

Does Soil Moisture Influence Climate Variability and Predictability over Australia?

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ABSTRACT

Interannual variations of Australian climate are strongly linked to the El Niño–Southern Oscillation (ENSO) phenomenon. However, the impact of other mechanisms on prediction, such as atmosphere–land surface interactions, has been less frequently investigated. Here, the impact of soil moisture variability on interannual climate variability and predictability is examined using the Bureau of Meteorology Research Centre atmospheric general circulation model. Two sets of experiments are run, each with five different initial conditions. In the first set of experiments, soil moisture is free to vary in response to atmospheric forcing in each experiment according to a set of simple prognostic equations. A potential predictability index is computed as the ratio of the model's internal variability to its external forced variability. This estimates the level of predictability obtained assuming perfect knowledge of future ocean surface temperatures. A second set of five experiments with prescribed soil moisture is performed. A comparison between these two sets of experiments reveals that fluctuations of soil moisture increase the persistence, the variance, and the potential predictability of surface temperature and rainfall. The interrelationship between these two variables is also strongly dependent upon the soil water content. Results are particularly marked over Australia in this model. A novel feature of this study is the focus on the effectiveness of ENSO-based statistical seasonal forecasting over Australia. Forecasting skill is shown to be crucially dependent upon soil moisture variability over the continent. In fact, surface temperature forecasts in this manner are not possible without soil moisture variability. This result suggests that a better representation of land–surface interaction has the potential to increase the skill of seasonal prediction schemes.

1. Introduction, background, and methodology

Australia experiences large variations of rainfall on different timescales with considerable impacts on social and economic activities (Nicholls 1985; Drosowsky 1993; Allan et al. 1996). Thus, seasonal prediction is a crucial activity for the Australian Bureau of Meteorology. The present seasonal rainfall prediction scheme uses a statistical forecasting method based on the lagged relationship between sea surface temperatures (SSTs) and Australian rainfall (Drosowsky and Chambers 1998). The single most important predictor used is a SST pattern centered in the Pacific Ocean, intimately

linked with the El Niño–Southern Oscillation (ENSO) phenomenon.

In this study we will explore the importance of soil moisture variability in helping to establish the lagged association between ENSO and Australian rainfall underpinning the operational scheme. There is a striking analogy between soil moisture and SST anomalies. The ocean acts as an integrator of high-frequency atmospheric thermal forcing (Hasselmann 1976; Frankignoul and Hasselmann 1977). The soil plays a similar role by integrating white-noise precipitation and creating a red-noise time series of soil moisture anomalies (Delworth and Manabe 1988). However, the timescale of the soil moisture variability is generally shorter than the timescales of the SST variability. Soil moisture interacts with the atmosphere through surface energy and water balances, and this has impacts upon the nature of the variability. This suggests that due to these characteristics and its high interannual variability, soil moisture could potentially play a role in affecting Australian seasonal

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forecasts. Because of the timescale of its variation, we might expect that properly included soil moisture may improve model prediction skill. Of course, the existence of slowly varying parameters (such as soil moisture) alone does not imply predictability, as even very simple models of the climate system show unpredictable long period responses to stochastic forcing. The first step, therefore, is to establish whether climate variations of interest are predictable.

The model used here was integrated for 10 yr following the experimental design described by Gates (1992) for the Atmospheric Model Intercomparison Project. The model is forced using observational estimates of SST and sea-ice extent for the years 1979–88, a period in which two El Niño events (1982/83, 1987) occurred. The atmospheric GCM used here is the Bureau of Meteorology Research Centre (BMRC) spectral model run with a rhomboidal resolution to 21 waves, and 17 vertical levels (McAvaney and Colman 1993). The soil moisture parametrization is a simple approach based on the Manabe (1969) bucket. Prognostic soil moisture is represented by a single-layer model; the soil is assumed to have a fixed depth. Changes in soil moisture are computed from the rates of rainfall, evaporation, snowmelt, and runoff. Evaporation from the soil is determined as a function of soil wetness and the potential evaporation rate. Two sets of integrations were performed. In the first set, the soil moisture content was allowed to vary freely (hereafter, experiment C). In the second one, the soil moisture was fixed (hereafter, experiment F) to the annual climatological cycle obtained from C ensemble mean. For each experiment, an ensemble of 5 realizations of 10 yr each, from 5 different initial conditions was run, yielding 50 yr of data for both C and F ensembles. Each set of initial conditions was generated by running the model for two days using the previous initial conditions, and then resetting the clock to the beginning of the run. The prescribed climatological soil moisture values were constructed as the mean seasonal cycle derived from the C ensemble. Thus, it does not include short-term variations (e.g., diurnal and synoptic scale) but more importantly this climatology removes interannual variations that result from precipitation variability and other meteorological forcing. This is equivalent to a decoupling of the atmospheric variability from land surface hydrological processes. For consistency with the SST forcing, soil moisture values were prescribed every five days using linear interpolation between monthly means. The model was first validated using several observational datasets (Viviani et al. 2000). The model reproduces the main features of the partitioning of surface fluxes into latent and sensible heat fluxes and outgoing longwave radiation. The simulated Southern Oscillation index (SOI) as defined by Troup (1965) is also realistic, and while mean rainfall patterns show some regional biases, the model reproduces the main features of the major teleconnections associated with ENSO.

