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A PRIMER ON SEASONAL CLIMATE FLUCTUATIONS

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Nature of climate variations and basis for predictability.

It is useful to begin this topic by considering the question of how climate differs from weather, and why there might be reason to expect predictability of climate. It is quite obvious from everyday experience that the ability to predict the state of the atmosphere – the weather – beyond a few days in advance is extremely limited. Considering then that seasonal climate involves statistics of the weather over months or even seasons in advance, why should one expect predictability? Moreover, the climate involves more than just atmospheric predictions, because at time scales longer than a few days additional interactions between the atmosphere, the oceans, the land surface, and the cryosphere become increasingly important. As it turns out, this added complexity brings with it a great bonus: the natural variations of the other components of the climate system, especially the oceans, occur on time scales much longer than the atmosphere. In effect, they carry much greater “inertia”. Thus, to the degree that the atmosphere is strongly coupled to these other components, there is a physical basis for predictability.

Historical and present understanding of prominent patterns of climate variability.

In the past two decades, considerable progress has been made in identifying aspects of atmosphere/ocean coupling. The premier example is the El Niño/Southern Oscillation phenomenon (or ENSO). The Southern Oscillation was identified more than a century ago by Sir Gilbert Walker, in connection with studies of year-to-year variations in the Indian monsoon. It involves a large “see-saw” pattern in the sea-level pressure field, with centers near Indonesia and the southeast Pacific region. The El Niño phenomenon was discovered independently, as a warming of the waters of the eastern Pacific, sometimes with dramatic effects on fish and other wildlife. Only in modern times did it come to be appreciated that the tropical eastern Pacific warming events are typically accompanied by a very large scale warming of the entire central and eastern tropical Pacific. Both phenomena were known to occur irregularly in time, between 2-8 years apart, and to play out over several seasons, once initiated. But only in the 1970s was it first hypothesized that these two phenomena were actually strongly linked – in effect, components of a single, coupled phenomenon. Fig. 1 shows a time series of two indices, representing the departures of ocean surface temperature in the eastern Pacific (a measure of El Niño or its negative counterpart, known as La Niña), and sea level pressure difference between the southeastern and western tropical Pacific (a measure of the Southern Oscillation). The correlation between the two is quite remarkable – the strongest known relationship affecting seasonal climate.

ENSO is now understood as a quasi-cyclic process, with a preferred time scale of several years, and a great deal of variability in both timing and amplitude that is due to a combination of nonlinear effects and the influence of random “noise” which is ever-present at the weather time scales in particular. The essential coupling has become understood over recent years; it involves, first, a set of positive feedback processes between the near-equatorial tradewinds and the east-west contrast of ocean temperatures at the surface and below the surface (near the so-called thermocline – the transition between near-surface

waters and deeper colder waters). But the critical additional element derives from the dynamic nature of the tropical oceans. Because of the slow evolution of currents and waves in the ocean, the subsurface state is never in balance with the atmosphere or the ocean surface, but rather represents the history of past events over seasons to years. This introduces a delayed effect on the ocean surface temperatures (in the strong upwelling areas of the eastern equatorial Pacific) that dictates a never-ending sequence of transitions between warm and cold states (El Niño and La Niña) with time scales of several years.

ENSO has impacts nearly global in reach. For example, areas of Australia, Indonesia, southeast Africa, and northeast Brazil typically experience drought during El Niño. In North America, the preferred wintertime effects include warmth in the northwest, and cooler and wetter than normal conditions in the southeast (Fig. 2). La Niña conditions are often roughly opposite of El Niño conditions, but this is not uniformly true (Fig. 3). Many of these effects can be traced to very large scale wave patterns that set up in the atmosphere as a result of the ENSO-related tropical Pacific shifts in primary centers of convection, which in turn, are closely linked to the changes in ocean surface temperatures.

