Estimate of predictability of monthly means in tropics from observations

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A method of separating the contributions from slowly varying boundary forcing and internal dynamics (e.g. intraseasonal oscillations) that determine the predictability of the monthly mean tropical climate is presented. Based on 33 years of daily low level wind observations and 24 years of satellite observations of outgoing long wave radiation, we show that the Indian monsoon climate is only marginally predictable, as the contribution of the boundary forcing in this region is relatively low and that of the internal dynamics is relatively large. It is also shown that excluding the Indian monsoon region, the predictable region is larger and predictability is higher in the tropics during northern summer. Even though the boundary forced variance is large during northern winter, the predictable region is smaller as the internal variance is larger and covers a larger region during that period (due to stronger intraseasonal activity).

THE predictability of weather (or the instantaneous state of the atmosphere) is limited to about two weeks[1] due to inherent instability and nonlinearity of the system. The atmosphere, however, possesses significant low frequency variability. If the low frequency variations of the monthly and seasonal means were entirely governed by scale interactions of the higher frequency chaotic weather fluctuations, then the time averages will be no more predictable than the weather disturbances themselves. However, it appears that a large fraction of the low frequency variability, specially in the tropics, may be forced by slowly varying boundary conditions such as the sea surface temperature (SST), and soil moisture variations. Hence, the predictability of climate (e.g. space–time averages) is determined partly by chaotic internal processes and partly by slowly varying boundary forcings such as the SST, sea ice and soil moisture. This understanding that anomalous boundary conditions (ABCs) may provide potential predictability has formed the scientific basis for deterministic climate predictions[2–4]. Research during the past decade has shown that the climate in large parts of tropics is primarily determined by slowly varying SST forcing[5], where potential for making dynamical forecast several seasons in advance exists. However, during the same period, we have also learnt that there are regions within the tropics whose climate is not strongly governed by ABCs. The Indian summer monsoon is such a system[6–8]. The intraseasonal oscillations (ISOs) such as the eastward propagating Madden–Julian Oscillations (MJOs) and the northward propagating monsoonal ISOs with period in the range of 30 to 60 days are quite vigorous in the tropics. Both the MJOs as well as the monsoonal ISOs are known to be driven by internal feedback between convection and dynamics. In addition to the scale interactions between weather disturbances, time-averaging of the chaotic ISOs can also contribute to the low frequency variability of monthly and seasonal means in the tropics. The nonlinear scale interaction associated with the weather disturbances in the tropics is likely to be weak as they are less vigorous compared to their counterpart in the extra-tropics. Therefore, we envisage that most of the internal contribution to the low frequency variations in the tropics comes from time-averaged residual of the ISOs.

The total low frequency variance of any variable in a given region (s^2) could be written as superposition of variance due to external forcing (s_e^2) and variance due to internal processes (s_i^2), i.e.

$$s^2 = s_e^2 + s_i^2.$$

A measure of predictability of the monthly and seasonal means in a place could be obtained from the ratio of variances associated with the external to the internal component (s_e^2/s_i^2).

Making unambiguous estimates of the 'internal' and 'external' components of variability from observations is rather difficult. Madden[9,10], Madden and Shea[11] and Shea and Madden[12] attempted to estimate the two variances in some extra-tropical regions. They estimated synoptic scale internal variability from short time series (such as within a season) and extrapolated the power spectrum to lower frequencies by assuming a white noise extension. This approach is simple but assumes that the low frequency power spectrum would be white and it could be extrapolated from power at higher frequencies. Shukla[13] commented at length on Madden's[9] approach and argued that the methodology used and assumptions made by Madden could have overestimated the natural variability or climate noise and underestimated the potential predictability. Madden[14] while disagreeing with Shukla that his method underestimated the potential predictability, agreed

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that there is considerable uncertainty in separating the so-called climate noise from the climate signal. Shukla and Gutzler[15] and Short and Cahalan[16] used a more general low frequency extension of the intraseasonal variance to estimate the level of climate noise. Trenberth[17,18] points out that these estimates depend crucially on the use of the correct value of *T*, the effective time between independent data. He pointed out that these studies may have underestimated *T* by using negatively biased estimates of the lagged autocorrelations, by improperly removing the annual cycle and inter-annual variability.

It is relatively easier to estimate this ratio from a long integration of an atmospheric general circulation model (AGCM) with observed boundary condition and another long integration with fixed boundary condition[8] or from an ensemble of long integrations of the AGCM with the same observed boundary conditions, but differing only in the initial conditions[19–21]. Kumar and Hoerling[22] estimated the ratio between the external and internal variability for the extra-tropics using a large ensemble of long simulations by an AGCM.

