The Seasonal Cycle of Interannual Variability and the Dynamical 
Imprint of the Seasonally Varying Mean State

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ABSTRACT

Various aspects of the seasonal cycle of interannual variability of the observed 300mb streamfunction are documented and related to dynamical influences of the seasonality of the mean circulation. The stochastically excited nondivergent barotropic vorticity equation linearized about upper tropospheric climatological mean states from each month of the year is used to identify characteristics of interannual variability that the seasonal cycle of the mean state should modulate. The result is interannual variability with a) extratropical centers of variance that are much stronger in winter than summer and that are confined to midlatitudes during the warm season, b) an annual cycle of preferred scales in midlatitudes with largest scales occurring during winter, and a semiannual cycle of scales in the subtropics, and c) streamfunction tendencies from interannual fluxes that adjust to the seasonally varying climatological eddies in such a way as to damp them. Because these same properties are also shown to exist in nature, it is concluded that the linear framework is a useful means of understanding the seasonality of interannual disturbances and that seasonality of the mean state leaves a pronounced imprint on interannual variability.

Analysis of an ensemble of general circulation model integrations indicates the signatures of seasonality produced in the stochastically driven linear framework are more useful for understanding intrinsic interannual variability than variability caused by seasonally varying sea surface temperature anomalies. Furthermore it is found that the intrinsic variability of the GCM has properties very much like those in nature, another indication that organization resulting from anomalous forcing structure is not required for production of many aspects of the observed seasonality of interannual variability.

1. Introduction

Most investigations of monthly and seasonal mean (i.e., interannual) atmospheric variability have dealt with the winter season, but from those studies that have examined other seasons it is apparent that in many key respects winter behavior is not representative of the rest of the year. For example Wallace et al. (1993) and Barnston and van den Dool (1993) both reported that sum-

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mertime Northern Hemisphere standard deviations of monthly or seasonally averaged midtropospheric geopotential heights are roughly half as large as their wintertime counterparts. And Barnston and Livezey (1987) noted that the leading patterns of interannual variability vary with the time of year. Apparently just as well-known features of the time mean state undergo a distinct seasonal cycle, so do various aspects of interannual departures from the mean fields. The purpose of the study reported on in this paper is to document several facets of this lesser known seasonal cycle and to find a dynamical framework for understanding the mechanisms that produce them.

The framework that we hypothesize will be useful for understanding the seasonal cycle of interannual atmospheric variability is the theory of planetary waves. In particular we are interested in linear, barotropic planetary wave theory and its prediction that many properties of disturbances with timescales from weeks to sea-
Figure 1. Climatological average, zonal mean zonal nondivergent wind at 300 hPa for each month of the year based on 40 years of NCEP/NCAR reanalysis. Contour interval is 5 ms$^{-1}$. Thick lines denote locations where the stationary wavenumber equals 4. Shaded are latitudes equatorward of 60° where the zonal gradient of climatological zonal wind, when summed over gridpoints with negative values and divided by the total number of gridpoints in a latitude circle, is (heavy) less than $-1.6 \times 10^{-6}$ s$^{-1}$ or (light) less than $-1.0 \times 10^{-6}$ s$^{-1}$.

Sons are influenced by dynamical consequences of the mean state on which these so-called low-frequency perturbations are superimposed. This theory has already helped to explain various aspects of wintertime low-frequency disturbances, ranging from their spatial scale (e.g., Held, 1983) to their structure (e.g., Hoskins et al. 1977, Simmons et al. 1983 and Frederiksen, 1983), to the geographical distribution of variance (e.g., Branstator (1990), Navarra (1993), Metz (1994), and Swanson (2000)), simply by taking into account the effect of the time mean state on perturbations. Given the common dynamics of and the statistical connections between low-frequency perturbations and interannual variability and assuming linear planetary wave theory is equally applicable to low-frequency variability in other seasons, linear barotropic theory should be a good candidate for the framework we seek.