Several other preferred patterns of climate variability operating on seasonal and longer time scales have been identified. The so-called North Atlantic Oscillation is a fluctuation in sea level pressure with centers roughly west of the Azores, and over Iceland. Associated with this are shifts of wind patterns over the north Atlantic, north-south displacements of the active wintertime “storm tracks” from west to east across the ocean basin, and temperature and precipitation shifts over regions in both North America and western Europe. Also associated with the NAO are changes in ocean temperature, but the changes are fundamentally different from those associated with ENSO because they do not appear to be important in affecting the atmosphere. Thus, at present there is little support for the idea of a strong two-way coupling between the atmosphere and ocean that could impart predictability. There is, however, recent evidence that there may exist a connection between occasional major warming events in the polar stratosphere (known as sudden warming events), and the state of the NAO. If this proves to be true, then there may exist some limited predictability over a 1-2 month time span in winters where a stratospheric warming event is observed to occur.

A pattern known as the Pacific decadal oscillation has been identified in recent studies. This is associated with changes in pressure and wind patterns over the north Pacific, and changes in Pacific ocean temperatures similar to El Niño, but extending much further poleward into the subtropics of the northern hemisphere. The pattern is also associated with changes in precipitation and temperature in the northwest United States in particular. Although this pattern has primarily been identified in the context of decadal variations, it appears at much shorter timescales as well, including seasonal. The dynamics are at present poorly understood. There appears to be little predictability on seasonal time scales.

The tropical Atlantic exhibits interesting variability at seasonal-interannual time scales in at least two forms. One of them is quite analogous to El Niño, and possibly is controlled by similar coupled ocean-atmosphere interactions. However, it is much less prominent a pattern, and is expressed clearly only in the northern summer season. Precipitation patterns in areas of west Africa are linked with this pattern. Although the association with ENSO suggests some predictability, the degree of predictability is still poorly understood. The tropical Atlantic also exhibits another important pattern, characterized by interhemispheric contrasts in temperature and changes in the north-south component of winds near the equator. This pattern exhibits variability on timescales from decades to a season, and affects strongly the precipitation of regions of northeast South America. Current understanding suggests there is some basis for limited seasonal predictability, but further research is needed.

Finally, there are hints of a preferred mode of variability in the Indian Ocean, sometimes referred to as the "Indian Ocean dipole". This appears episodically, and plays out over several months once initiated, with associated impacts on east Africa precipitation and possibly Indian monsoon variations. The dynamics are still poorly understood, as is the predictability.

Prediction of ENSO.

Predictions of the state of ENSO alone are of interest, as this represents the most prominent mode of climate variability, and the areas of influence are global in scope. The prospects for predictability were first raised in the mid-1980s as both statistical and dynamical modeling approaches were first applied with some success. Statistical approaches search for precursor patterns in atmospheric and oceanic variables, based on past observations. Dynamical approaches involve the application of numerical models derived from basic physical laws, often simplified to include only what is regarded as essential physics to capture the salient features of the observed phenomenon. The tools for ENSO predictions are coupled models, as both the ocean and atmosphere are critical to the process. One of the most challenging aspects of dynamical prediction is the forecast initialization problem. This is complex because of several factors: the sparseness of observations (especially the subsurface ocean), errors in observational analyses, and biases/errors in the models used for predictions. In the end, a synthesis of observational and model data which minimizes model-data misfits of specific types – those that lead to the fastest growing forecast errors – are needed. The skillful diagnosis of these patterns, and the process of creating the optimal blending, is enormously complex, and the subject of ongoing research. The earliest predictions simplified the process enormously, using only limited observational data for the surface winds that drive the ocean state, and deriving all other field from the model equations. Even with such an overly simple approach, skill in ENSO prediction was demonstrated. A typical result is shown in Fig. 4, in the form of correlation and rms-error of predicted and observed values of the index NINO3 (measuring SST variations in the eastern Pacific) as a function of lead time of the forecasts, for different verification periods. In comparison to a baseline measure of skill – the persistence of anomalies – the model based predictions are decidedly superior. Also indicated is the sensitivity of performance to initialization. In one case the observational analyses of surface winds are inserted directly into the model, and in the other they are blended with model counterparts so as to produce a state more consistent with the coupled model (but perhaps less consistent with observations!) The result for the periods shown is much better for the latter case.

