefficients (ACC) and spatial correlations to assess the performance of the forecast skills for precipitation (Prec), maximum temperature (Tmax) and minimum temperature (Tmin) anomalies over Australia and the globe. These anomalies are created against a mean climatology derived from ensemble mean hindcasts that is a function of start date, lead time and grid box. The climatology is subtracted from a given ensemble mean
forecast to produce the forecasted anomalies, and in doing so we effectively make a first-order linear correction for the model bias or drift. The forecasts are then compared with observational data using the 0.25° resolution Australian Water Availability Project (AWAP) gridded datasets (Jones et al. 2009). The observed anomalies are calculated using the AWAP climatology for the same 23 year period (1990-2012) as in the ACCESS-S1 hindcasts.

3.1 Impact on surface temperature diurnal range

In GC2 which ACCESS-S1 is based on, UKMO applied mean drift correction to climatological soil moisture to initialize the land surface model JULES (personal communication with UK). Figure 2 shows the differences of soil moisture climatology between UKMO GC2 (the same as ACCESS-S1 CTL run) and JULES offline at each soil layer. At the top layer, the JULES offline is normally dryer than GC2 roughly in between 40°S to 50°N. It shows dryer top soil wetness over the north and eastern Australia. In contrast, the JULES offline is much wetter than GC2 in layers 2 to 4 over a large part of the continental areas, including over the Europe, North Africa, African monsoon region, east and north Asia, east North America and Brazil. The most significant differences occur at the bottom soil layer where the difference is up to 500 kg/m³. In Northern Hemisphere, the differences show more zonal contrast whereas in the Southern Hemisphere it shows more north-south contrast, especially over Australia where the JULES offline is wetter in the north Australia but dryer in its south.

Such climatology differences of soil moisture impact on the temperature diurnal range up to 3-month lead time. Figures 3 and 4 show the differences of Tmax and Tmin between LIC and CTL runs at lead time 0, 30, 60 and 91 day (left and middle panels) and at lead time 0, 1 and 2 month (right panel). At the lead time 0 day, the spatial pattern of Tmax and Tmin differences is quite similar but with the opposite sign except for high latitudes (north of 65°N). This means that using JULES offline soil moisture leads to increases in Tmax but decreases in Tmin, thus, increase the temperature diurnal range (see right panel in Figure3, ld0). The regions with increased diurnal range match well the regions where the surface layer soil moisture climatology differences are dryer in JULES offline than GC2. With increased lead time, these
soil moisture differences remain influential on Tmax, over the middle and high latitudes in the Northern Hemisphere, middle Africa and Brazil, especially over Eurasia and east of America. This well matches the regions where the differences at the deep soil layer have the positive sign in Figure 2 (e.g., wetter in JULES offline climatology). In contrast, the impact of soil moisture differences on Tmin weakens with longer lead time and tends to show the same sign to Tmax and leads to decrease the surface temperature diurnal range (ref Figure 3 right panel, lead time 1 and 2 month (e.g., lt1 and lt2). It implies that fast responses of surface temperature to drier soil moisture initial condition. Whereas, the response to wet soil moisture initial condition is slower and it mainly impacts on Tmax.

Note that soil moisture initialisations in LIC and CTL hindcasts differs in two aspects: (i) their mean climatologies are different due to the drift correction as shown in Figure 2; (ii) climatological soil moisture was used in the CTL runs (i.e. each hindcast used the same soil moisture initial conditions regardless the year of hindcast) while it is time-varying in LIC in which each hindcast used the corresponding JULES offline soil moisture as its initial condition for that year. Therefore, another possible reason causing the difference between LIC and CTL could be due to the fact that LIC used different soil moisture initial conditions for each hindcast years. To explore that effect, we have examined the differences between LIC and LICC runs in which climatological soil moisture from JULES offline was used (Figure 4). The magnitude of the overall impact is nearly 10 times smaller than the impacts due to biases in soil moisture initial condition (Figure 3, right panel). The spatial pattern of the impacts is also different. There
are some different features over Australia: the impact is large at shorter lead time between LIC and CTL but the impacts due to time varying vs. climatological soil moisture (LICC against LIC) is significant up to 2-month lead time. Furthermore, due to the major impact driving by the differences between soil moisture, the different soil temperature initial conditions between JULES offline and GC2 seem to only have notable impacts on the high latitudes for both Tmax and Tmin up to 2 month lead time (compared Figure 3 and Figure 5), but with very small impact on the diurnal range since it has the similar impact on Tmax and Tmin (Figure 4).

