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Alternative Measures of Potential Predictability Applied to Ensemble Simulations of Seasonal Land-Surface Climate

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1. Introduction

The potential predictability (**PP**) of seasonal climate at the land surface is of enormous human import, and therefore merits close investigation. The **PP** of a seasonal land-surface variable may be defined as the upper bound in mean forecast accuracy to be expected when the seasonal state of the oceans is known precisely (as when SST's are prescribed), but when the initial conditions are known imprecisely. The **PP** of a seasonal land-surface variable is related to its degree of *insensitivity* to the choice of initial conditions when the ocean boundary conditions are invariant. There are various ways of measuring this initial-condition insensitivity, two of which are utilized here.

The **PP** of a seasonal-mean variable can be estimated from an *ensemble of repeated simulations* of a multiseasonal period in which the ocean boundary conditions are the same, but in which the initial conditions of the model's land/atmosphere system are different. It should be noted that a truly accurate determination of **PP** following this approach requires use of a "perfect" model. *Estimates of* **PP** *made with current-generation models therefore must be regarded as quite imprecise.*

2. Ensemble Experiments

In this study, an ensemble of 6 realizations of decadal climate (for the period 1979-1988) were generated by the ECMWF cycle 36 atmospheric model (operational circa 1990--see **Table of Salient Features**). In each experiment, the specified SSTs and sea ice extents were the same: the monthly observational data used as boundary conditions in the Atmospheric Model Intercomparison Project (AMIP). However, in these simulations the initial states of the model atmosphere, soil temperature/moisture, and snow cover were different. The first two realizations were initialized from ECMWF analyses, while subsequent realizations were initialized from values at the last time step of the preceding integration.

Table: Salient Features of the ECMWF Cycle 36 Model Applied in this Study

- **Spectral T42 (~ 3 x 3 degree) horizontal resolution, 19 vertical levels (5 below 800 hPa)**
- **Morcrette radiation, Slingo cloud formation, Tiedtke mass-flux convection**
- **Blondin Land-surface scheme:**
  - **Stability-dependent surface fluxes**
  - **2 prognostic soil layers for heat, moisture (overlying a deep prescribed layer)**
  - **surface and deep runoff**
  - **vegetation canopy, stomatal resistance**

3. Methodology

Two different measures of initial-condition insensitivity (as an indication of **PP**) were applied: a cross-correlation (**CC**) measure and a fractional variance (**FV**) measure.

The Cross-Correlation (CC) Measure

The **CC** is a measure of the mean "reproducibility" of different realizations of a seasonally averaged land-surface variable **V**(x, y, t) for different initial conditions. The measure is calculated on *anomaly departures* **A**(x,y,t) of variable **V** from its simulated ten-year seasonal cycle, since seasonal prediction implies the ability to forecast anomalous deviations from climatology.

The **CC** algorithm involves drawing an independent pair (A_m, A_n) of **A**(x,y,t) from the available 6 realizations and computing at each grid point (x,y) a zero-lag temporal correlation **r**(x, y) over the 10 years (t = 1, 2, ..., 40 seasons). This procedure is repeated for all 15 independent pairs [N!/(2!(N-2)!] that can be drawn from a collection of N = 6 realizations. The ensemble mean {**r**(x,y)} then is computed as the value of **CC**(x, y) for land-surface variable **V**(x, y, t).

The advantages of the **CC** statistic are that it provides a single measure of reproducibility over the entire simulation, and that it is based on [N!/(2!(N-2)!] samples rather than only N. Its main disadvantages are that the minimum value of **CC** to be identified with potentially predictable signals is not obvious, and the seasonal dependence of **PP** is not accounted for.

The Fractional Variance (FV) Measure

FV –historically the "conventional" measure of **PP**–involves estimating the fraction of total temporal variance σ_T^2 that is attributable to the ocean boundary forcing σ_B^2, as opposed to that part of σ_T^2 due to chaotic (unpredictable) internal variability σ_I^2:

$$\mathbf{FV}(x, y) = \sigma_B^2(x, y) / [\sigma_B^2(x, y) + \sigma_I^2(x, y)]$$

The value of σ_B^2 is usually estimated from the interannual variability of the ensemble mean of the available realizations, while the value of σ_I^2 is estimated from the intraensemble scatter about this ensemble mean. The respective variances typically are computed after stratifying the available realizations by season, so as to identify a possible dependence of **PP** on time of year.