The large El Niño event of 1997 provided new challenges, and new insights for climate prediction. Some models failed to capture the event entirely. In retrospect, the performance could be improved greatly by including additional observational data for the subsurface ocean that was available by 1997 from a network of moored buoys in the tropical Pacific. Models and forecast systems that were already using subsurface data in 1997 fared much better. This illustrated the importance of this source of information, and furthermore is consistent with the understanding of the crucial dynamic role played by the subsurface ocean in ENSO dynamics. However, even the best predictions in 1997 were not able to anticipate the occurrence or the extraordinary magnitude of the warming event at lead times more than a month or two before the observed onset. A possible reason for this is the impact of "noise" in the climate system, defined as short-term weather fluctuations not directly connected to the ENSO process itself. In early 1997 a very strong wind event occurred in the western Pacific – a so-called westerly wind burst – which created a strong push toward El Niño conditions. Such bursts are observed quite often, including non-El Niño years. However, the magnitude of this, and a subsequent such event in 1997, were exceptional, and the timing was optimal for supporting a rapid development. If this diagnosis is correct, and the presence of such events is not predictable, then additional limitations on

predictability of ENSO are implied. An appropriate approach to the problem may then be probabilistic rather than deterministic. Such topics are being pursued in current research.

A related issue has recently been addressed in studies analyzing ensembles of predictions from several current ENSO forecast systems. It has been found that the simplest statistic of the ensemble – the mean – outperforms all of the individual forecast models over a multi-year retrospective evaluation period (Fig. 5). This addresses another sort of uncertainty; namely, that due to individual models errors and biases, in limiting forecast skill. The ensembling over several models appears to provide, on average, a better prediction. This raises the possibility of even better results from more sophisticated combination methods that explicitly factor in each individual skill levels.

Forecasting seasonal climate.

The above discussion offers a somewhat sobering picture of climate predictability, as only ENSO currently offers prospects for long-lead predictions, and even this is seen to have limitations and uncertainties. While further research is likely to improve matters at the longer leads in at least some respects, for some regions, there is additional predictability to be harnessed at shorter leads. This derives from the persistent nature of the ocean surface temperature globally. Because of the thermal inertia of the upper ocean, the near-surface temperatures in the global ocean are quite persistent over several months, as seen by the lag-autocorrelation field (Fig. 6). Regional climate globally is impacted by local, and in many cases, non-local ocean surface temperature conditions; thus predictability in ocean conditions over 3-5 months implies a degree of predictability of seasonal climate at similar leads for many regions of the world. However, even more than in the case of ENSO, regional climate cannot be predicted in a deterministic sense, due to the large influence of chaotic weather variability. The internal “weather noise” introduces a significant stochastic component into the system at seasonal and longer time scales. On the other hand, the influence of more slowly evolving ocean temperatures (and to a lesser extent land surface and sea ice conditions) imposes a limited order within the randomness, by shifting the likelihood of particular events. It is roughly analogous to throwing dice that are “loaded”; all events are still possible, but certain events become more likely when the dice are loaded in a particular manner.

Dynamical climate models have proven successful in simulating some aspects of seasonal precipitation and temperature variability, when forced with prescribed observed ocean surface temperatures over many years. Such models serve as the basis of most routine climate prediction products. In general, they exhibit quite realistic variance associated with weather time scales, and therefore exhibit the same limitations for climate as previously ascribed to nature. However, the models afford the possibility of addressing the uncertainty through the use of ensembles. In the IRI forecast system, several different climate models are run in ensembles of 10 or more, using the same SST (forecast) forcing, which is derived from a coupled comprehensive model forecast in the tropical Pacific, and statistical or persistence forecasts in other parts of the global oceans. From the ensembles of individual climate model forecasts, probabilistic forecasts can be generated by observing the frequency of occurrence of particular events in the model ensemble (Fig. 7). For example, probability distributions can be defined for a climatological period, and then compared against a particular forecast distribution to measure the significance of predicted shifts. The standard forecast product produced by IRI consists of predicted probabilities for precipitation or temperature falling in each of the three terciles of the climatological distribution at each location. Over much of the world in any given forecast, no significant shift of the climatological distribution can be detected, either because all climate signals are too weak (in comparison to the noise in the system), or because the model biases or errors mask them.