In all the studies of estimating potential predictability from observations mentioned earlier, the total inter-annual variability (i.e. the climate signal) is compared to the climate noise. The so-called climate signal actually contains contributions from the external forcing as well as the internal climate noise. To the best of our knowledge, no attempt has been made to separate the contributions from the external and the internal components to the observed inter-annual variability. In the present study, we propose a method of separation of inter-annual variances of monthly means associated with the slowly varying externally forced component and from the internally determined component. The data used and the methodology for separating the two components and assumptions involved are described next. The variances associated with the internal and external components are then estimated. It is also demonstrated that the external component separated by our method indeed represents the response of the tropical atmosphere to the slowly varying SST forcing. A predictability index defined as the ratio between the external and the internal components is presented in the article, which shows geographical locations where predictability is high (or low). Finally, the results are summarized. We also show that the internal variability essentially arises from the intraseasonal oscillations.

Data and methodology

The main data used in this study are the daily low level zonal winds (850 hPa) from NCEP/NCAR reanalysis[23] for 33 years (1965–1997) and daily outgoing long wave radiation from the NOAA polar orbiting satellites[24,25] for 24 years (1974 to 1997).

Here, we propose a method to separate the ‘externally forced’ monthly mean anomalies from raw daily data. Our methodology is based on the following premise. The anomalies associated with the synoptic and intraseasonal oscillations may be defined as the deviations from the annual cycle. The annual cycle at any place can be defined by the sum of the first few harmonics. In the present study, the annual cycle is defined as the sum of the first three harmonics of daily data for each year. The annual cycle defined in this manner varies from year to year. An example of such inter-annual variations of the annual cycle of low level zonal winds at a point over the Indian Ocean is shown in Figure 1. It is clear that the annual cycle has significant year-to-year variations. We hypothesize that the inter-annual variations are essentially due to the slowly varying boundary forcing. The dominant slowly varying boundary forcing in the tropics is that associated with the El Nino and Southern Oscillation (ENSO)-related SST variations. Since the time scale of variations of the boundary forcing is much longer (3–4 years to decadal) than that of the annual cycle, it essentially modulates the annual cycle. Thus, the inter-annual variations introduced by the external (slowly varying) forcing can be estimated from the monthly means constructed from the deviations of the individual annual cycles from the climatological mean annual cycle. The annual

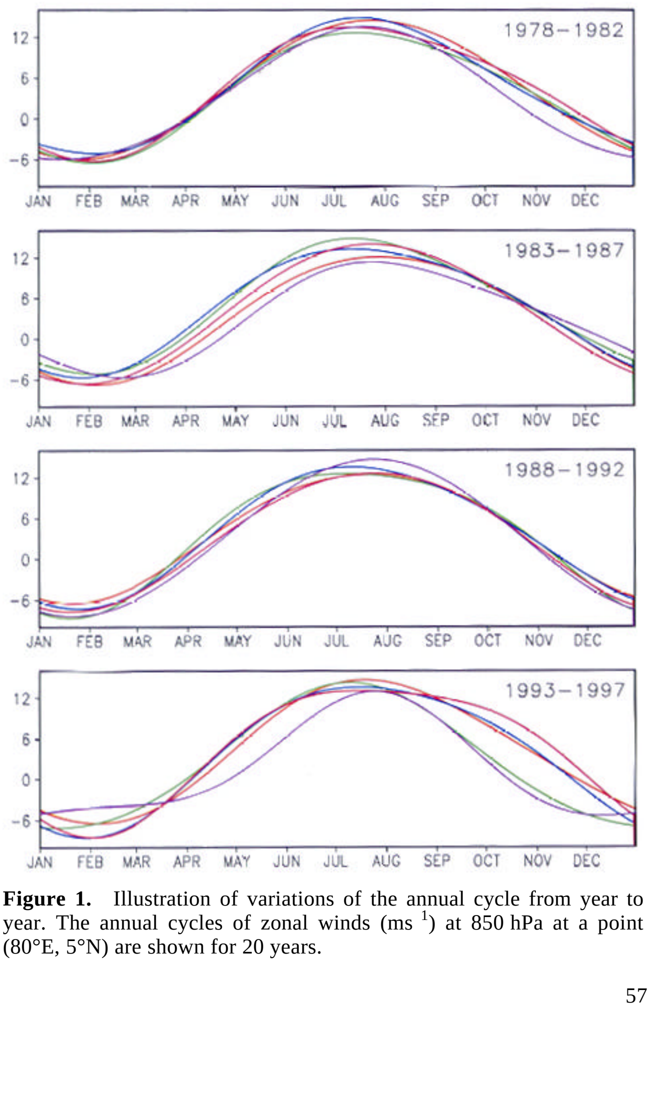

Figure 1. Illustration of variations of the annual cycle from year to year. The annual cycles of zonal winds (ms $^{-1}$) at 850 hPa at a point (80°E, 5°N) are shown for 20 years.

cycles of zonal winds at 850 hPa each year from 1965 to 1997 and those for OLR for all years from 1974 to 1997 are calculated and from the daily annual cycles, climatological daily annual cycles are calculated. Monthly external anomalies are estimated as monthly means of deviations of individual annual cycles from the climatological annual cycle.