That interannual anomalies can take on different characteristics throughout the year as a result of seasonality of the mean state can be inferred from Newman and Sardeshmukh’s (1998) study of the linear response to tropical heating and by Frederiksen and Branstator’s (2001) eigenanalysis of a barotropic model with a seasonally varying basic state. Dynamical reasons for this sensitivity can be seen by examining the seasonality of the mean state. The contours of Fig. 1 depict one dynamically important facet of this seasonal cycle, namely the seasonal dependence of the zonal mean upper tropospheric zonal wind. From the stationary wavenumber analysis of Hoskins and Karoly (1981) and the resonance ideas of Held (1983), we would expect the prominent seasonal shifts in position and amplitude evident in this diagram to influence the scale of quasi-stationary disturbances. The stationary wavenumber, $K_s = \left( (\beta + \zeta)/u \right)^{1/2}$, is the total wavenumber of disturbances that planetary wave theory indicates should have zero phase speed and which thus would be expected to be prevalent in interannual observations. The thick contours on Fig. 1 show the boundary between regions where the stationary wavenumber is greater than 4 (generally the tropics) and where it is less than 4 (generally high latitudes) based on the zonal mean zonal winds of the same diagram. This calculation indicates that in both hemispheres the time mean’s seasonality has the potential of favoring large scale low-frequency disturbances in winter and smaller scale disturbances in summer.

Like the zonal mean, the configuration of the climatological eddies can also affect properties of low-frequency perturbations. Simmons et al. (1983) showed how slowly evolving disturbances near negative longitudinal gradients in the mean winter upper tropospheric zonal wind field can draw energy from these gradients resulting in large disturbance amplitude near these gradients. And Swanson (2000) has argued that such gradients can cause local maxima in low-frequency transients via energy accumulation. But there is marked seasonality in these mean waves as can be seen in Fig. 2, which shows two aspects of their seasonal dependence. Panel a of that figure, which displays the climatological mean eddies in the 300hPa streamfunction field averaged between 35N and 60N, indicates that the amplitude, scale and phase of these waves are highly dependent on season. Panel b further quantifies the seasonal dependence of the structure of these waves by displaying the pattern correlation of the Northern Hemisphere climatological mean 300mb streamfunction eddies for various pairs of months. With correlations as low as zero for some pairs it is not surprising that seasonality of the mean eddies is accompanied by a pronounced seasonality in even the latitudinal distribution and strength
of the dynamically important zonal wind zonal gradients. This fact is highlighted in Fig. 1, in which shaded regions indicate locations where the average negative gradient of the climatological zonal wind exceeds an arbitrary threshold. Clearly there is potential for the seasonality of the mean eddies to induce seasonality in the strength and geographical distribution of low-frequency (and hence, interannual) variability.

One further attribute of interannual anomalies that is likely to be influenced by the seasonality of the mean documented in Figures 1 and 2 is their structure. If those disturbances with structures that enable them to gain energy from mean gradients are expected to be most prevalent, then the shifts in the position, spacing and strength of those gradients implicit in these figures has the potential to induce a seasonality in the structure of the dominant perturbations that contribute to interannual variability. One indication of the large seasonality in anomaly structure that can potentially occur in this way is the substantial sensitivity to basic state season that Frederiksen and Branstator (2001) found leading barotropic eigenfunctions have.

Motivated by the above results and ideas, we carry out a three component study directed at determining whether the mean circulation’s seasonal cycle produces an imprint that is important enough to serve as a framework for interpreting the seasonal dependence of interannual disturbances. First, in Section 2 we quantify the effect that seasonal changes in the mean circulation would be expected to have on the scale, geographical distribution and structure of interannual flow anomalies using the linear nondivergent barotropic vorticity equation. Second, in Section 3 we analyze observations to determine whether the effects found in the linear framework are also present in nature. These results suggest that much of the observed seasonality can be traced to the influence of the mean state, but there are some features of interannual variability that do not appear to be explainable in this fashion. In Section 4 the source of some of these latter features is traced to the effects of interannual variations in sea surface temperatures. This is accomplished by repeating our analysis for ensembles of atmospheric general circulation model integrations as this allows the seasonal cycle of inter-
nally generated interannual variability to be separated from that of externally produced interannual variability. Section 5 summarizes our results and discusses their interpretation.

2. Linear signatures of the seasonal cycle

a. Linear planetary wave model formulation

To quantify the potential effect of the seasonally varying time mean on interannual variability, we begin with the barotropic vorticity equation, which we express using variables that are decomposed into climatological averages ($\overline{\psi}$) and departures ($\psi'$).

$$\frac{\partial \psi'}{\partial t} = -\nabla \cdot \nabla \psi' - \nabla \cdot \nabla (\zeta + f) + R$$

(1)

or

$$\frac{\partial \psi'}{\partial t} = -L(t)\psi' + \nabla^{-2}R$$

(2)

Here $\zeta$ is relative vorticity, $\psi$ is streamfunction, $f$ is the Coriolis parameter, and $\nabla \psi$ stands for the nondivergent wind components. In our application ($\overline{\psi}$) is a function of time and year leading to the time-dependence of $L$. For (1) and (2) to be complete representations of atmospheric dynamics, $R$ must include all terms not explicitly expressed in (1) including the effects of divergence and nonlinearities. Under this partitioning, the characteristics of perturbation quantities will be a function of season for two reasons, namely the seasonality of $L$ and the seasonality of the processes that are incorporated in $R$.