For the final forecast product, it is necessary to combine the results from each of the climate models. While simple averaging was found helpful in other contexts, somewhat more elaborate methods have proven advantageous for climate forecasts. Fig. 8 shows a map of skill measures for a unequal weights combination algorithm currently used at IRI. It can be noticed that only a small portion of the globe exhibits significant skill, relative to a simple climatological forecast (predicting equal probabilities for each tercile category). This is a statement of the current forecast model limitations as well as the inherent limits of predictability for seasonal climate. Notice also that in general, the prediction skill is higher in the tropics than in the higher latitudes. This arises from the more direct influence of ocean temperatures on the atmosphere, and lower levels of internal variability (noise) in the tropics. Recently we have conducted an evaluation of real-time forecast skill over the past 4 years (Fig. 9). It is notable that globally averaged skill scores are highest during times of strong ENSO signals; related to this, it was possible to detect significant shifts of the climatological probabilities over more of the global domain during these times. Both are consistent with the fact that ENSO is the largest climate signal operating on seasonal to interannual time scales.

Tailoring forecasts.

In order to allow seasonal predictions to be utilized in the context of particular applications such as agriculture, a scale matching problem must be addressed. In many applications it is necessary to translate seasonal information into plausible scenarios with high spatial and temporal detail. This is not practical using global models because of computational expense. Two approaches are currently taken: statistical methods of downscaling in space and time, and nested, high-resolution regional climate models. Encouraging results have been obtained in both arenas, although considerable further work is needed for a rigorous assessment. In many instances, progress is limited by the lack of high resolution data with which to validate any product. Regional dynamical models offer a clear advantage over global models in their capability to simulate the structure and evolution of synoptic scale weather disturbances, which are ultimately responsible for extreme events and high order statistics of the seasonal climate important for many applications.

Summary and Outlook.

Fundamentally, seasonal climate variability assumes structure and limited predictability due to coupling between the atmosphere and “slower” components of the climate system: the oceans, the land surface, and the cryosphere. Of these, the most important is the oceans.

Several identifiable preferred patterns of low-frequency climate variability have been identified, including ENSO, the North Atlantic Oscillation, the Pacific Decadal Oscillation, an ENSO-like Atlantic pattern, an interhemispheric Atlantic pattern, and an Indian Ocean dipole pattern. Of these, only ENSO is known to exhibit long-lead predictability, although the implications for this alone are significant for global climate. Some of the others hold promise.

Global scale predictions of seasonal climate are often possible, and are currently being made. They have been shown to have limited skill for 1-2 seasons in advance, in some, but not all regions of the world. Generally, the best results are obtained for the tropics, although particular regions of the extratropics, including portions of the north America, also show some systematic skill. All seasonal predictions are aided by the fact that ocean temperatures everywhere possess considerable persistence from one season to the next. Because of internal variability, and its influence on predictability, seasonal forecasts must be considered in a probabilistic sense. Model based projections can best address this problem through the use of ensembles. Downscaling, and other tailoring of seasonal predictions through statistical and

dynamical means offers promise to render seasonal predictions of greater value for agriculture and other application areas.

For future research, it is important to gain a better understanding of the most prominent patterns of climate variability, in order to develop a more reliable assessment of associated predictability. In some instances, this will require additional observations and diagnostics. Forecast development must address three major challenges: model systematic errors, forecast initialization, and the realistic handling of “noise” in the climate system. Forecast product development must further refine ensembling methods within and across models, and downscaling methods, still relatively new topics in the climate context. Research is active in most of these areas now, and there is good reason to anticipate future advancements. Important to progress is the engagement of real problems, such as agriculture, in the assessment and development of future tools and methodologies.