Our first aim is to compare the potential predictability between the two ensembles. To do this we compute an index R for both sets of experiments (i.e., soil moisture fixed, soil moisture varying). Index R measures the relative importance of internal chaotic variability with the variability associated with external (SST and sea ice) forcing (see Power et al. 1995). Index R is a measure of predictability if external changes imposed on the atmosphere (e.g., SSTs) were perfectly known ahead of time. In other words, R calculates the relative magnitude of variability between each ensemble member (or *run*) compared with the magnitude of the variability of the ensemble mean:

$$R = \frac{\sigma'}{\bar{\sigma}}. \quad (1)$$

Here σ' is a measure of the model's internal variability, that is, the variability exhibited from run to run when each run is initiated from slightly different initial conditions. Here σ' is given by

$$\sigma' = \frac{1}{N} \sum_{m=1}^N \sigma_m(X_{m,k}, k \in [1, 5]), \quad (2)$$

where σ_m is the standard deviation of variability of parameter X between the K different runs at month m . Each ensemble contains five members (i.e., $K = 5$). Index R is calculated at each grid point. Seasonal means are presented for which there are 30 samples (N) available. Here $\bar{\sigma}$ is the variability of $X_{m,k}$ associated with SST forcing. It is defined as the standard deviation of the ensemble mean of the five realizations:

$$\bar{\sigma} = \sigma(\bar{X}_m), \quad (3)$$

where

$$\bar{X}_m = \frac{1}{K} \sum_{k=1}^K X_{m,k}, \quad \text{for } m = 1, N.$$

The R index is one measure of predictability; small (large) values of R indicate a high (low) level of potential predictability, and is a simple but straightforward tool to compare the two sets of experiments. See Power et al. (1995) for further details. The significance of the difference in R between the two ensembles will be assessed using a Student's t test with $K - 2$ degrees of freedom. It is worth noting that no attempt is made to differentiate between the direct effect of soil moisture and mixed effects due to soil moisture and SSTs combined. Such discrimination is possible with more elaborate techniques, such as the analysis of variance (ANOVA) described by Zwiers (1996), Rowell (1998), and Zheng and Frederiksen (1999), but it would require additional experiments to be performed. Here, both are included in what is described as the variance due to soil moisture. A permutation procedure allows us to establish the statistical significance of any difference between the two ensembles (Preisendorfer and Barnett 1983).

TABLE 1. Externally forced variance of DTR over land in each ensemble C and F (units are K²). The percentage of DTR variance explained by the variability of soil moisture is shown in the right-hand column. Stars indicate results significant at the 90% level.

Variance	Season	C	F	% variance decrease due to soil moisture variability
Northern Hemisphere	DJF	0.36	0.22	38*
	JJA	0.20	0.09	58*
Southern Hemisphere	DJF	0.50	0.13	74*
	JJA	0.34	0.15	56*
Australia	DJF	1.03	0.30	71*
	JJA	0.34	0.15	56*

2. Results and discussion

The impact of suppressing the interannual (and interseasonal) soil moisture variability on the model’s behavior is examined by comparing the F ensemble with the C ensemble. Global results are presented but discussion focuses on the analysis over the Australian continent.

First, the variability of diurnal temperature range (DTR) is analyzed (Table 1). The $\bar{\sigma}$ term [Eq. (3)] over land is averaged over summer and winter for the ensemble means of C and F. Variability is substantially reduced when soil moisture is “decoupled” from the atmosphere in experiment F. The percentage decrease in the variance ranges from 38% to 74%. The reduction of variance is more marked in summer [June–August (JJA) in the Northern Hemisphere and December–February (DJF) in the Southern Hemisphere]. This is consistent with smaller potential evaporation during the winter limiting the influence of soil moisture in the partitioning of heat fluxes and on surface temperatures. Furthermore, precipitation variability is higher in summer (see Table 3, later) when soil moisture is allowed to vary, inducing higher soil moisture variability. Delworth and Manabe (1988) found somewhat similar results: coupled soil moisture makes a substantial contribution to summer air surface temperature variability. However, in the present experiments, the contribution of soil moisture to DTR variance in winter is not negligible.

In the same way that soil moisture affects externally

TABLE 2. Ratio of internal variability (*R* index), over land, for DTR in C and F experiments. The right-hand column is the percentage increase of the *R* index for the F experiment over the C one. Stars indicate results significant at the 90% level.