Figure 4  The differences of temperature diurnal range between LIC and LICC at lead time 0, 1 and 2 month.
3.2 Impact on the precipitation biases and atmosphere circulation

Different soil moisture initialization not only affects forecasting surface temperature and its diurnal range, but also impacts its precipitation biases and atmosphere circulation (Figures 6 and 7). In Figure 6, precipitation differences not only exist over the continents but also over the Indian Ocean and Maritime Continent up to 2 month lead time between LIC-LICC and between LICC-CTL. These differences account for about 20% of the model precipitation biases over these regions (Figure not shown). Over the land, our results tend to suggest the impacts due to soil moisture climatological biases in the model initialisation (LICC-CTL) are more significant than using climatological soil moisture against interannually varying soil moisture (LIC-LICC) in ACCESS-S1 initialization. ACCESS-S1/GC2 has wetter soil in the whole soil column compared to JULES offline. Therefore, it produces more surface evapotranspiration to moisten the overlying atmosphere. The evaporative cooling effect also results in reduced surface sensible heat and therefore reduced Tmax. Land-air interactions not only affect the surface energy and water partitions, but also influence the atmospheric circulation. Thus, different soil moisture initializations not only have impacts on the land but also over the ocean (Figure 7). Over the land, changes in the mean sea level pressure (MSLP) have some linkage to different soil moisture conditions used in the initialization. For instance, JULES offline soil moisture is much drier over a large part of the Tibetan Plateau and nearby Eurasian inland region between LIC and CTL, LICC-CTL and over this region lower MSLP is shown in Figure 7. This can be linked to the development of surface heat-low. At the same time, dry soil moisture in southern part of the Australian continent in LIC corresponds to high pressure anomalies and some poleward shift of the storm track in the austral autumn season. This can partly be understood as such that reduced soil moisture in LIC does not favour the convection and rainfall generation due to weakened local water recycling through evapotranspiration, therefore less storm track inland penetration due to reduced atmospheric diabatic heating. Note, a large part of the changes in MSLP in the polar region and high latitudes could well be the model internal noise and we
need further analysis to examine such region. Throughout this analysis, we are more focused on the regions over land areas.

Figure 6 The differences of precipitation between LIC and CTL (top panel), LIC and LICC (middle panel), LICC and CTL (bottom panel) at lead time 0 (left panel), 1 (middle panel), and 2 (right panel) month in May.

Figure 7 The differences of mean sea level pressure between LIC and CTL (top panel), LIC and LICC (middle panel), LICC and CTL (bottom panel) at lead time 0 (left panel), 1 (middle panel), and 2 (right panel) month.
3.3 Impact on the forecast skill

In this section, we assess the skill of the model seasonal forecasts for the 23-yr period with 0-month lead which means the forecasts are initialized on 1st of May and the forecast period is May-Jun-Jul (MJJ). In addition, 1–6-week multi-week forecast and sub-seasonal forecasts skills are also evaluated. The AWAP datasets are used for such skill assessment.