Fig. 1. Indices of the Southern Oscillation (SOI) and eastern Pacific sea surface temperature (NINO3).

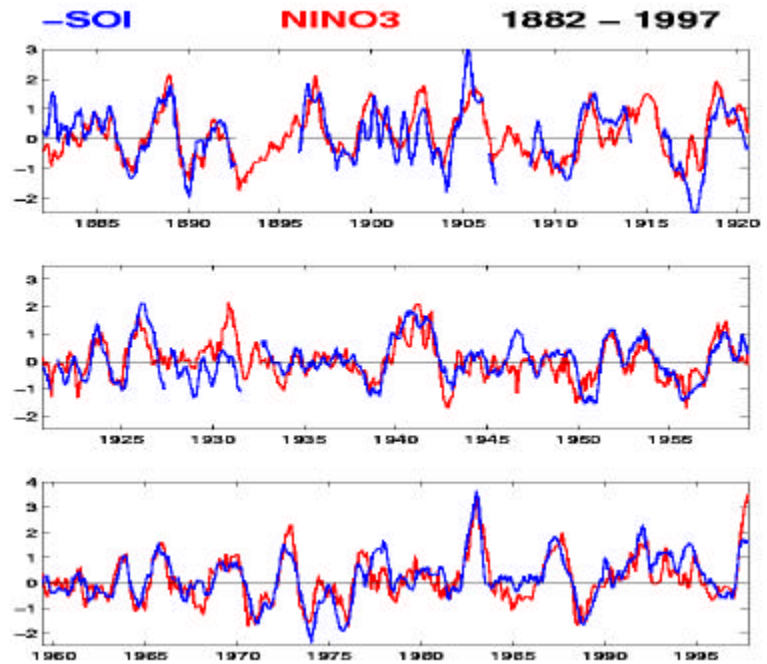
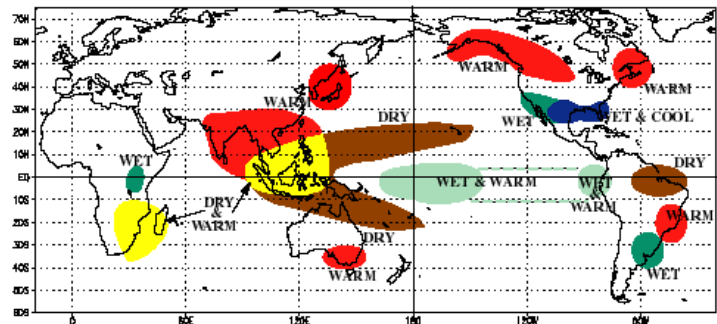
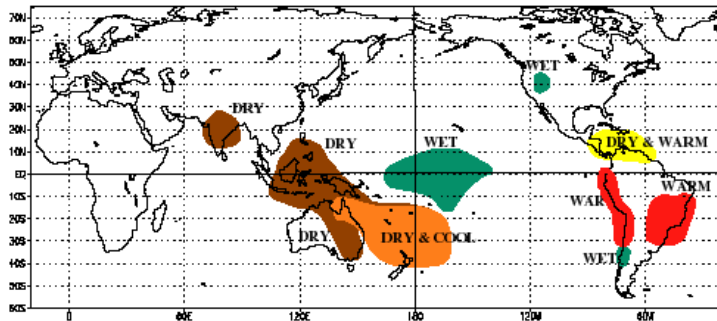


Fig. 2. Characteristic El Niño related climate anomalies.