To test our claim that the external anomalies as estimated by us are essentially driven by slowly varying SST changes associated with the ENSO, we carried out a combined EOF analysis of the monthly mean external anomalies of OLR and winds at 850 hPa. We have chosen the period between 1979 and 1997 for this analysis. The dominant EOF explaining about 20 per cent of the total variance is shown in Figure 2. The spatial patterns of both OLR and low level winds indicate the canonical patterns associated with ENSO[26,27]. The PC1 (normalized by its own temporal s.d.) is also shown in Figure 2 together with normalized Nino3 SST anomalies. The correlation coefficient between PC1 and Nino3 SST anomalies is 0.84, indicating a strong link between the variability represented by the external component and the ENSO. The second EOF and corresponding time coefficients (PC2) are not shown. However, PC1 and PC2 are strongly correlated at a lag of about 6 months. This lag-correlation together with the spatial patterns of the external component represent an eastward propagation of the anomalies, again characteristic of the ENSO anomalies. Therefore, the external component separated here clearly represents the slow response of the atmosphere to the slowly varying SST forcing associated with the ENSO. Actual anomalies of low level winds and OLR along the equator associated with the slow external forcing are shown in Figure 3. The magnitudes of the anomalies during the warm and cold events are similar to those known to be associated with typical warm or cold phases of ENSO[26] and the eastward propagation is also clearly seen.

If daily anomalies in a particular year are defined as the departure of daily observations from the annual cycle of that year, they represent the internal contribution as the external component represented by the inter-annual variation of the annual cycle is removed in this process. Thus, the monthly means of the daily anomalies constructed in this manner define the internal component. This definition implies that averaged over the whole year, the daily anomalies vanish. However, due to the intraseasonal oscillations, the monthly means are non-zero. The internal and external monthly mean anomalies calculated in this manner are statistically independent, as the temporal correlation between the two is nearly zero everywhere (Figure not shown).

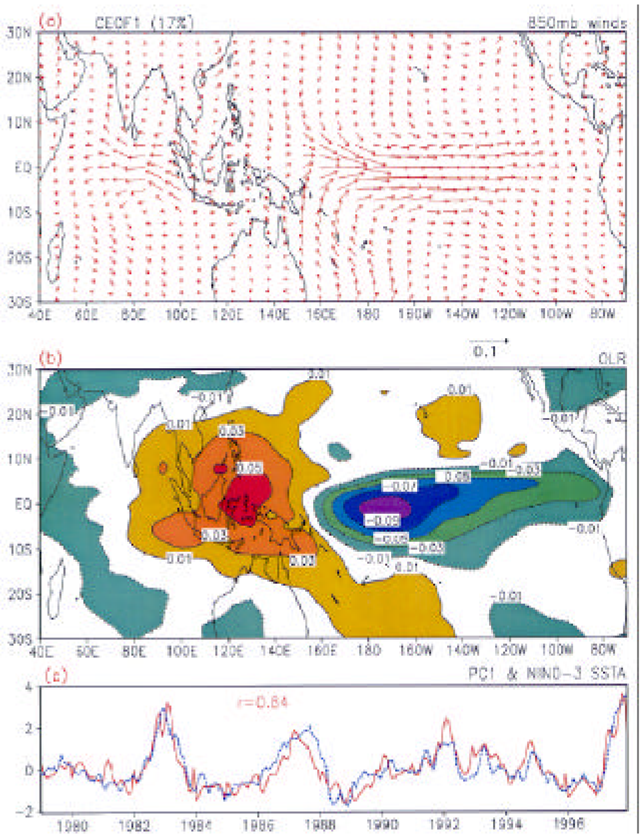

Figure 2. First combined EOF of mean monthly external anomalies for the period January 1979 to December 1997 (228 months). ***a***, Zonal winds EOF at 850 hPa; ***b***, OLR EOF; and ***c***, PC1 (solid line) and Nino3 SST anomalies (dashed line). Both the time series are normalized by their own standard deviation. Units of the EOFs are arbitrary.