3.3.1 Seasonal forecast skill

Figure 8 shows the Anomaly Correlation Coefficient (ACC) skill over Australia. Given the relatively small sample size (n=23) only correlations exceeding 0.4 can be considered as statistically significant (at the 90% confidence level). Seasonal forecasts of Tmax are usually more skilful than forecasts of Prec and Tmin. Comparing forecasts from CTL with LIC experiments, the results show that different land initial conditions have the largest impact on Tmax over the whole Australia, especially over the north and east of Australia. The impacts on Tmin and Prec are relatively moderate and mainly over the southern part of Australia. Comparing skills from ACCESS-S1 with POAMA (e.g., CTL/LIC and E24a run), ACCESS-S has better rainfall forecast skill over north-west Australia but less skill over its east. For Tmax, ACCESS-S has better skill over the southern part of the Australian continent except for the south west western corner. For Tmin, ACCESS-S has better skill over western and eastern Australia but less skill over central Australia.
Figure 8 Anomaly Correlation Coefficient (ACC) between LIC, CTL, E24a run and AWAP data for seasonal mean Prec (top), Tmax (middle) and Tmin (bottom) anomalies for 0-month lead in MJJ season. Statistically significant correlations exceed 0.4 is at the 90% confidence level (n=23).
3.3.2 Monthly forecast skill

Figure 9 compares the model skill for forecasting monthly surface climate anomalies at LT-0. It shows the impacts due to different soil moisture climatologies (i.e., LICC against CTL) and due to climatological vs. interannually varying soil moisture (LIC against LICC). For Prec, LICC has better skill over the south-east of Australia than CTL, but using interannually varying soil moisture initial condition seems to reduce the skill in this region. Over north-central Australia, both LIC and LICC runs offer better skill than CTL regardless whether it used an interannually time varying or invariant soil moisture initial conditions in the 23 hindcasts. Comparing ACCESS-S1 with POAMA, its major skill improvement occurs over the central (especially north-central) and south-eastern parts of Australia but less over the central-east of Australia. For Tmax, our results clearly show that using realistic soil moisture initial condition leads to significant improvement over eastern Australia, and using realistic climatological soil moisture contributes to better skill over the north-central and south-east Australia. Compared with POAMA, the skill improvement occurs over a large part of Australia except for west coastal and some regions over northeast. For Tmin, using realistic climatological soil moisture contributes to the skill improvement over eastern Australia whereas using interannually varying soil moisture only contributes to the skill improvement over the south-eastern region. Comparing ACCESS-S1 with POAMA, it has better skill over western and eastern Australia but less skill over areas in the states of South Australia and Western Australia.

Figure 9 Anomaly Correlation Coefficient (ACC) between LIC, LICC, CTL, E24a run and AWAP data for monthly Prec (left panel), Tmax (middle panel) and Tmin (right panel) anomalies at 0-month lead in May (i.e., the first column from top to bottom). The second column is the difference between LIC and CTL, LICC and CTL, LIC and LICC, and LIC and E24a from top to the bottom.
Besides the ACC skill assessment, we have also calculated the spatial pattern correlation over the whole Australia for Prec, Tmax, and Tmin anomalies in each hindcast year (Figure 10). For Prec, using realistic and time-varying land initial condition (LIC) does not show significant impact except for year 2007. We rather see some decadal signal in the year-to-year variations of Prec hindcast skill, which reflects the Inter-decadal Pacific Oscillation (IPO) signature. In the early hindcast period (1990-1999) when the IPO was in its positive phase (i.e., El Nino-like pattern with broader meridional extents), the performance of POAMA is close to that of ACCESS-S1, and the performance of the hindcasts by using climatological soil moisture (CTL and LICC) is even slightly better than LIC with interannually varying soil moisture initial conditions. By contrast, POAMA skill drops in the late period of 2000-2012 when the IPO was in its negative phase (i.e., La Nina-like pattern with broader meridional extents) while ACCESS-S1 maintains its skill. Furthermore, using interannually varying soil moisture has better skill than by using climatological soil moisture as its land-surface initial condition. We find that is partly due to the fact that the precipitation anomalies in the late period showed more localised features. Thus, higher spatial resolution in ACCESS-S1 gains better skill than the low resolution system such as POAMA. For Tmax, using realistic time-varying soil moisture initial condition always has better skill in both periods. Both ACCESS-S1 and POAMA show higher skill in the early period than in the late period and ACCESS-S1 is always better than POAMA in both periods. For Tmin, the IPO signature is not as significant as Prec and Tmax. It is also not sensitive to different land initialisation (i.e., using climatology vs. interannually varying). Again, the skill of ACCESS-S1 is always better than the skill in POAMA for both periods. However, the skill in the late period is slightly better than in the early period for both systems.