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WARM EPISODE RELATIONSHIPS JUNE - AUGUST



COLD EPISODE RELATIONSHIPS DECEMBER - FEBRUARY

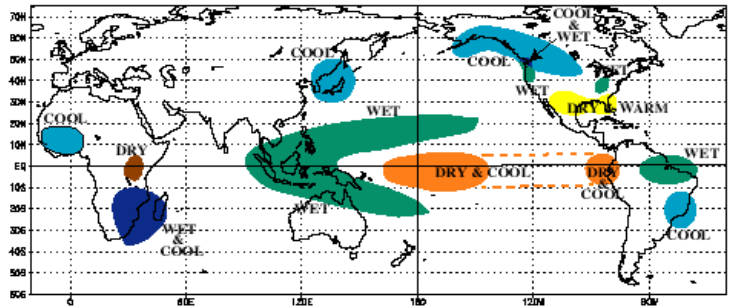


Fig. 3. Characteristic La Niña related climate anomalies.

COLD EPISODE RELATIONSHIPS JUNE - AUGUST

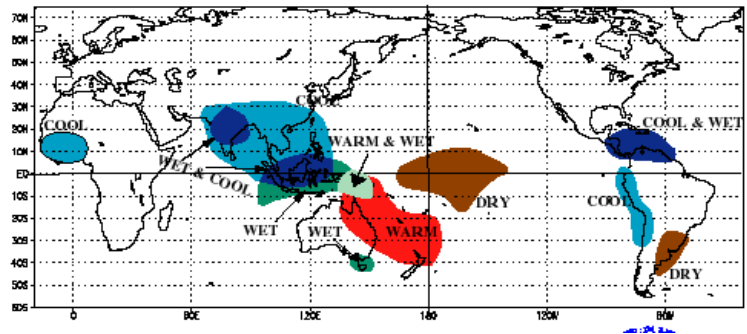
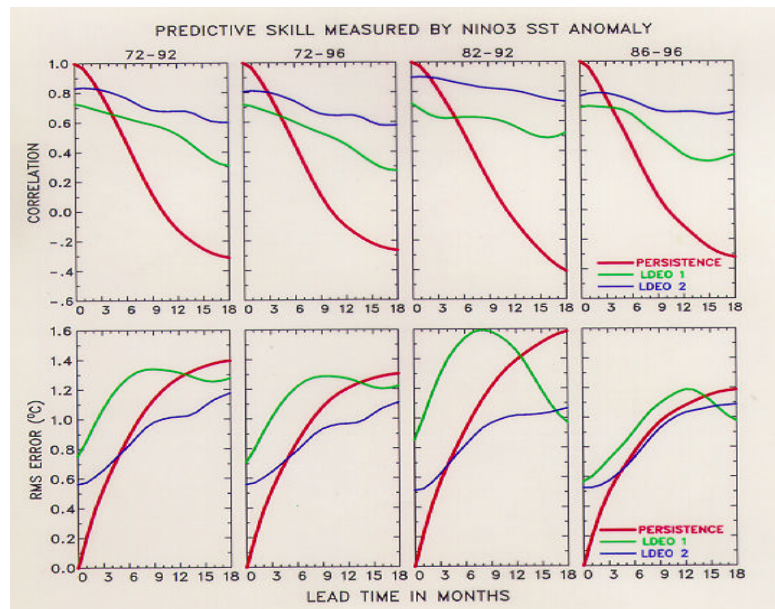


Fig. 4. Forecast skill in terms of correlation and RMS error of predicted v. observed NINO3 index for the validation periods shown. The two versions of the LDEO model differ in the method of initialization. Skill measures for forecast using simple persistence is also shown.



NINO3 Skill Score Comparison (Systematic Error Removed)