<i>R</i> index	Season	C	F	% increase of <i>R</i> index F over C
Northern Hemisphere	DJF	1.73	1.82	5
	JJA	1.86	1.92	3
Southern Hemisphere	DJF	1.45	1.62	12*
	JJA	1.84	1.92	4
Australia	DJF	1.23	1.45	17*
	JJA	1.94	2.15	10*

TABLE 3. As per Table 1, but for precipitation (units are mm²).

Variance	Season	C	F	% variance decrease due to soil moisture variability
Northern Hemisphere	DJF	0.11	0.09	12
	JJA	0.22	0.16	30*
Southern Hemisphere	DJF	1.22	0.78	37*
	JJA	0.09	0.07	22
Australia	DJF	1.33	0.83	37*
	JJA	0.06	0.04	24*

forced variability of surface temperature (measured by $\bar{\sigma}$), it is also expected to modify internal model variability. One measure of this is the predictability, or *R* ratio (Table 2). The Northern Hemisphere does not exhibit marked seasonality in *R*. Moreover the contribution of soil moisture to variability is modest in both winter and summer. In the Southern Hemisphere the seasonal response is much stronger: predictability is high (*R* index small) in summer and the influence of soil moisture is also more important. This feature is particularly noticeable over the Australian continent where the percentage increase in the *R* index is much larger than for the whole Southern Hemisphere. At the same time, the percentage increase in the variance, for Australia and the Southern Hemisphere, is very similar (cf. Table 1). This suggests that over Australia soil moisture variability is a key parameter in determining the model variability, and the inclusion of interannual variation of soil moisture should increase potential predictability.

Next, the standard deviation of externally forced precipitation variability for the ensemble mean in C and F is presented in Table 3. Globally, the variance explained by soil moisture variability is smaller than that for temperature. In the Southern Hemisphere and Australia in particular, the impact of soil moisture is again greater than in the Northern Hemisphere, and precipitation variability is characterized by a very strong seasonal dependence. In general, the variance explained by soil moisture variability is greater in summer than in winter. The stronger influence of soil wetness in summer is consistent with larger potential evaporation and larger precipitation variability, as proposed by Delworth and Manabe (1988).

Higher potential predictability (lower *R*) for precipitation (Table 4) is found in the Southern Hemisphere,

TABLE 4. As per Table 2, but for precipitation.

<i>R</i> index	Season	C	F	% increase of <i>R</i> index F over C
Northern Hemisphere	DJF	1.61	1.70	5
	JJA	1.64	1.76	7
Southern Hemisphere	DJF	1.38	1.59	15
	JJA	1.47	1.58	8
Australia	DJF	1.07	1.47	37*
	JJA	1.47	1.72	17*

TABLE 5. Autocorrelation at lag 1 month of the anomalous precipitation time series over Australia for the two experiments sets (observations from Simmonds and Hope 1997).

Autocorrelation	C	Observations	F
All months	0.25 [☆]	0.18 [☆]	0.10
NDJFMA	0.26 [☆]		0.10
MJJASO	0.28 [☆]		0.14

with a striking seasonal difference; austral summer precipitation is much more predictable than is the case for winter (as also shown by Frederiksen et al. 1999). Australia appears to be the most predictive continent. This is partly due to its position within the Tropics [where up to 80% of the interannual variance is predictable, Rowell (1998)]. The decrease in rainfall predictability in F compared with C is noticeable for each season over both hemispheres but is more important in summer. The contribution of soil moisture to precipitation potential predictability, estimated by the percentage increase of experiment F's R index over that of C is more important over the Southern Hemisphere. Australia appears once again as one of the most sensitive regions. In a similar study, Koster et al. (2000) also found that the land surface is more strongly coupled with the atmosphere during summer, but they did not find such a pronounced influence over Australia as in the present experiments.

To further investigate this particular behavior over Australia, the autocorrelation at one month lag of total precipitation anomalies in the two ensembles of experiments is averaged over Australia (Table 5). Two 6-month periods are presented, corresponding with lagged periods, as well as an annual value, which can be compared with observations from Simmonds and Hope (1997). All correlations that are significantly different from zero at the 90% confidence level are underscored. The comparison of the C autocorrelation with the observational one for all months suggests that the experimental value seems reasonable (although slightly overestimated). Scott et al. (1995) have shown that models without a canopy interception reservoir (such as the land surface scheme used here) tend to increase autocorrelation. The main feature is that precipitation persistence is significantly reduced in the F experiment. The reduction exceeds 50% for the three periods considered.