Unlike the **CC** measure, the criterion for potential predictability is unambiguous: **FV** > 0.5 implies potential predictability. The chief disadvantage is that **FV** is based on only N samples, and therefore may be a substantially less robust statistic than **CC**.

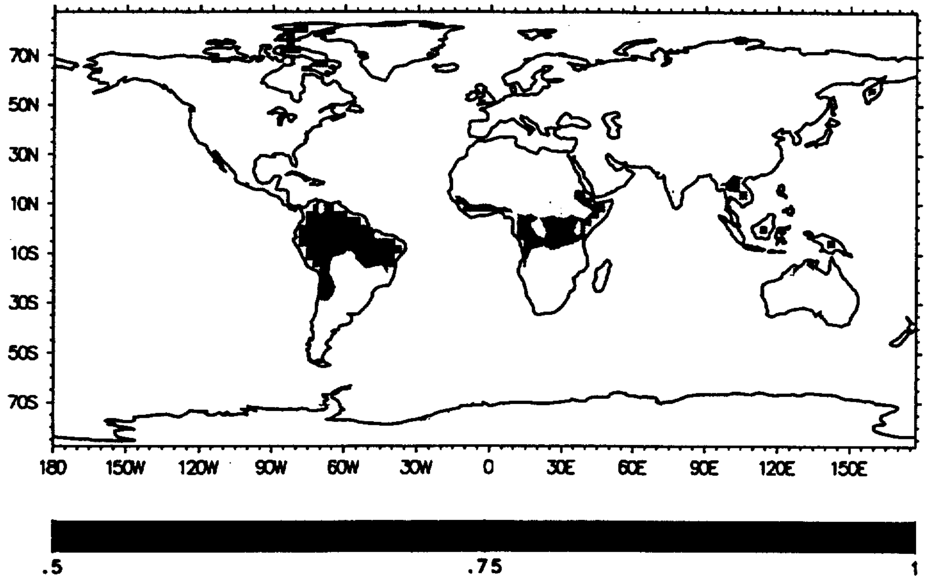
4. Results

A total of 11 dynamic, thermodynamic, and hydrological land-surface variables were analyzed in this study. *Here, for reasons of space, results are shown for only one variable--the land-surface air temperature--which exhibited more widespread evidence of apparent **PP** than was the norm.*

Figure 1 shows those regions where **CC** for land-surface air temperature exceeds a value of 0.5. (Because the precise level of **CC** to be identified with a potentially predictable signal is not apparent, a minimum value of 0.5 was chosen as a *practical* criterion of **PP**; for this value one realization explains, on average, only 25% of the variance of another.) Continental regions where

CC > 0.5 are limited to the tropics, in particular Amazonia, equatorial Africa, and parts of southern Asia. This is an indication of the low reproducibility of seasonal land-surface in the extratropics where chaotic dynamics predominates.

Figure 1: Continental regions where the CC measure for seasonal surface air temperature is > 0.5, a value assumed to indicate *practically significant* predictability.



In Figure 2, regions where the **FV** statistic is > 0.5 (a variance fraction, rather than a correlation coefficient as in Figure 1) for land-surface air temperature in December-January-February (DJF) are shown. In this season, the implications are qualitatively similar to those of Figure 1, although the tropical areas evincing **PP** are somewhat broader. However, there is an indication that surface air temperature is potentially predictable in March-April-May (MAM) over some extratropical regions, particularly in North America (Figure 3). Other work by the author suggests that at least a part of this extratropical predictability in boreal spring is associated with ENSO phenomena.

5. Summary

Assuming that the ensemble simulations of the ECMWF cycle 36 model are roughly realistic, seasonal land-surface air temperature would appear to be potentially predictable in the tropics--especially over Amazonia, equatorial Africa, and southern Asia--but not in most parts of the extratropics. This is a general result, to varying degrees, for the 10 other land-surface variables that were considered. With respect to extratropical seasonal prediction, however, there are disagreements between inferences based on **CC** vs **FV**, with the latter measure implying somewhat more encouraging conclusions in certain seasons and regions. It should be kept in mind, though, that the **FV** statistic is based on substantially fewer samples than **CC**. In any case, it seems important to consider changes in potential predictability with time of year and in relation to longer-period fluctuations such as ENSO events.