To achieve our goal we isolate the effect of the seasonality of $L$ by replacing $R$ with terms that are independent of season. And to ensure that the characteristics of the resulting solutions are an indication of general properties of $L$ and are influenced as little as possible by characteristics of the new terms, we replace $R$ with very simple terms representing Rayleigh damping, diffusion and noise. Equation (2) then becomes

$$\frac{\partial \psi'}{\partial t} = -(L(t) + \alpha - c\nabla^2)\psi' + \nabla^{-2}n(t)$$

(3)

where the elements of $n$ are white in time and space and are randomly drawn from a Gaussian distribution that is independent of season and space. Scientists from Leith (1971) to DelSole and Farrell (1995) have pointed out that such a combination of terms may be a reasonable replacement for the equilibrating and scale-scattering effects of nonlinear terms. Studies including Branstator (1990), Metz (1994) and Newman et al. (1997) have used similar approaches to investigate the effect of the mean boreal winter state on low-frequency variations. The one way that any spatial organization is imparted to our solutions via the forcing is that for our study the zonal mean components of $n$ are removed. This is done to minimize the zonal mean component of responses since zonal mean anomalies are largely maintained by ageostrophic circulations and by bandpass eddy fluxes, neither of which are represented in our model.

To apply (3) to our problem we must decide on the temporal behavior of $L$. The most straightforward means of representing the dynamical effects we are interested in would be to specify $\psi$ as a cyclic function of season. Instead, we report here on the results of using twelve different time-independent operators, $L_m$, one for each month of the year formed by linearizing the vorticity equation around the climatological mean state for that month. We do this because we have found these two methods produce solutions with essentially the same low-frequency statistics while the influence of the basic state in the time-independent operator approach is much easier to interpret. The similarity of results for the two methods suggests that the perturbations that dominate our analysis have timescales that are short compared to the timescales of the climate state. This timescale separation, which is discussed more fully in Appendix A, helps justify the use of a stochastic model in our investigation.

We have also found, since it is the slowly evolving component of the solutions that we focus on, the time-dependence of the noise can be simplified. Because $L_m$ is linear and time-independent, we can either specify $n$ to be white in time and consider time averages or we can specify $n$ to have only slow variations without affecting our results. In fact we find our results are little affected if we use the limiting case, namely that of steady forcing and steady solutions, so this is what we employ.

The model’s specification is completed by choosing $\alpha$ to be (4 days)$^{-1}$, based on Klinker and Sardeshmukh’s (1992) analysis of the effective damping of the barotropic component in nature, and by setting $c$ to $2.5 \times 10^5 m^2s^{-1}$, a value commonly used in models. These have the consequence that all of the operators ($L_m + \alpha - c\nabla^2$) we consider are stable (but of course this does not preclude the possibility that perturbations can locally gain energy from basic state gradients). 3

3If we had used a value of $\alpha$ less than about (6 days)$^{-1}$, the model would be close to resonance for some values of $\alpha$ as is evident from eigenspectra in Branstator (1985) and Frederiksen and Branstator (2001). Near resonance markedly changes the
The noise variance is assigned a value that leads to solutions with annually-averaged mean variance similar to the average variance found in the observations of Section 3.

In summary then our approach will be to find the response of

\[(T_m + \alpha - c\nabla^2)\psi' = \nabla^2\epsilon \tag{4}\]

where \(\epsilon\) is steady in time. We do this for 500 different spatially uncorrelated forcing functions \(\epsilon\) applied to each of the 12 operators and summarize the solutions in terms of various statistics. In this section the mean fields used for basic states are derived from average 300 hPa streamfunction as produced by the NCEP/NCAR reanalysis project (Kalnay et al. 1996) for the years 1958-97. Solutions are found by discretizing \(\psi\) using spherical harmonics rhomboidally truncated at total wavenumber 15.

b. Solution characteristics

The first of the properties we study is the geographical distribution of variance. As in other studies, the distribution of standard deviations we find for a January mean basic state is geographically dependent (Fig. 3a) with maxima in the northern ocean basins. These maxima are located near regions of negative zonal gradients in the background zonal winds (heavy contours) as anticipated by the discussion in the introduction. One feature that has not received much attention is the maximum across southern Asia, which the theoretical results of Branstator (1983) and Hoskins and Ambrizzi (1993) indicate is probably a result of the waveguiding effect of the subtropical jet.