Physically, precipitation persistence can be considered as a feedback mechanism. Positive anomalies of precipitation produce positive anomalies of soil moisture; this soil moisture increase then feeds back on the precipitation. It is generally accepted that this feedback operates through a diminution of the Bowen ratio: an increase in the latent heat flux and a decrease in the sensible heat flux. Delworth and Manabe (1988) have shown in a climate model that the changes in these fluxes lead to increased relative humidity, since an increase in latent heat flux results in an increase in atmospheric

moisture, while a decrease in sensible heat flux leads to a decrease in air temperature. Higher relative humidity may lead to an increased likelihood of precipitation. More detailed studies, using a weather prediction model (Betts et al. 1996) and a regional climate model (Schär et al. 1999) on shorter timescales have shown that the efficiency of convective precipitation processes is actually increased through the development of a warmer, moister, and shallower boundary layer, which provides instability, while the release of this instability is facilitated by the lowering of the free convective level.

Another impact of soil moisture variability can be found in its impact on the relationship between rainfall and DTR. Power et al. (1998) have shown that less sunshine reaching the surface in rainy years lowers the maximum daily surface temperature (T_{\max}), while reduced soil moisture during dry periods limits the effect of the evaporation. Schär et al. (1999) have shown that these dual mechanisms overall increase the net energy flux that contributes to the increased convective efficiency, mentioned above. The combined action of surface shortwave radiation and surface latent heat flux changes put rainfall and temperature out of phase. These findings are supported here (Fig. 1a). Calculated over the entire year, negative correlations between precipitation and DTR are found everywhere (a coefficient with magnitude greater than 0.2 in Fig. 1a is significant at the 99% level). This is also verified when rainfall is correlated with daily maximum surface temperature, daily averaged surface temperature, and to a lesser extent with daily minimum surface temperature (not shown). When soil moisture is decoupled, correlations are reduced over most parts of the globe (Fig. 1b). The difference is largely significant, in particular over the Australian continent during summer (not shown). In summary, changes in both latent and sensible heat fluxes from the surface due to modifications of soil moisture variability lead to the considerable weakening of the relationship between surface temperature and precipitation seen in these results.

So far we have only considered potential predictability. Potential predictability here refers to predictability given a perfect knowledge of future SSTs. It therefore provides an upper estimate on our ability to predict the model atmosphere. With potential predictability we are interested in quantifying the degree to which the atmosphere, for example, is a slave to the underlying SST; that is, quantification of the relative magnitude of internal chaotic variability over variability driven by the underlying SSTs. We now turn to actual predictability in the model. To do this we use the model's SOI prior to time t , to predict modeled rainfall and land surface temperature for time after t forced by observed SSTs. The importance of this approach is that it forms the basis of the method used in most operational forecast centers.

The correlation coefficients between ensemble mean simulated SOI and the observed one are only slightly