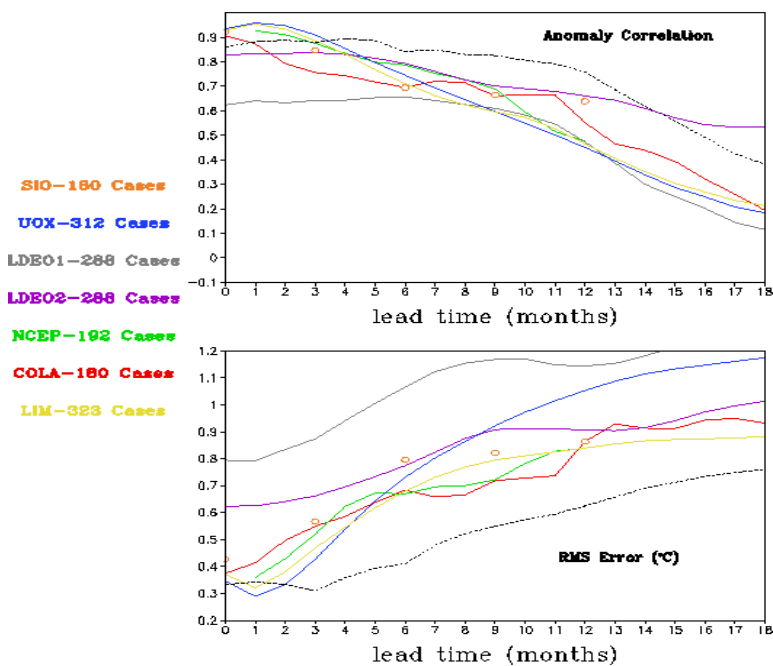


Fig. 5. Correlation and RMS error skill for forecasts of NINO3 over a multi-year period from several individual forecast models, and from a consensus forecast, the simple average of the individual forecasts (dashed lines).

SSTA Persistence from Observation (All Seasons)

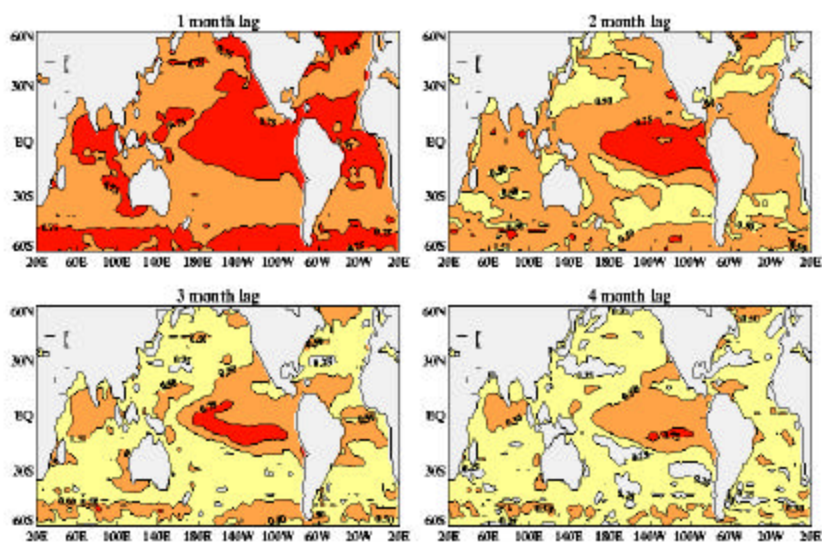


Fig. 6. Correlation of SST anomalies with the same fields at the indicated lead times, coutoured at intervals of 0.25..

Fig. 7. Ensemble simulations of precipitation for a region of SE Australia. Individual simulation values are shown for the hindcast period 1950-1997, together with the ensemble mean, and observed. From these results the climatological distribution (shaded) in the right panel is constructed. Also shown are the forecasts from individual ensemble members, and ensemble mean, for Jan-Mar. 2002, and associated distribution (outline, right panel).

