Collaborative Research: Separating Forced and Unforced Decadal Predictability in Models and Observations

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Recipient Name: Columbia University
Award Number: ER65095
Reporting Period: 1 September 2010 - 31 August 2013
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Program Office: Biological and Environmental Research Program (BER)
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This report is a progress report of the accomplishments of the research grant "Collaborative Research: Separating Forced and Unforced Decadal Predictability in Models and Observations" during the period 1 May 2011- 31 August 2013. This project is a collaborative one between Columbia University and George Mason University. George Mason University will submit a final technical report at the conclusion of their no-cost extension.

1 Summary of the Basic Research Plan

The purpose of the proposed research is to identify unforced predictable components on decadal time scales, distinguish these components from forced predictable components, and to assess the reliability of model predictions of these components. Components of unforced decadal predictability will be isolated by maximizing the Average Predictability Time (APT) in long, multimodel control runs from state-of-the-art climate models. Components with decadal predictability have large APT, so maximizing APT ensures that components with decadal predictability will be detected. Optimal fingerprinting techniques, as used in detection and attribution analysis, will be used to separate variations due to natural and anthropogenic forcing from those due to unforced decadal predictability. This methodology will be applied to the decadal hindcasts generated by the CMIP5 project to assess the reliability of model projections. The question of whether anthropogenic forcing changes decadal predictability, or gives rise to new forms of decadal predictability, also will be investigated.

2 Diagnosis of Decadal Predictability

Our work has established a scientific basis for decadal predictions by explicitly identifying patterns in climate models that are predictable on decadal time scales and showing that these structures also are predictable in the observed climate system. In particular, DelSole et al. (2011) identified a pattern that maximized the average predictability time in multiple climate simulations of the CMIP3 data set. The simulations were from pre-industrial control runs with no interannual variations in climate forcing, ensuring that the multidecadal variability found in the models was generated internally by the climate system and occurs irrespective of anthropogenic or natural forcing. The pattern that maximizes the average predictability time in the CMIP5 pre-industrial control runs is shown (for the first time) in fig. 1. This component has maximum loadings in the North Atlantic and North Pacific and varies on multidecadal time scales in many models, and is remarkably similar to the pattern shown in DelSole et al. (2011) derived from CMIP3 models. The similarity in structure suggests that the basic spatial pattern of multidecadal predictability is robust across a suite of models. It turns out that maximizing predictability over land and ocean separately leads to essentially the same structure. The predictability for this component in different models is shown in the bottom panel of fig. 1. As indicated in the figure, different models show widely different levels of predictability, with some models showing insignificant predictability after two years while others showing significant predictability as long as 16 years. **The fact that this component can be predicted on decadal time scales in some models provides a scientific basis for decadal prediction of surface air temperature**.

The most predictable component of annual mean precipitation in the CMIP5 models is shown in fig. 2. In contrast to surface air temperature discussed above, the most predictable precipitation component has maximum loadings in the tropical pacific, and the models more or less agree that the predictability persists only for two or three years. Because this component has been statistically optimized, **these results demonstrate that predictability of annual mean precipitation is at most three years, and hence decadal predictability of precipitation is weak or non-existent in the CMIP5 models.**

The above results are summarized in Jia and DelSole (2012a).