Panels b, c, and d of Fig. 3 show standard deviations from the stochastically excited model when it is linearized about months from each of the other seasons. Consistent with the weak background wind gradients in these plots, the variability of the stochastically excited anomalies is weaker than the winter results, especially for summer. Even so, the perturbations are highly organized with concentrations over the northern oceans in the vicinity of negative zonal gradients in the background winds.

Figure 3. Thin contours: standard deviation of 300 hPa streamfunction fields produced as steady solutions to the linear barotropic vorticity equation when it is forced by a collection of vorticity sources that are white in space and have a standard deviation that does not vary with position of month of the year. Contour interval is $1 \times 10^6 m^2 s^{-1}$. Light shading begins at $7 \times 10^6 m^2 s^{-1}$ and heavy shading begins at $9 \times 10^6 m^2 s^{-1}$. Thick contours: zonal gradient of climatological mean 300 hPa zonal wind. Only $-6 \times 10^{-6} s^{-1}$ and $-2 \times 10^{-6} s^{-1}$ contours north of 15N are shown.

Given the predominance of seasonality being reflected in the meridional distribution of variability in Fig. 3, a useful way of displaying seasonality is to summarize variability in each month by calculating the root mean square of the standard deviation fields for each character of our solutions.
Another property of low-frequency perturbations that we anticipated being influenced by the mean state is horizontal scale. Based on calculations of the stationary wavenumber one might expect scale to be a function of latitude (as addressed in the introduction) and longitude. Indeed, Hoskins and Ambrizzi (1993) have produced a plot of stationary wavenumber for the northern winter mean state and found large meridional and zonal variations in this quantity. To detect this geographical dependence in our stochastic solutions we carry out the following calculation. For a given location on the globe \((\lambda_0, \phi_0)\) we calculate the correlation within one of our sets of 500 solutions between responses at that location and responses at each neighboring location. Using these values we can then determine the average spatial correlation as function of distance from \((\lambda_0, \phi_0)\). We define the scale at \((\lambda_0, \phi_0)\) as being the distance at which this correlation takes on the value \(e^{-1}\) and dub this the “decorrelation distance”.

When we calculate the decorrelation distance for the stochastically excited solutions from each month we find that, except for northern winter, in midlatitudes the geographical distribution of distances is not well organized and bears little correspondence to the stationary wavenumber. If one examines zonal means of these plots, however, a well-defined latitudinal and seasonal dependence emerges. This can be seen in Fig. 5 which shows zonal mean decorrelation distance for solutions corresponding to operators from each month of the year. Especially in the Northern Hemisphere midlatitudes, we see that winter has long spatial scales that extend nearly to the sub tropics. For spring basic states, scales throughout the extratropical Northern Hemisphere are diminished and by summer at 40N they are roughly 75% of what they were in winter. Furthermore the latitudinal functionality of the scales has changed with the seasons so that the longest scales are confined to high latitudes. From Fig. 5 we also see that the seasonal progression of scale produced by the mean state’s seasonality in the Northern Hemisphere, just like the seasonality of variability, is nearly symmetric about July. In the Southern Hemisphere midlatitudes the preference for longer scales in high latitudes than in low latitudes also holds, but the seasonality of these scales is more muted. In both hemispheres the general tendency for midlatitude scales to be longer than subtropical scales and for the shorter subtropical scales of winter to extend more deeply into midlatitudes during summer is similar to the behavior anticipated by the (thick) stationary
Figure 6. Pattern correlation between observed climatological mean zonally asymmetric 300 hPa streamfunction and the mean zonally asymmetric streamfunction tendencies produced by vorticity fluxes (5) associated with stochastically forced steady anomalies. Contour interval is .1. Light shading begins at -.2, medium shading begins at -.4 and heavy shading begins at -.6.