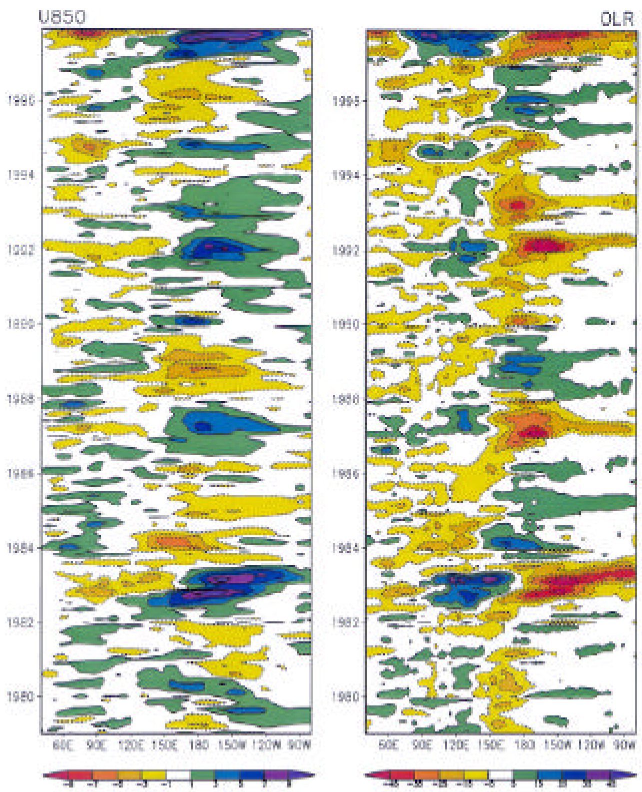

Figure 3. Time-longitude section of mean monthly external anomalies of zonal winds at 850 hPa ($m^2 s^{-2}$) and OLR ($(Wm^{-2})^2$) averaged around equator (5°S–5°N).

Let us define total monthly anomaly of any field (say, zonal wind) as sum of monthly anomalies associated with internal and external components.

$$U_T(x, y, t) = U_e(x, y, t) + U_i(x, y, t),$$

where subscripts e and i refer to the external and the internal components. Squaring both sides and summing over all months we can write the total variance to be given by sum of variances associated with the internal and the external components, namely

$$s_T^2 = s_e^2 + s_i^2,$$

as the correlation between the internal and the external components is zero. The total inter-annual variance may be estimated in two ways. The traditional way of calculating it is to construct monthly mean data from the raw daily data. Then construct a climatological monthly mean annual cycle. Deviations of the monthly means from this climatological monthly mean annual cycle are the total monthly mean anomalies. The total inter-annual variance may be calculated from these total anomalies. Alternatively, daily anomalies can be constructed with respect to the daily climatological mean annual cycle. The monthly means obtained from these daily anomalies give us the total monthly mean anomalies.

Estimation of internal and external inter-annual variances

The total variance of monthly means as well as the internal and external components of the variance of zonal winds at 850 hPa are calculated as described earlier based on daily data for 33 years (1965–1997). The three variances are shown in Figure 4. Similarly, the three variances for OLR are calculated based on available 24 years of daily data (1974–1997). The OLR variances are shown in Figure 5. To start with, we note that the sum of the external and internal variances almost exactly equals the total variances in all geographical locations in the tropics for both the fields. Secondly, it is clear from Figure 4 *b* and 5 *b* that the geographical distribution of the external variances of low level zonal winds as well as OLR has the canonical pattern of the individual fields associated with the ENSO[27–29]. The external variance of U850 has a major maximum centred around the dateline and a secondary maximum in the eastern equatorial Indian Ocean. Both the regions are known to be associated with large zonal wind anomalies during peak ENSO phases. The major maximum on the external variance of OLR is also centred around the dateline, but has large extension to the eastern Pacific. It is also noted that most of the appreciable external variance of either OLR or U850 is confined between 10°N and 10°S, characteristic of the Walker response