Figure 10 Spatial correlations over Australia for forecasted monthly anomalies of Prec (top), Tmax (middle) and Tmin (bottom) between CTL, LICC, LIC, E24a hindcasts and AWAP observations in May. On the X-axis, “total” denotes the value averaged in the whole hindcast period (1990-2012); “early” denotes the value averaged from 1990 to 1999 (IPO positive phase); “late” denotes the value averaged from 2000 to 2012 (IPO negative phase).
3.3.3 Multi-week skill

In the analysis, we have assessed impacts of different land initial conditions on the model the multi-week forecast skill at 1~6-week (Figure 10). Own to better atmosphere initial condition (e.g., ERA-Interim, Dee et al. 2011) used to initialize the ACCESS-S1 and better dynamics and physics scheme in the model, ACCESS-S1 demonstrates higher forecast skill in the first two weeks for Prec, Tmax and Tmin than POAMA. The relatively high skill remains up to the third week. Again, averaged over Australia, the impact of using different land initial conditions (LIC vs. CTL) is relatively small compared with the gain from the system upgrade in the first 3 weeks of the forecasts. In contrast, the use of climatological soil moisture initial conditions including the drift correction in ACCESS-S1 causes significant forecast errors in Tmax, especially at week 4 and 5.

![Figure 11](image)

**Figure 11** Anomaly Correlation Coefficient (ACC) between LIC, LICC, CTL, E24a hindcasts and AWAP data averaged over Australia for Prec (left), Tmax (middle) and Tmin (right) anomalies at multi-week LT.

4. DISCUSSION AND CONCLUSIONS

ACCESS-S1 is the next version of the Bureau of Meteorology's seasonal prediction system. Due to the fact that ACCESS-S1/GC2 used unrealistic soil moisture climatology to initialize the ACCESS-S1 land surface model (JULES), in this study we have investigated the impacts of different land initial conditions on the hindcast skill from the ACCESS-S1 system. We have also compared its skill with that of POAMA. In addition, we report some issues (see Appendix A and B) in ACCESS-S1 to be considered in the ACCESS-S2 development. In this report we have focused on the performance of ACCESS-S1 for forecasts of Australian climate anomalies at multi-week, monthly and seasonal timescales for Prec, Tmax, and Tmin from a suite of hindcasts initialise on the 1st of May.

The impacts of using different land initial conditions on ACCESS-S1 hindcast skill are consistent with many other studies (Koster et al. 2004, 2011): it has larger impact on the skill of
surface temperature than on the skill of precipitation and the impact can be seen up to 90 day integration period. The clear impacts on surface temperature over north-east Australia are also similar to multi-model results from GLACE-2 experiments (Koster et al. 2011) although GLACE-2 was focused on JJA season. Soil moisture conditions affect surface energy and water partitions, and thus surface latent heat and sensible heat fluxes will be affected at longer time-scale due to some slowly-varying soil hydrological processes. Its impacts on the temperature forecast skill can be directly linked to its partition of surface radiative energy into more sensible heat flux (Figure 12) and more warmed temperature when the soil is dryer. But the impact of soil moisture on precipitation is complex. It can be realised by surface evaporation as a moisture source to the atmosphere and by the fact that surface fluxes affect the atmospheric boundary-layer processes. In this analysis, we have not conducted in-depth analysis of such processes involved. Furthermore, we have separated the skill differences due to two different reasons: one is the difference between LIC and CTL which display the impact due to different land initial conditions; the other is the difference between LIC and E24a which indicates the impact associated with system upgrade.

Figure 12  The differences of ACC skill between (a) LIC and CTL and (b) LIC and E24a for sensible heat flux (Hsens) at 0-month lead in May. Verification data is JULES offline result.