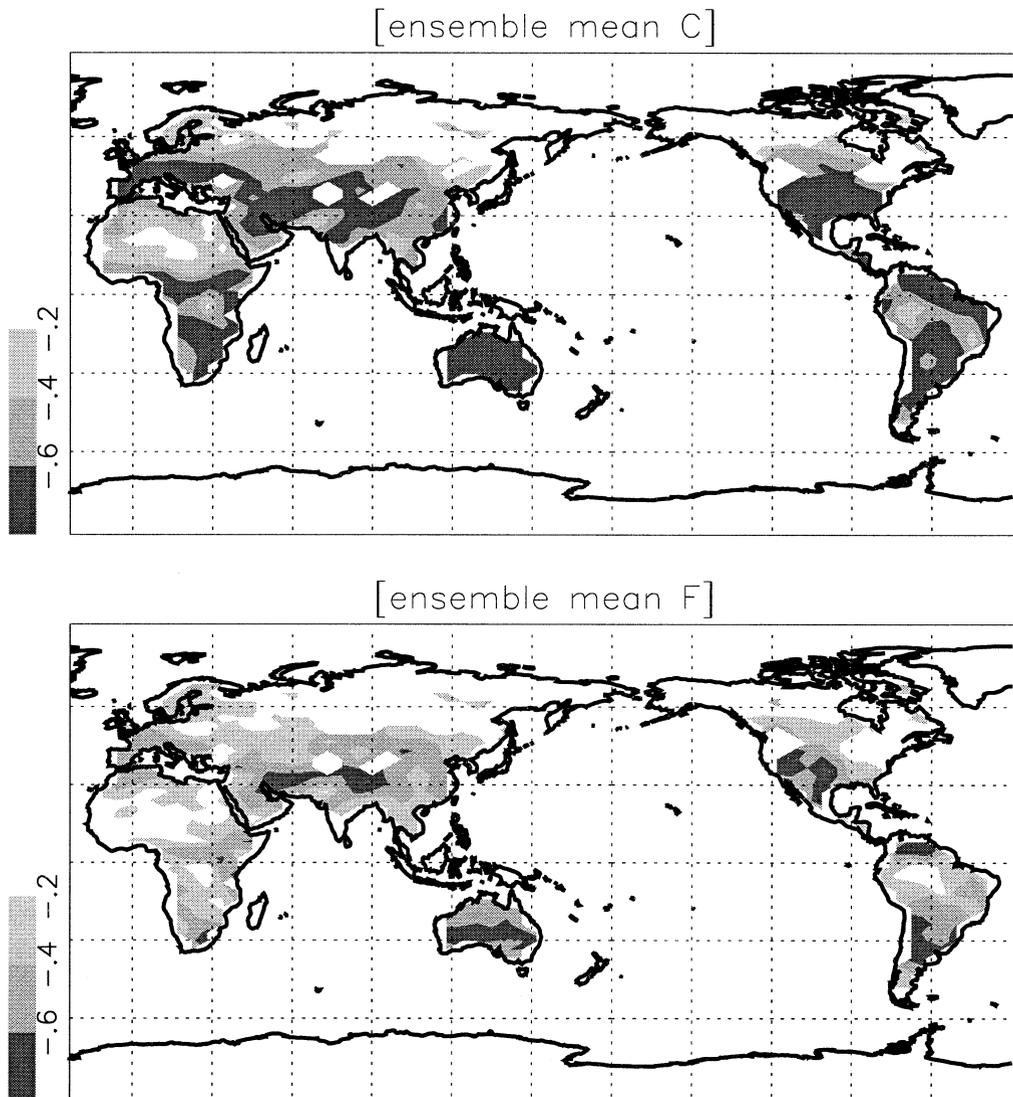


FIG. 1. Correlation at lag 0 between precipitation and DTR for all months during the period 1979–88: (top) C ensemble mean and (bottom) F ensemble mean.

reduced in the F experiments (0.81) compared to the C ensemble (0.84). Therefore correlations in both ensembles are worth investigating. The correlation of the SOI with precipitation over Australia is evaluated year-round with precipitation being lagged from 0 to 3 months (Fig. 2). In experiment C (first column), the relationship strengthens during the early period. Peak values are reached at lag 1 month in the east, and between 1 and 2 months in the northern part of the continent. At lag 3 months, the correlation is still large. For the F experiments (middle column), the correlation weakens after the first month. At lag 2 and 3 months, it has completely vanished. This marked difference in the experiments is significant in the extreme east of the continent at lag 1 month and over most of the region of interest after 2 months (Fig. 2, last column). The prescription

of climatic soil wetness amounts does not take account of hydrological conditions created by past events. These unrealistic conditions appear to break the SOI–precipitation relation. Thus soil moisture plays a crucial role in the maintenance of this relationship and keeps a memory of recent past climatic events over the continent. These results suggest that a poor knowledge of the soil hydrology could severely limit the skill of seasonal rainfall predictions over Australia using a climate model. Thus an accurate initialization of soil moisture and an improved simulation of its subsequent evolution should improve seasonal to interannual rainfall predictions. Considering the simplicity of the soil moisture scheme, the model results compare fairly well with the observed correlations taken from longer records: 1950–99 (Fig. 3). Although the model lagged correlations are some-