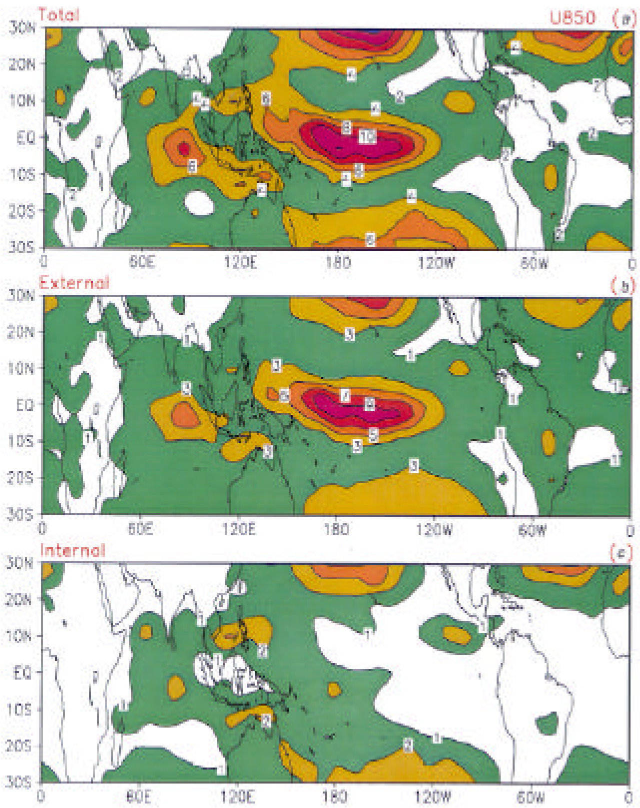

Figure 4. Monthly variance of zonal winds ($m^2\ s^{-2}$) at 850 hPa based on 396 months for the period January 1956 to December 1997. ***a***, Total variance; ***b***, external variance; and ***c***, internal variance.

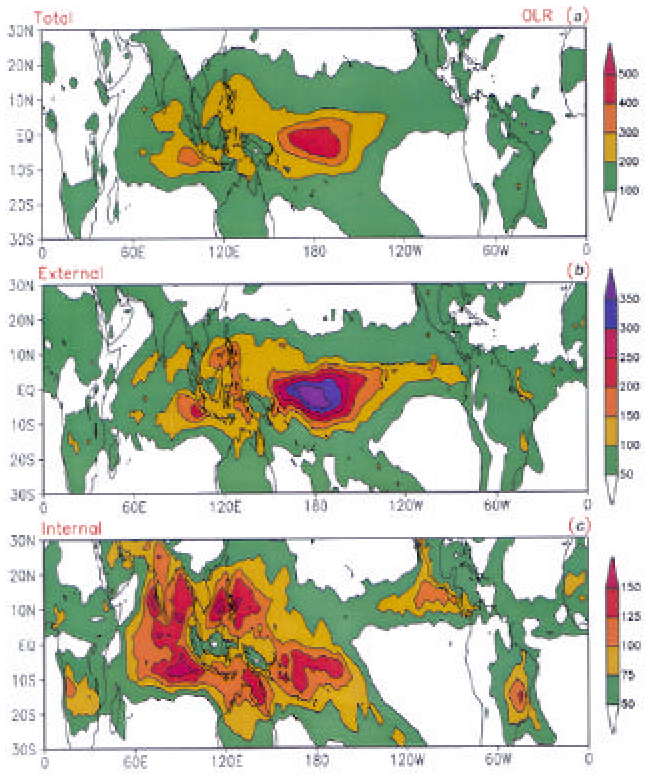

Figure 5. Same as Figure 4, but for OLR for the period January 1974 to December 1997 (288 months). Units $(Wm^{-2})^2$.

associated with the ENSO. On the other hand, the internal variances of U850 have large amplitude (Figure 4 *c*) in the 'monsoon' regions of the tropics, namely the Indian summer monsoon region, the South China Sea monsoon region and the Australian monsoon region. We note that the internal variance is generally smaller than the external variance in the tropical Pacific. However, it could be comparable or even larger than the external variance in the monsoonal regions mentioned above. The internal variance associated with the OLR (Figure 5 *c*) also has large amplitude in the same monsoonal regions. In contrast to the external variance, the internal variance is not confined to the equatorial belt but extends even up to 30 degrees latitude in the Indian and Australian monsoon regions.

Predictability of monthly means

As mentioned in the beginning of the article, the predictability of the climate (monthly means) is given by the ratio of 'signal' to 'noise', the signal being the predictable component or the external component and the noise being the internal unpredictable component. Let us define a predictability index as