From results seen in Figure 12 and Figure 9, we can, by and large, identify three regions with significant skill improvement caused by the impact of land initial condition and one region where the skill gain can be attributed to the system upgrade.

- In the light green circle region (Fig. 12a), Prec skill has relatively large improvement. This is due to the impact of climatological soil moisture differences and due to climatological vs. interannually varying soil moisture initial conditions. Tmax also has skill improvement in this region but it is mainly due to the impact of climatological soil moisture vs. interannually varying. Tmin has the least improvement and it is mainly due to different soil moisture climatology used in initialising land-surface.

- In the magenta circle region, Tmax has significant skill improvement and it is largely due to climatological vs. interannually varying soil moisture initial conditions. Tmin has weak skill improvement in the region close to the inland and south due to the improvement in the quality of climatological soil moisture (i.e. LICC compared to
 Prec has slightly skill improvement and the location is in line with Tmin skill gain.

- In the blue circle region, Prec, Tmax and Tmin all show skill improvements. For Prec, it is largely due to the improvement in the climatological soil moisture (LICC compared to CTL). For Tmax and Tmin, skill improvements come from improvements in both better representation of climatological soil moisture and the use of time-varying soil moisture information.

- In the dark green circle region (Fig. 12b), Prec and Tmax have relatively large skill improvements due to the system upgrade. However, for Tmin, the skill improvement is shifted to the east from the central region. Prec, Tmax and Tmin all have relatively large skill improvements over the southeast part of the continent due to the system upgrade.

From all the skill assessment (ACC and spatial correlations), the impact of land initial condition is larger than the impact of system upgrade for Tmax, but not for Prec and Tmin. Also, the impact of land initial condition for Tmax is mainly due to climatology vs. interannual, but for Prec and Tmin are largely due to two different soil moisture climatologies. The impact of land initial condition is located where soil moisture has large standard deviations, whereas the impact of system upgrade is located where the skill is relatively lower in POAMA.

In the skill measured by spatial correlation of observed and forecasted climate anomalies, we do not find notable ENSO signature, but we do find a decadal signal reflecting the IPO in forecast skill of precipitation. Generally, during the IPO positive phase (before 1998-1999), the skill differences between the two systems are small and the impact of land initial condition on the skill is relatively small. By contrast, during the IPO negative phase (after 1998-1999), the skill differences between two systems appear to be larger and forecast skill for Prec and Tmax shows greater sensitivity to the different land initial conditions used in our three ACCESS-S1 experiments. This implies that high-resolution model and realistic land initial condition have more impact during the IPO negative phase since the forecast pattern of Prec and Tmax shows more localized features.

In addition, we have shown the impact of land initial conditions on the mean state, such as temperature diurnal range, precipitation biases and atmosphere circulation. The land initial condition has more impact on Tmax than on Tmin, and this impact can lead up to 3 months. The surface temperature response to dry soil initial condition is quicker than over the wet soil initial condition. However, the impact associated with dry soil initial condition decreases with longer lead time, whereas the impact associated with wet soil initial condition increases with longer lead time. It implies that a positive feedback between precipitation and evaporation. The impact of land initial conditions not only changes the local surface temperature and precipitation, but also changes the large scale atmosphere circulation. Therefore, it leads some remote effects on the precipitation and even causes rainfall differences over Indian Ocean and Maritime Continent. Nevertheless, we acknowledge more investigations are needed to explore the underlying processes on the remote effects of different soil moisture initialisation.
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APPENDIX A: ISSUES IN ACCESS-S1 SYSTEM

We found some issues in ACCESS-S1 hindcast, therefore, we report in here and give the guideline for ACCESS-S2.