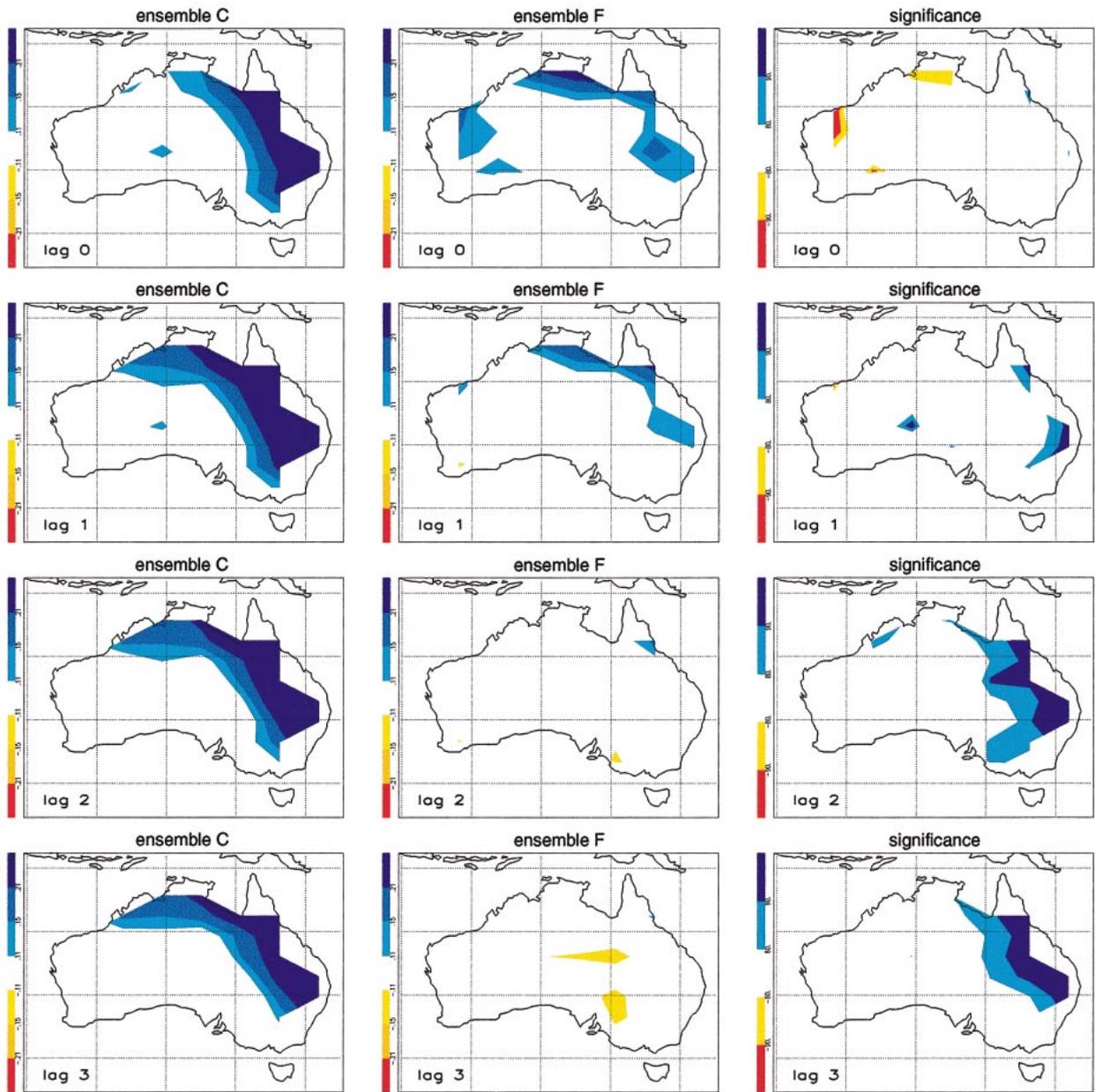


FIG. 2. Correlation between precipitation and the SOI over Australia for all months during the period 1979–88 at lag from 0 to 3 months: (left) C ensemble mean, (middle) F ensemble mean, and (right) significance at the 80% and 90% level.

what higher than observed. As noted earlier it is a known feature of the “bucket” soil moisture model to increase the autocorrelation of precipitation.

It is also interesting to note that the temporal evolution of correlations between SOI and maximum temperature (Fig. 4) strengthens, in the C ensemble, during the lagged period 0–3 months. Halpert and Ropelewski (1992) also found such a lag between extreme ENSO events and extreme temperature anomalies. The annual behavior is dominated by spring and summer conditions. The results in experiment F are again completely dif-

ferent. A large pattern of positive correlation covers almost the whole country at lag 0. When results are analyzed using seasonal means, it appears that the large negative correlation in austral summer disappears, while the positive correlation in winter becomes the dominant signal year-round. The differences are significant over most of the northern part of the continent. The almost complete disappearance of significant correlations at lag 2–3 months with decoupled soil moisture suggests a crucial role for soil moisture variability in maintaining the ENSO-related signal for the seasonal forecasting of