The third characteristic of interannual anomalies that is of interest to our study is their structure. As a dynamically important manifestation of anomaly structure, we examine the streamfunction tendency

\[- < \nabla^{-2} \nabla \cdot (v'_\psi \zeta') > \]  

(5)
as associated with the stochastically generated solutions. Here \(< >\) stands for an average over the 500 solutions for a given \( \overline{T}_m \). When we plot (in diagrams not shown) these tendency fields for basic states from each month, and compare them to plots of the monthly climatological mean states, we find that in the Northern Hemisphere the similarity of the tendency patterns and the mean eddies is unmistakable, though the signs of the two fields are reversed. We quantify this similarity by calculating the pattern correlation between the tendency and corresponding mean state eddies in the Northern Hemisphere, and the values are displayed on the diagonal of Fig. 6 that runs from the upper left to the lower right hand corner. The anticorrelation of the two fields is especially strong during winter with values as great as -0.7 and diminishes to about -0.4 in summer.

From Fig. 2 we know that the structure of the climatological eddies changes a great deal from season to season, so the fact that the streamfunction tendencies remain anticorrelated with the climatological eddies throughout the year probably indicates that the perturbation structures are different for each month and those perturbation structures emerge that tend to weaken the basic state eddies. This would be consistent with our earlier statements that perturbations that can gain energy from background gradients will be prominent; such perturbations, through the action of their fluxes, generally tend to decrease the gradients on which they feed. As a way to verify this interpretation we calculate additional pattern correlations between tendency and basic state eddy fields, but now for tendencies and basic states from nonmatching months. These are the values plotted off the diagonal of Fig. 6. They support our conjecture in that, by reading horizontally across the diagram, we see that the perturbations generated under the influence of the basic state from a given month of the year induce tendencies that are more highly anticorrelated with the mean state from that same month or neighboring months than with basic states from months occurring at other times of the year. The only exceptions to this rule happen in spring and fall. For example, tendency fields produced with spring basic states are nearly as highly anticorrelated with autumn basic states as they are with basic states from spring. But as we see in Fig. 2b spring and autumn mean states are very similar so this exception does not contradict our interpretation.

3. Observed seasonality of low-frequency anomalies

The second element of our study entails documenting interannual variability in nature and determining whether the seasonality caused by the seasonality of the mean state in the linear framework is detected in the observations. The data we use are the same NCEP/NCAR reanalysis 300mb streamfunction fields whose averages were employed for construction of basic states. We analyze monthly means which, for the reasons given in Appendix B, are pooled into running three month seasons whenever two-dimensional fields are considered.

The variability of observed monthly means for each
of four seasons is shown in Fig. 7 in terms of standard deviations. For winter (Fig. 7a) we see a distribution of variability in midlatitudes that is familiar to that in other studies, including that of Blackmon (1976) and Barnston and van den Dool (1993), with maxima in the northern ocean basins being the most prominent features. Because we are using streamfunction rather than the geopotential height fields used in those earlier studies, we see other maxima located in the subtropics which are not as familiar, including a maximum in the tropical Pacific and one stretching across south Asia. Presumably, the former is the local effect of El Nino and La Nina events, while the latter reflects the anomalies trapped in the south Asia jetstream waveguide that have been identified in observations by Hsu and Lin (1992) and Branstator (2002). Plots in Figures 7b, c, and d indicate that variability is markedly different during other seasons of the year in that the warmer the season, the weaker and closer to the pole is the variability. Any seasonality in the longitudinal positions of the maxima is modest.

Comparison of the seasonal dependence of variability in Fig. 7 to that in Fig. 3 indicates that at least qualitatively the observed seasonality is like the seasonality expected from the influence of the seasonality of the mean circulation. Not only is the general poleward contraction and weakening from winter to summer present in both but so are many of the detailed features of the distributions. These include the south Asia maximum that occurs in all four seasons and its shift to the north during summer, the minimum in variance over east central Asia that is especially evident in the transition seasons, and the southwesterly extensions of both northern oceanic maxima in fall. That observed variability has the main features we found in the linear stochastic frameworks is equally apparent from the zonal mean perspective afforded by Fig. 8, which is the observational counterpart to Fig. 4.

Turning to scale, Fig. 9 shows the seasonal cycle of the decorrelation distance for nature. This plot makes it clear that especially in northern midlatitudes the prevailing scales do change markedly with the seasons. In winter there is a region of especially large scale in high latitudes and another in the subtropics separated by a region of shorter scale disturbances. The high latitude scales are reduced to about 75% of their winter values in summer while in the subtropics scale undergoes a semiannual variation with peaks in both winter and summer. By contrast, in the Southern Hemisphere, though there too there is a strong contrast between high latitudes and the neighboring region at about 30S, the seasonality of scale is much weaker than in the Northern Hemisphere.
All of these features have their counterparts in the linear stochastic solutions (Fig. 5), though, overall, scales are larger there. (Note the different shading boundaries in Figures 5 and 9).