$$\Gamma = s_{\mathrm{e}}^2 / s_{\mathrm{i}}^2 .$$

Larger the value of this ratio compared to unity, higher the predictability. The monthly mean climate may be considered marginally predictable if Γ is greater, but of the order one. If Γ is less than one, the climate would be unpredictable as the internal variability exercises a dominating influence on the total monthly variability. Having separated the two components, it is now possible to estimate the predictability by calculating the ratio between the external and internal variances. This ratio for zonal winds at 850 hPa based on 396 months is shown in Figure 6 *a*, while that for OLR based on 288 months is shown in Figure 6 *b*. Figure 6 *a* represents the geographical distribution of predictability index for large-scale flow, while Figure 6 *b* represents the same for convection (or precipitation). For the large-scale flow (Figure 6 *a*), predictability is high wherever the ENSO influence is large. This includes equatorial Pacific between 10°S and 10°N, equatorial Atlantic and equatorial Indian Ocean east of 70°E. Parts of Africa indicate high predictability, as this region is also known to have strong influence of ENSO. It is seen from Figure 6 *b* that a significant predictable region (e.g. $\Gamma \geq 2$) for convection (or precipitation) is much smaller than that for circulation. This region is mainly confined to the central and eastern equatorial Pacific coincident with the core predictable region for convection. This is probably to be expected as the interannual variability in convection (or precipitation) is much higher. However, if we include the 'marginally predictable' region (e.g. $\Gamma \geq 1$) in the predictable region for convection, it roughly coincides with the predictable region of circulation (e.g. $\Gamma \geq 2$ in the case of U850).

Probably the most important information provided by Figure 6 is identification of the regions over which the monthly climate is likely to be unpredictable. These are essentially the monsoon regions of the world, namely the Indian summer monsoon region, the Baiyu region, the central American monsoon region and the Australian monsoon region. In these regions the predictability index for circulations is between 1 and 1.5. The smallest ratio is found over the Indian monsoon region, where it goes down to even less than 1. For convection the predictability index is between 0.75 and 0.5 over the Indian monsoon region.

As Figure 6 is based on all months, it brings out an averaged picture of predictable (and unpredictable) regions. The synoptic activity and the ISOs in the tropics is dependent on mean background flow. Since the mean flow in the tropics has a strong seasonal cycle, the synoptic and ISO activities also have a seasonal cycle. Hence, we can expect the internal variability also to have a strong seasonal cycle. Therefore, it may be more interesting to examine how the predictable (and unpredictable) regions depend on the season. For this purpose, we calculated the ratio between the external and the internal variances taking all the northern hemispheric (NH) summer months (June–August) together and all the winter months (December–February) together. The NH summer and winter ratios for zonal winds at 850 hPa are shown in Figure 7. It may be noted from Figure 7 that during the NH summer, not only are the peak values of the predictability index Γ higher than those during northern winter, also the area covered by $\Gamma > 2$ is much larger during NH summer compared to that in NH winter. Thus, during NH winter the monthly mean predictability not only decreases com-

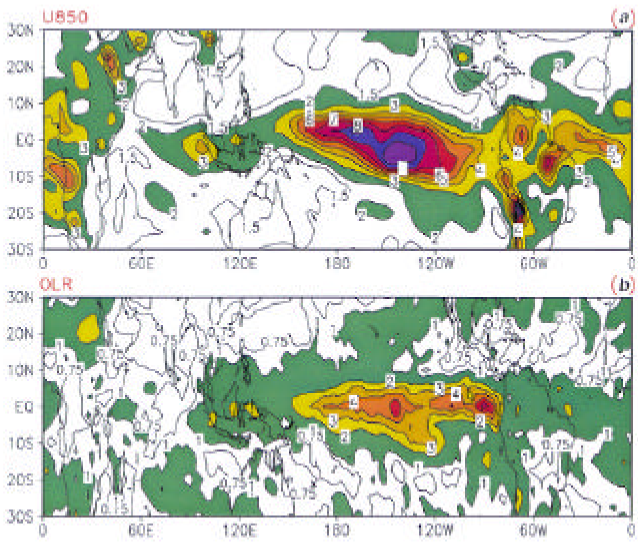

Figure 6. Predictability index for (***a***) zonal winds at 850 hPa (396 months); and (***b***) OLR (288 months).

pared to that in NH summer, the predictable region also shrinks. Poor predictability over the Indian monsoon region, however, appears to be a robust feature and remains unchanged during both seasons.

The qualitative difference in the predictability regimes during NH summer compared to NH winter is probably not very surprising if we take into account the seasonality of the external and the internal variances. As the external component of the variance arises from a slowly varying signal (with time scales longer than a year), we do not expect much seasonality in the external variance. This is shown in Figure 8 for zonal winds at 850 hPa. Except that the maximum variance occurs in the western Pacific during NH summer compared to central Pacific during winter, the general pattern of external variance is similar in the equatorial wave-guide during both the seasons. However, the internal variance has a pronounced seasonality (Figure 9). Barring the Indian monsoon region and a small portion of the American monsoon region, the internal variability is very weak throughout the equatorial wave-guide during NH summer. This explains the larger magnitude and extension of Γ during NH summer (Figure 7). On the other hand, the internal variance during NH winter is quite strong from Indian Ocean to central Pacific, the maxima being over the Australian monsoon region and the South Pacific Convergence Zone (SPCZ). The larger internal variability during NH winter is consistent with the fact that the ISO activity in the tropics is strong during boreal winter and spring and weak during boreal summer, except over the Indian monsoon region[30,31]. Even though the external variance remains similar in magnitude and extent in winter compared to that in summer, the predictability index becomes smaller and the predictable region shrinks to a smaller region in the far eastern Pacific due to vigorous internal activity in the Indian Ocean and central and western Pacific.