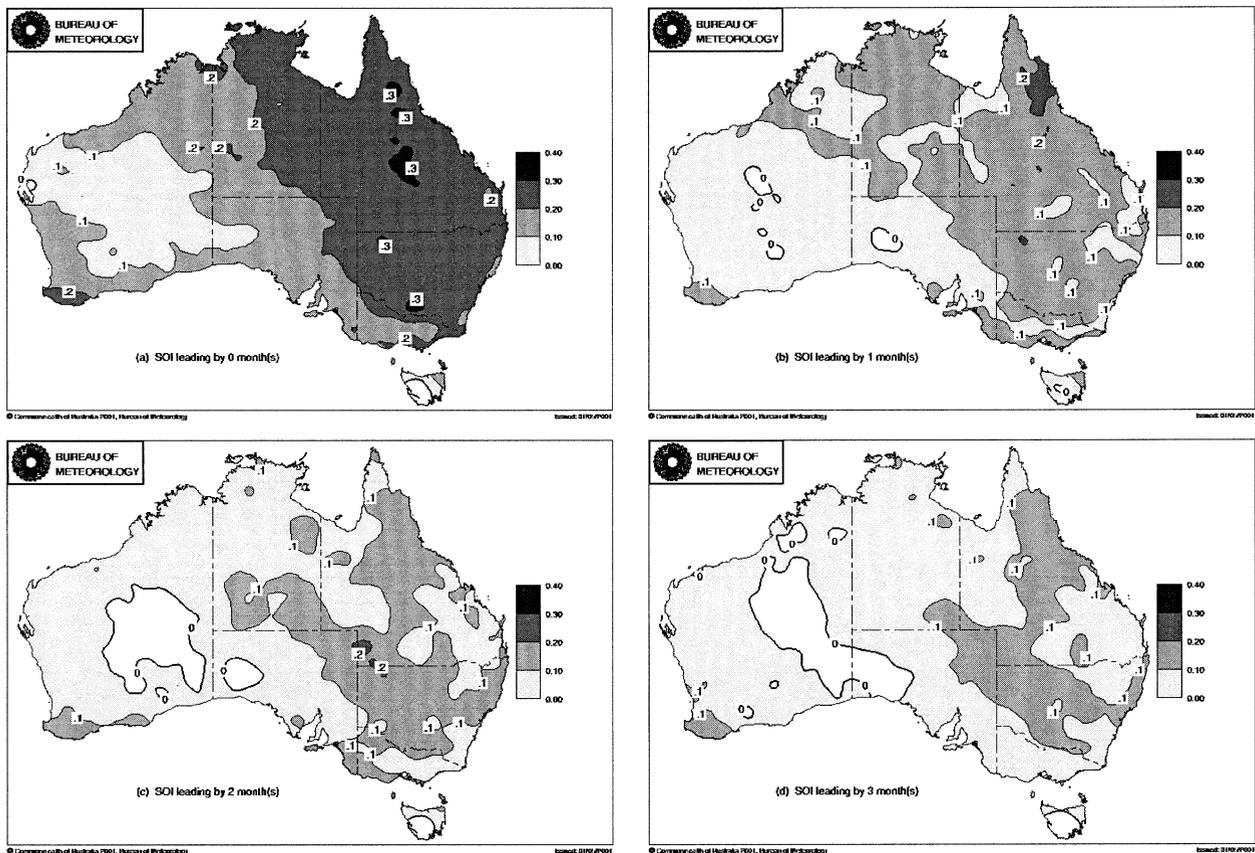


FIG. 3. Correlation coefficient maps of Australian monthly precipitation with monthly SOI leading by (a) 0 month, (b) 1 month, (c) 2 months, and (d) 3 months for the period from 1950 to 1999.

temperature—without the variability the observed relationship simply would not occur.

3. Conclusions

The impact of soil moisture variability on (i) potential predictability and (ii) actual predictability has been investigated by comparing two ensembles performed with an AGCM, one with the soil moisture being prescribed as the mean seasonal cycle. The results show that in this model, atmospheric variability over land is strongly linked to variability in soil moisture. Soil wetness fluctuations contribute to an increase in the persistence and the variability of surface temperature and precipitation. Moreover, they increase the potential predictability defined as the R ratio of certain atmospheric components. The potential predictability of rainfall and surface temperature variability in Australia is higher in summer, and more heavily influenced by soil moisture than elsewhere. Examination of the linear relationship between surface temperature and rainfall confirms that the lagged relationship between these variables is crucially dependent upon soil moisture fluctuations. The central role played by soil moisture as a memory of the recent past was shown. It permits the maintenance of the in-phase

SOI–rainfall relationship and is critical for the lagged SOI–surface temperature relationship. Indeed, when its variations are ignored, climate predictability based on the lagged association between climate variables over Australia and the SOI almost completely vanish after one month.

These results emphasize that the soil moisture is a crucial parameter in determining both the variance and the predictability of the atmosphere. Nevertheless, it must be noted that the period 1979–88 was dominated by two strong El Niño events. Thus, it remains possible that this signal is not representative of interannual variability in other periods, which could limit the more general applicability of these results. It must also be kept in mind that the land surface scheme used is a very simple one. Previous studies (Scott et al. 1995) showed that schemes such as this tend to overestimate atmospheric persistence and variance. This too provides a caveat on the present results. A further caveat is that it is possible that the present results may also depend on other parameterizations present in the model. Thus it remains possible that they could be significantly different in a different GCM. Overall however, the fact that the correlations (SOI–rainfall and SOI–surface temperature) in the control experiment compare well with ob-