The one prominent scale feature that appears in nature that was not produced by the effects of the mean circulation is the minimum along the equator in Fig. 9. If we repeat our linear calculations with one modification, namely assuming that $\epsilon$ is antisymmetric about the equator, then this feature (in a figure not shown) is also reproduced. The importance of antisymmetric forcing in this region should not be surprising considering the effect there of upper tropospheric divergence associated with interannual equatorial sea surface temperature anomalies.

To detect seasonality in the structure of interannual perturbations in nature, we make plots of the streamfunction tendencies their vorticity fluxes produce by applying the expression in (5) to our reanalysis data, with $\langle \rangle$ now referring to 40 year averages and $(\cdot)'$ indicating monthly mean departures from 40 year averages. We find that for these data too the tendencies are anti-correlated with the corresponding climatological waves. This behavior can be seen by comparing the evolution of the mean waves in Fig. 2a with Fig. 10a, which shows the anomaly-produced tendency fields for each month of the year, averaged between 35N and 60N. Zonal mean tendencies have been removed in this figure. During summer, when the mean waves are weak, the tendency field is rather bland, but during the rest of the year the tendencies are highly organized and undergoing subtle phase variations. In many cases these shifts line up with similar shifts in the phase of the mean waves. For example, the axis of the strongest feature in the figure, namely the positive tendencies over eastern Asia, migrates from about 110E in fall to 135E in midwinter and then back to 120E in spring. This corresponds to a similar evolution of the mean eddies in this location.

For a more quantitative comparison between the seasonality of the flux-induced tendency fields and the annual cycle of the mean eddies, we have calculated the pattern correlation between these two quantities for various pairs of months (Fig. 10b). Most of the relationships between these fields found in the linear setting carry over to nature; especially in fall, winter and early spring, tendencies and mean waves are most strongly anticorrelated when taken from the same or neighboring months. Once again, the transition seasons are an exception to this. The one feature of Fig. 10b that does not agree with the linear framework is the lack of a local extremum for summer mean states and tendencies.

### 4. Seasonality in GCM experiments

Though Section 3’s results suggest that many aspects of the observed seasonality of interannual variability can be understood in terms of the seasonality of the mean circulation, there are certain interannual features that the stochastic linear framework does not appear to be adequate to understand. One example of this is the secondary maximum in winter and spring variance seen in the subtropics near the dateline (Fig. 7a, b). Another is the lack of a clear anticorrelation between summertime mean eddies and tendencies resulting from interannual perturbation fluxes (Fig. 10b). Further examination of the observations suggests that shortcomings in the stochastic linear framework may be attributable, at least in part, to a specific component of interannual variability, namely the component forced by anomalous conditions external to the atmosphere. For example, if we calculate pattern correlations between stochastically modeled (Fig. 3) and observed (Fig. 7) standard deviations, we find larger values if we exclude that part of the domain most strongly linked to sea surface anomalies, namely the tropics.

To more carefully examine whether the linear, stochastic framework is less applicable to externally caused in-
terannual variability than to variability produced by mechanisms internal to the atmosphere, we reapply much of our analysis to data generated by a GCM. The GCM we use is version 3 of the Community Climate Model of the National Center for Atmospheric Research. This model is described by Kiehl et al. (1998) and some attributes of its climate have been analyzed by Hurrell et al. (1998). We use the same ensemble of 22 integrations described and analyzed by Branstator (2002), each of which has been forced by SSTs as they were observed to evolve between 1950 and 1994. To separate external (which is to say SST-forced) variability from internal variability, we identify ensemble mean behavior as being externally produced and departures from ensemble means as being internally produced. Rowell et al.’s (1995) method is applied to our estimates of external variance as a means of removing contamination by internal variability and a straightforward extension of this approach is applied to our estimates of mean vorticity fluxes by externally generated disturbances.