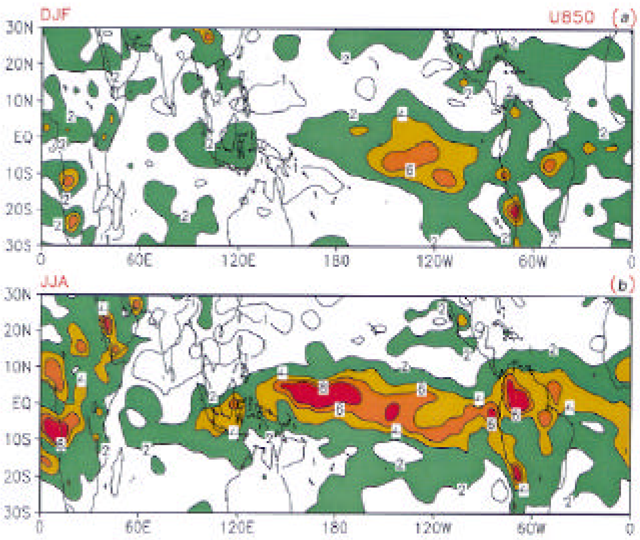

Figure 7. Predictability index for zonal winds at 850 hPa (***a***) for all northern hemisphere winter months (December–February); and (***b***) for all northern hemisphere summer months (June–August).

Discussion and conclusions

What is responsible for the internal variability of the monthly means in the tropics? The synoptic disturbances in the tropics are much less energetic than their extra-tropical counterpart. Therefore, nonlinear interaction amongst the tropical synoptic disturbances is unlikely to result in significant energy in the low frequency regime (e.g. monthly and seasonal means). Moreover due to their higher frequency, the monthly mean residuals from them

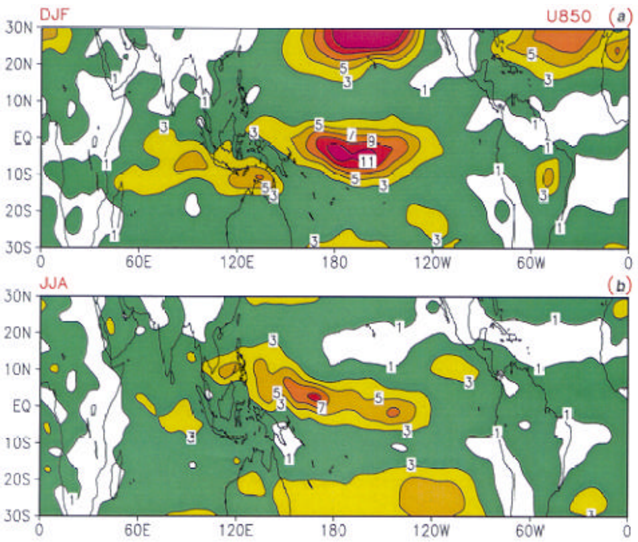

Figure 8. External variance of zonal winds at 850 hPa ($m^2 s^{-2}$) during (***a***) NH winter months (December–February); and (***b***) during NH summer months (June–August).

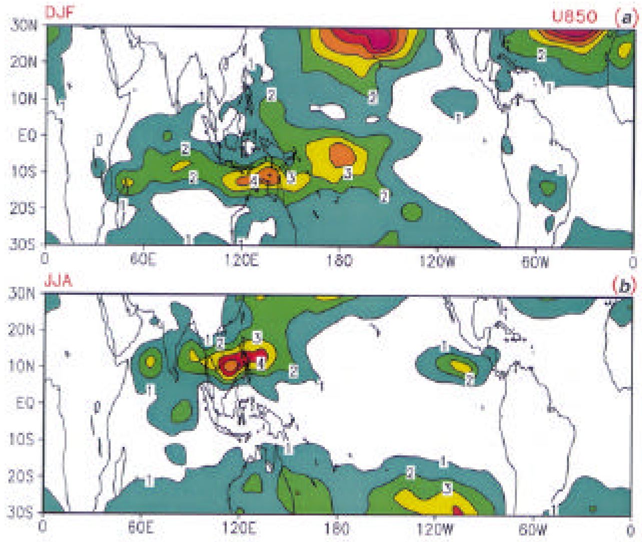

Figure 9. Internal variance of zonal winds at 850 hPa ($m^2 s^{-2}$) during (***a***) NH winter months (December–February); and (***b***) during NH summer months (June–August).