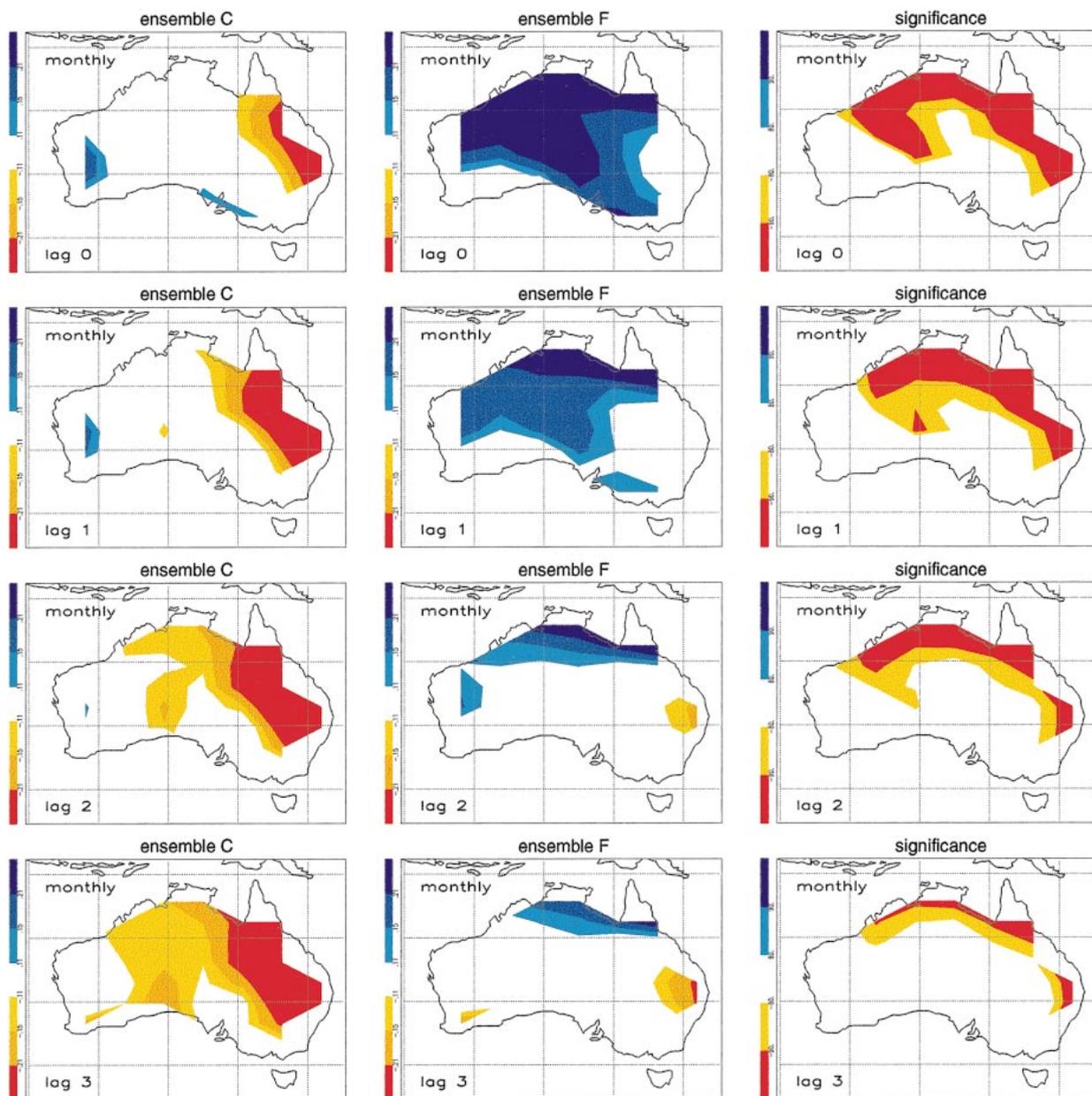


FIG. 4. As per Fig. 2 but for maximum temperature.

servations, and that they differ significantly from the decoupled experiment strongly underlines the central role of soil moisture. As a result, it would be desirable to test the present results with a more sophisticated land surface scheme, since it has been demonstrated that the bucket scheme behavior may be different from that of more sophisticated schemes (Timbal and Henderson-Sellers 1998). However, as shown here, even capturing the basic features of soil moisture variation (with a very simple surface scheme) may be enough to significantly improve model skill. In this light, it is notable that Power et al. (1998) did not find significant differences in the

modeled relationship between temperature and rainfall with two different land surface schemes, one a simple “bucket” and one including the role of vegetation.

Following these results, it appears that a representation of soil moisture variation is a prerequisite for the skilful forecast of interannual variations of the Australian climate. Using coupled climate models, this may require two steps. First, it may be necessary to accurately initialize and assimilate the soil moisture, as done in weather forecasting models (Mahfouf 1991). Second, skill may be added by enhancing the land surface parameterization, for example, by using multilayer surface

schemes. In a statistical approach, on the other hand, it may be difficult to take soil moisture into account. It is probably not suitable directly as an additive predictor to the SOI or global SSTs. Nevertheless it may be possible to calibrate the statistical prediction relationships according to the hydrological conditions (drier, normal, or wetter year) in a similar manner to that for the Interdecadal Pacific Oscillation (Power et al. 1999). This study focused on the Australian continent where the most pronounced signal was found, however many of our conclusions also apply in other areas. In particular, most of the Pacific region, and other regions linked to the ENSO phenomenon, appear sensitive to soil moisture variability (Viviand et al. 2000). It would be interesting to see the results of similar studies of soil moisture impact on seasonal prediction using other global climate models.

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