Geographical distributions of standard deviations of internally generated monthly mean variability for the GCM are shown in Fig. 11, and for comparison the corresponding plots for SST-forced variability are in Fig. 12. (Note that different contour intervals are used in these plots; in this GCM internal variability has standard deviations that are roughly twice as large as the standard deviations of external variability.) There are two aspects of these figures that are of special pertinence for our study. First, there is a great deal of similarity between the amplitudes, distributions and seasonality of GCM internal standard deviations and observed standard deviations (Fig. 7). This fact indicates that the organization of atmospheric anomalies that occur by the direct forcing of sea surface temperature anomalies is not crucial to most features in the observed distribution and seasonality of interannual variability. Second, though many features, including the seasonal swings in hemispheric average variance, are similar between GCM internal and external variability, there are also prominent differences. One of the most striking is the subtropical maximum in east Pacific external variability which when seen in our results from nature we associated with El Niño. Another is the maximum in external variability over North America during all seasons that
Figure 11. Standard deviations of the internal component of CCM3 monthly mean 300 hPa streamfunction fields. Contour interval and shading boundaries are as in Fig. 3 and 7.

Figure 12. Standard deviations of the external component of CCM3 monthly mean 300 hPa streamfunction fields. Contour interval is $5 \times 10^5 m^2 s^{-1}$. Light shading begins at $3.5 \times 10^6 m^2 s^{-1}$ and heavy shading begins at $4.5 \times 10^6 m^2 s^{-1}$.

is largely absent in the internal variability diagrams. A third is the North Atlantic maximum in variability that occurs in all seasons of internal variability but only in summer and fall for external variability.

Because of the distinctions in internal and external variability we can check our conjecture that the stochastic, linear framework is more appropriate for internal than external variability. To do this carefully we first recompute the stochastic solutions utilizing the GCM climatology for basic states. We find that the climate means from the GCM are similar enough to those from nature that the statistics of these new solutions are very similar to the solutions described in Section 2. For example, with the exception of the April south Asian maximum, every shaded feature in the standard deviation plots based on nature’s mean states (Fig. 3) have a similarly located feature in plots for the GCM mean states. Given this similarity, though we use the GCM-based stochastic solutions for quantitative results, it is sufficient to think of Figures 1 through 6 when visually comparing stochastic and GCM behavior.

Comparing the standard deviations of stochastic linear variance in Fig. 3 to Figures 11 and 12, one sees that for each of the three features where we have noted a large difference between internal and external variance, the linear stochastic framework matches the internal rather than the external variability. For a quantitative comparison of stochastic and GCM behavior we calculate pattern correlations between the zonally asymmetric components of Northern Hemisphere standard deviation maps. Figure 13a shows the resulting correlations between the stochastic solutions and GCM internal variability for various pairs of months. The unmistakable influence of the seasonal cycle of the mean state on the internal variability is reflected in the fact that its geographical distributions are invariably much more similar to distributions stochastically generated with basic states from the same or similar months than from basic states with a very different structure (Fig. 2b). By contrast, when stochastically produced standard deviations are matched with external standard deviations (Fig. 13b), distributions from the same month have weak similarities. The pattern correlations on the diagonal of this diagram are not much larger than zero and during the cold months the GCM patterns actually match stochastic solutions corresponding to spring and fall much better than they match solutions from the same time of year.
Figure 13. a) Pattern correlation between the zonally asymmetric component of charts of standard deviations of solutions to the stochastically driven linear barotropic vorticity equation and charts of standard deviations of the internal component of CCM3 monthly mean hPa streamfunction fields. b) Same as a) except the ordinate corresponds to charts of standard deviations of external CCM3 variability. Contour interval and shading as in Fig. 2b.

A second field where the distinction between the annual cycle of internal and external variability is apparent is the streamfunction tendency field resulting from interannual vorticity fluxes. When in Fig. 14a we plot Northern Hemisphere pattern correlations between tendencies and 300 hPa mean streamfunction in the same way we have for stochastic linear solutions (Fig. 6) and nature (Fig. 10b) the now familiar X-shaped pattern results. In this case, however, the imprint of the background state and linear dynamics is even more pronounced than it was for nature. For all months of the year, not just cold months, the tendency fields are most anticorrelated with mean states taken from the same month or months with similar mean circulations. By contrast, a similar diagram (Fig. 14b) for tendencies produced by externally induced anomalies has much weaker anticorrelations and wintertime GCM tendencies are no more anticorrelated with winter mean states than they are with summer mean states.