are expected to be small. Therefore, the internal variability that could influence tropical monthly means are the monsoonal ISOs during NH summer and the MJO in the other parts of the tropics. To test the correctness of this conjecture, we calculate internal variance after removing the synoptic disturbances from the daily anomalies. For this purpose, a Butterworth low-pass filter that keeps all periods greater than 10 days and throws out all periods shorter than 10 days was applied on the daily anomalies of all years, after removing the annual cycle of each individual year. Monthly mean anomalies describing the internal component, are again calculated by averaging the filtered anomalies over calendar months. The internal variance calculated from the monthly means of the filtered data has no contribution from the synoptic variations and is solely contributed by the ISOs. The internal variance calculated in this manner for U850 and OLR are shown in Figure 10. A comparison of Figure 10 *a* with Figure 4 *c* and Figure10 *b* with Figure 5 *c* reveals that removal of the contribution of the synoptic disturbances from the daily data had no effect on the internal variance, either in magnitude or in spatial distribution. This analysis establishes that the internal variability of the monthly means is entirely governed by the tropical ISOs.

In this study, we present a method to determine the part of monthly mean climate variability governed by internal dynamics and that governed by external slowly varying forcing from long daily observations. A predictability index is defined as the ratio of variance between the external and the internal components. Low level daily zonal winds (at 850 hPa) from NCEP/NCAR reanalysis for 33 years (1965–1997) and daily OLR for 24 years (1974–1997) are used. Two important conclusions may be drawn from this analysis.

(i) The predictability of the monthly mean climate over the monsoon regions of the world appear to be marginal at best. The worst among them is the Indian summer monsoon region, where predictability index goes down to less than one. In many recent studies, the difficulty in simulating and predicting the Indian summer monsoon has been attributed to the role of the ISOs[6,8,32]. Goswami[8], had shown that the strength of the GCM simulated ENSO response decreases as we reach the Indian Ocean and Indian monsoon region and the internal variability could compete with the externally forced variability in this region. The present analysis shows, from observation that the internal variability in the Indian summer monsoon region is indeed comparable to or even larger than the boundary forced variability. Thus, deterministic prediction of the monthly mean summer monsoon climate may continue to be a difficult problem.

(ii) The other important result is that barring the Indian summer monsoon region, the monthly mean climate during the boreal summer is more predictable over a much larger region in the tropics than during boreal winter. As

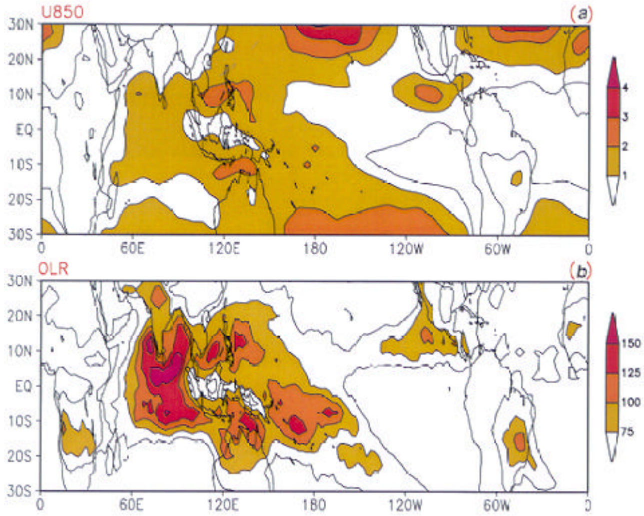

Figure 10. Internal variance of (***a***) zonal winds at 850 hPa ($m^2 s^{-2}$) and (***b***) OLR $(Wm^{-2})^2$ based on all months after removing the higher frequencies with period shorter than 10 days.

it is well known that the SST signal associated with the ENSO tends to peak during NH winter, it appeared rather strange that predictability should be weaker during this season. However, we show that the weaker and limited predictability during boreal winter is due to stronger internal variability associated with stronger ISOs during winter, while the amplitude of the boundary-forced variability remains similar to that in boreal summer. Thus, the monthly mean tropical climate seems to be more predictable in NH summer compared to NH winter.

It may be noted that nonlinear interaction between the synoptic events and intraseasonal oscillations may introduce some variations of the annual cycle (albeit small). This rather small contribution from internal variability to the low frequency variations is contained in our definition of external variation. Therefore, the external variance may be slightly overestimated. Thus, our measure of predictability may also be slightly overestimated. In this study we have confined ourselves to the predictability of the monthly mean climate. The predictability of the seasonal mean climate will be addressed in a separate study.

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