Figure 2: Continental regions where the FV measure for DJF surface air temperature > 0.5, implying potential predictability.

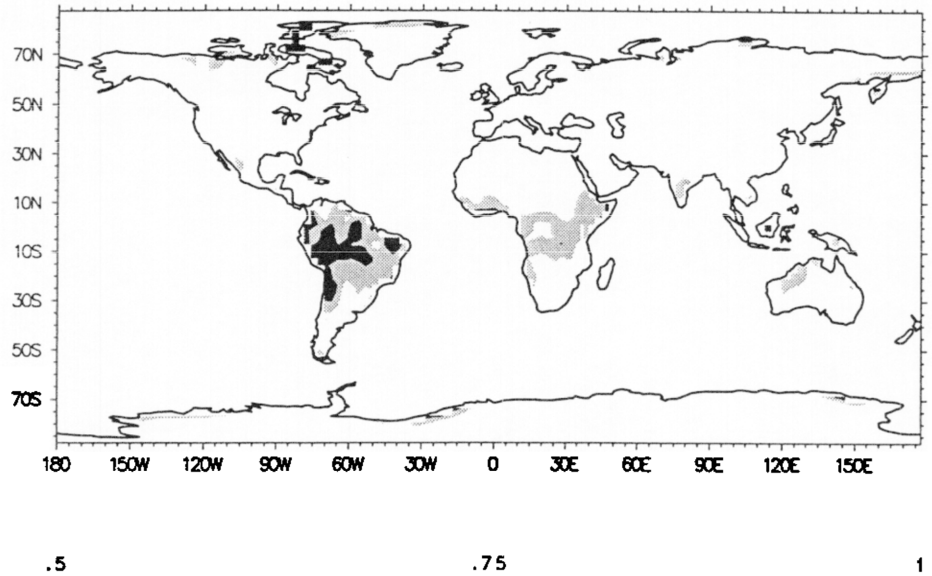
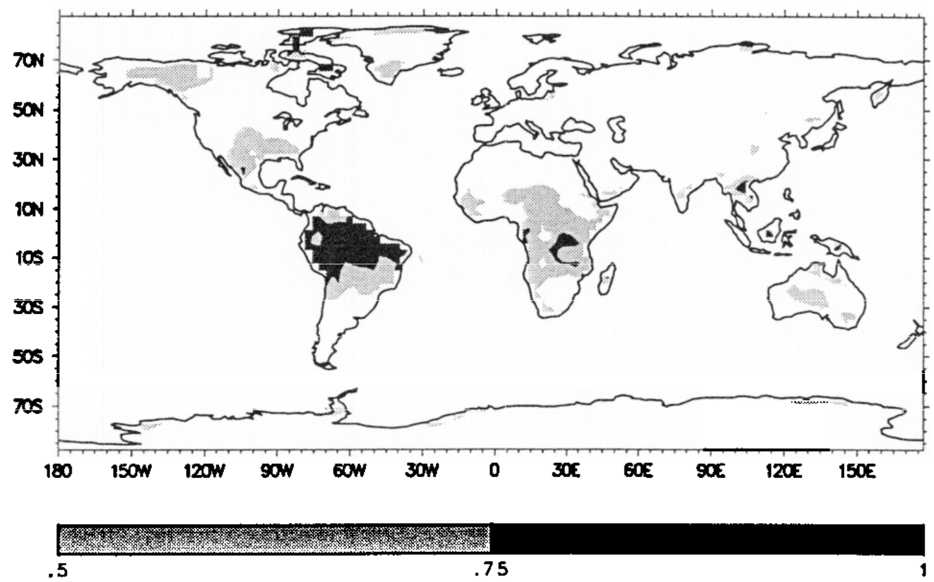


Figure 3: As in Figure 2, except for MAM surface air temperature.



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