5. Summary and discussion

Guided by attributes of steady solutions to the stochastically forced nondivergent barotropic vorticity equation linearized about mean states from each month of the year, we have documented various aspects of the seasonal cycle of interannual variability in nature. Among the most prominent of these properties are

- In the Northern Hemisphere standard deviations are roughly twice as strong in winter as in summer; in the Southern Hemisphere this ratio is about 1.5.
- The latitudinal extent of high midlatitude variability extends much more deeply into the subtropics in winter than in summer.
- Though their amplitude and latitude change with the seasons, the well-known winter maxima of variability over the northern oceans exist throughout the year as does a maximum in the south Asian subtropical jet.
- The dominant spatial scales of interannual disturbances are a function of latitude and change with the seasons. In midlatitudes they have a simple annual cycle with largest scales in winter. In the subtropics they have a semiannual cycle with
maxima in summer and winter. Seasonal variability is weaker in the Southern Hemisphere than in the Northern Hemisphere.

- The structure of interannual disturbances changes with the seasons in such a way that they produce momentum fluxes that induce streamfunction tendencies that tend to be spatially anticorrelated with the (seasonally varying) climatological mean eddies. Summer may be an exception to this rule.

Because each of these attributes is also present in the stochastically driven linear solutions, we conclude that the linear stochastic framework is useful for understanding key properties of interannual variability and its seasonality and that to a significant extent the seasonality of interannual variability occurs as a consequence of the structure and seasonality of the mean circulation.

We have also found evidence that the stochastic linear framework is not as successful at explaining the statistical properties of externally forced (in particular SST-forced) variability as it is at explaining internally forced variability. We interpret this as meaning that, compared to solutions of the linear stochastic model, interannual perturbations forced by highly organized external sources have an additional constraint. In the stochastic setting perturbations are favored that have intrinsically long timescales and that can gain energy by interacting with the mean state. These same conditions affect externally forced perturbations, but since externally forced disturbances must also balance the forcing, their structure must reflect this constraint too. This idea is consistent with Barnston and Livezey (1987) and Straus and Shukla's (2002) finding that the midlatitude response to El Nino SST anomalies probably has a different structure than the leading structure of internal North Pacific variability.

Our results and conclusions may seem puzzling when compared to those of Newman et al. (1997) who performed calculations much like our wintertime experiments and found the resulting geographical distribution of variance did not resemble observations. We have repeated their experiments and found the key distinction with our winter solutions is that we have reasoned it was not prudent to force the zonal mean. If their calculations are repeated but with the zonal mean component of the stochastic forcing removed then their results match other similar winter studies (e.g., Branstator, 1990 and Metz, 1994) and support the notion that much of the geographical distribution of interannual variability is controlled by the time mean and not by details of external forcing.

Figure 14. a) Pattern correlations between climatological mean streamfunction and streamfunction tendencies from interannual vorticity fluxes as in Fig. 6 and 10b except here the vorticity fluxes result from internal CCM3 monthly mean anomalies. b) Same as a) for external variability. Contour interval and shading are as in Figures 6 and 10b.
The entire study could have (and has) been carried out using 10 day averages, so that the timescale separation would have been obvious. But with 10 day averages, not only are the stochastic results essentially unchanged, the observational are also little affected (except all amplitudes are larger). (This agrees with Feldstein’s (2000) result that the characteristic times of the leading Northern Hemisphere winter patterns are less than 10 days.) So to be consistent with other studies of interannual variability and for simplicity of interpretation of the dynamics influencing the linear solutions, we have chosen to report our findings using 30 day means and steady linear solutions.

Appendix B
Pooling of Results

Barnston and van den Dool (1993) have pointed out that, if one estimates two dimensional distributions of standard deviations of monthly means for datasets of the length of the observed record, one cannot have confidence in many features of the estimates. They recommend pooling standard deviations of monthly departures from climatological means for three month seasons as a way to alleviate this difficulty, and this is the approach we follow here when dealing with reanalysis data. Newman and Sardeshmukh (1998) caution against pooling because the response of their linear model to the tropical forcing function they employed was sensitive to differences in the mean states from some neighboring months. But when we compare pooled and unpooled standard deviations in large datasets (e.g., stochastic and GCM solutions) whose size gives us con-
We take this as evidence that for the statistical properties we study pooling of observational data does not affect features of interest while adding to their statistical significance.

Following the same reasoning we also pool the statistics of other fields from nature, including decorrelation distance and streamfunction tendency as well as results for ensemble mean GCM fields. On the other hand, because zonal averaging increases the number of samples contributing to a statistic, quantities displayed in latitude/time plots are not pooled. Likewise, since there are 990 samples contributing to the statistics for each month, no pooling is used for intrinsic GCM variability.

References