- **Bullseyes problem:** When we verified ACCESS-S1 hindcast results with AWAP or JULES offline data, we found the bullseyes problem in forecast all the surface variables and only show Tmax as example in Figure A1. ACCESS-S1/GC2, GA6, and TransposeAMIP runs share the same features, but not in APS2/APS3/JULES offline runs in which the river routing scheme not used. Bullseyes are caused by the river routing model coupled with JULES, river-flow transporting water to inland basins and wetting the soil. The outflow from the rivers is used for fresh water fluxes for the ocean, but if the river stops inland, then the water just disappears as it is not added back into the system (e.g., add in the soil moisture). Obviously this is an issue for a climate model as it does not conserve the water balance. In reality a river ending inland should form a lake. However, this would have required major development because it would require interactive surface fractions and an interactive lake depth, neither of which were capabilities at the time. For seasonal forecast, we are not concerned about conservation of water, and therefore, the easiest solution will be to turn off the re-routing part in ACCESS-S2 and coupled data assimilation to avoid bullseyes problem. It is worth pointing out that this is not an error but inconsistency between the configurations of coupled models and land surface models (i.e., the verification data - AWAP or JULES offline data do not include the river routing effect). We suggest turning off this option for seasonal forecast (see Figure A2), but it should not be turned off for multi-year or climate change simulations.

![TRIP RIVER PATHWAY](image)

**Fig. A1** The bullseyes show in the difference of Tmax forecasts at 20 day lead time between LIC and CTL runs (right panel) which are co-located well with the river sequence ancillary value equal to "9" – inland basin/depression (left panel).
TOPMODEL problem: Improving the treatment of subgrid-scale soil moisture variations is recognized as a priority for the next generation of land surface schemes. TOPMODEL used probability functions to describe the sub-grid distribution of soil moisture. The Probability Distributed Model (PDM) based model only change the calculation of surface runoff and retain the standard description of subsurface runoff, and this limits the possible improvement in performance. The TOPMODEL is applied in coupled ACCESS-S1 but not in JULES offline run (see Figure A3). The topographic index is a hydrological quantity describing the propensity of the soil at landscape points to become saturated with water as a result of topographic position (i.e. not accounting for other factors such as climate that also affect soil moisture but are accounted for separately). However, the Australian continent is not included in the current version of the ancillary file for parameters: mean topographic index and the standard deviation of topographic index (see Figure A4). Figure A5 shows the differences of soil moisture at each layer between LIC and JULES offline at lead time 91 days. It indicates that including the TOPMODEL mainly affects the high topography regions along the coast line over Australia.
The options for large-scale hydrology scheme (LSH), TOPMODEL in UMUIX and the options in ACCESS-S1 are: lhydrology=.true., lsoil_sat_down=.true. and ltop=.true.

The ancillary files (index and parameter) for TOPMODEL model.
Fig. A 5 The differences of soil moisture at each layer between LIC and JULES offline at lead time 91 days.
APPENDIX B: MEASURE OF ENSEMBLE PERFORMANCE

It is well known that in a perfectly reliable ensemble the spread of ensemble members around the ensemble mean forecast should equal or close to the root mean square error of the mean.

Figure B1 shows the normalized root mean square error (NRMSE, solid line) and normalized spread (NSPREAD, dash line) for daily Tmax averaged over Australia verified with AWAP data for CTL, LICC, LIC and E24a runs. Since ACCESS-S1 only applied the ensemble perturbation for the atmosphere initial condition but not to the land and ocean initial conditions, the spread of CTL, LICC, and LIC runs is much smaller than E24a run which used coupled breeding scheme to generate the ensemble perturbation for the land, atmosphere and ocean initial conditions, especially within the first 5 days. No matter whether a drift correction climatology soil moisture (CTL) or JULES offline interannual time varying soil moisture (LIC) is used as the initial condition, they both have quite large NRMSE within the first 3 days, especially in the first day compared to E24a run. It indicts that the initial shock over the land is quite large in ACCESS-S1. Generally, POAMA system has relatively smaller NRMSE than ACCESS-S1 system. This is due to POAMA system applied the coupled breeding scheme to generate the initial conditions for land, atmosphere and ocean. It includes a part of the model drift and makes the three components more dynamic balanced. Therefore, it reduces the initial shock and NRMSE as well as increases the NSPREAD. In addition, it makes the NSPREAD more close to the NRMSE after 20 days.