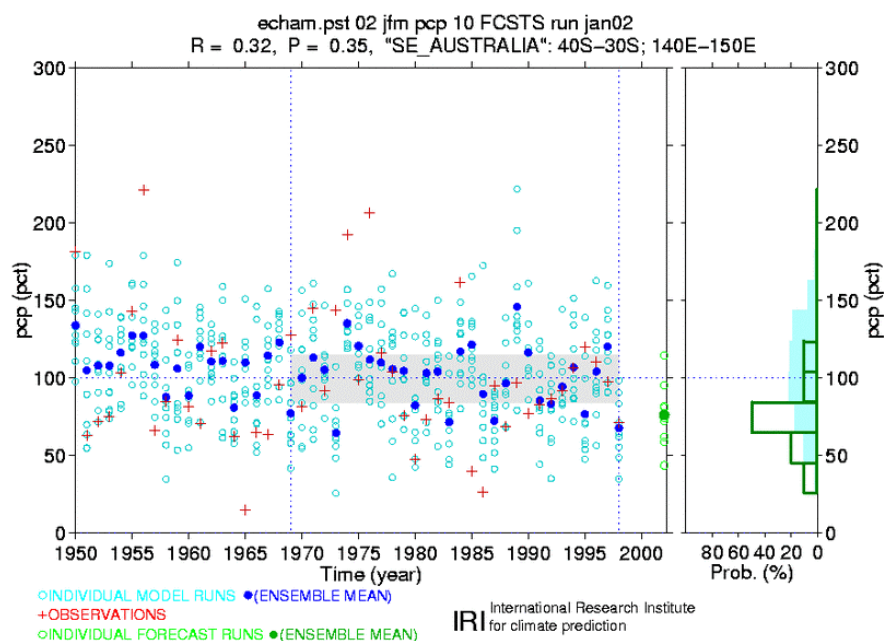


Fig. 8. Probabilistic skill of model combination forecast, relative to climatology forecast, for Apr-Jun surface temperature (upper panel) and Jan-Mar precipitation (lower panel). Skill levels significant at the 90, 95, and 99 percent level are indicated.

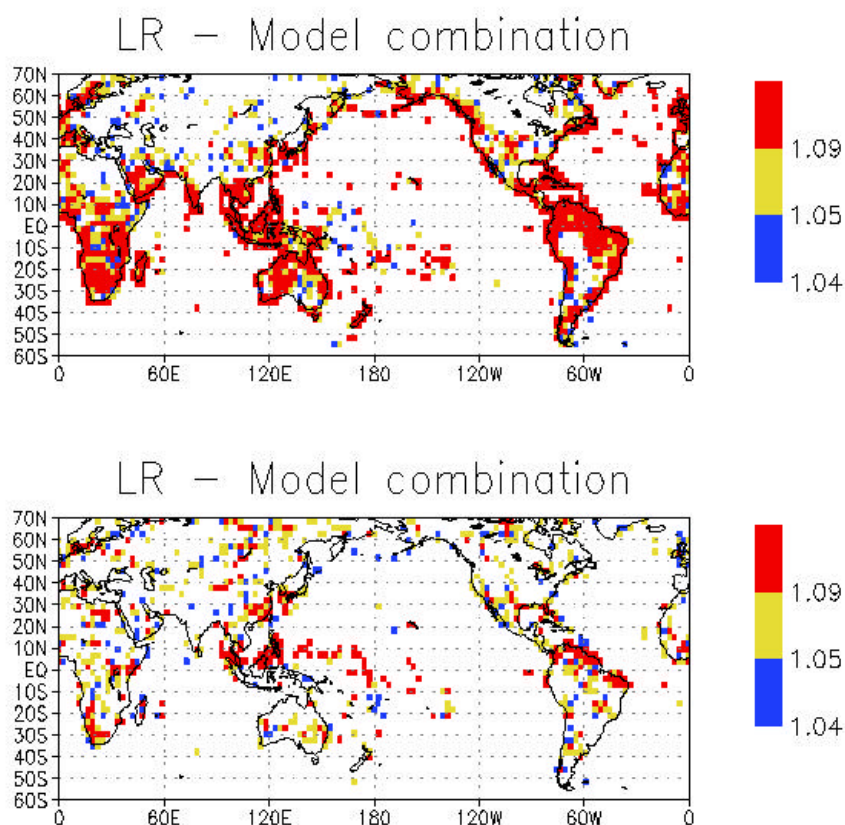


Fig. 9. Real-time forecast skill scores for IRI precipitation forecasts during 1997-2001 (based on ranked probability skill score). Lower panel shows the coverage of global land area where forecasts (other than climatology) were issued.