3 Empirical Decadal Prediction

The above results demonstrate that temperature and precipitation are predictable on multi-year time scales *in the models*, but whether this model-derived predictability translates into skillful predictions of observed anomalies is a separate question. To test whether these components are predictable in observations, we constructed a linear regression model from the pre-industrial control runs, and used this model to predict observations. The skill of predicting observed SST for the North Atlantic, after removing the forced component by regression techniques, is shown in fig. 3. The figure shows that the statistical model can predict the observed North Atlantic mean with positive skill for ten years. The correlation skill (not shown) also is statistically significant up to ten years. The mean skill averaged over twentieth century runs and control runs separately (solid red and blue lines) are virtually identical. Recall that only the control runs were used to fit the model, so the twentieth century runs provide independent validation data. The fact the skill is nearly identical in the two cases suggests that the regression model does indeed predict North Atlantic temperature anomalies with skill. The skill in individual forced and control runs, shown as dashed lines in fig. 3 for different realizations, varies considerably with model. For some models, the statistical model has no skill in the North Atlantic even after one year, but has skill as long as ten years for other models. This fact reveals that different models give widely different estimates of skill. **These results demonstrate that predictable components identified in CMIP3 models can be predicted with skill in observations on decadal time scales.** A paper summarizes these results for the CMIP3 data (DelSole et al., 2013). We are currently extending these calculations to longer time periods and to the CMIP5 data set. We also are analyzing projections of these components into the next decade.

4 Optimal Determination of Time-Varying Climate Change Signals

In the original proposal, we proposed to apply a form of discriminant analysis to diagnose the forced response of individual models, and to use these results as part of a detection and attribution procedure. During the course of the proposed research, we discovered that **the time-dependent climate change signals that maximize average detectability can be derived by a minor modification of the original procedure**. The new procedure is discussed in Jia and DelSole (2012b). This procedure was applied to determine the most detectable pattern *in the CMIP3 models* of precipitation over land. No single pattern of five-year mean JAS precipitation over land could be detected in all the models, indicating that **the forced response of precipitation is not robust across state-of-the-art climate models**. Moreover, since the procedure is optimal, we can be make the sweeping (but defensible) claim that *no* five-year mean precipitation pattern is *consistently* detectable in the models. It should be recognized, however, that this conclusion does not preclude detectability of other expressions of the signal, such as ones constructed from other time averages, statistics, or time-lag information. The amplitude of the climate change statistic in different twentieth century simulations is shown in fig. 4. The figure indicates that while most models show no detectability of precipitation (as evidenced by the fact that their time series lie within the 90% confidence interval for unforced variability), the models that do show detectability of five-year mean JAS precipitation exhibit two very different characters: a systematic trend, and enhanced frequency of extreme values. These results appear to be a significant advancement in detection capabilities, as previous attempts to identify forced precipitation patterns were restricted to zonal averages within certain latitudinal bands (Zhang et al., 2006). We intend to investigate the most detectable forced patterns in the CMIP5 data set.

5 Contribution of Individual Collaborators

Timothy DelSole is the lead PI for this project and is responsible for all aspects of the proposed research. He supervises research conducted by the PhD graduate students Emerson LaJoie, Xiaoxin Yan, and Liwei Jia (now graduated). Dr. Jia performed the analysis leading to Jia and DelSole (2012a), Jia and DelSole (2012b), DelSole et al. (2013). Xiaoxin Yan entered the PhD program in Fall 2011 and has been focused on her core graduate courses in the first two semesters, which has involved significant training in the statistical analysis described in the proposal. Since formally leaving this project, Dr. Jia has been writing up papers based on her thesis work essentially "on the side." Michael Tippett has collaborated on all aspects of the proposed research. This collaboration has involved two-to-three phone calls a week between Drs. Tippett and DelSole.

6 Publications

The following papers have been generated as part of this research project: Jia and DelSole (2012a), Jia and DelSole (2012b) and DelSole et al. (2013).

References

DelSole, T., L. Jia, and M. K. Tippett, 2013: Decadal prediction of observed and simulated sea surface temperatures. *Geophys. Res. Lett.*, **40**, 2773–2778.

DelSole, T., M. K. Tippett, and J. Shukla, 2011: A significant component of unforced multi-decadal variability in the recent acceleration of global warming. *J. Climate*, **24**, 909–926.

Jia, L. and T. DelSole, 2012a: Multi-year predictability of temperature and precipitation identified in climate models. *Geophys. Res. Lett.*, **39**, doi:10.1029/2012GL052 778.

Jia, L. and T. DelSole, 2012b: Optimal determination of time-varying climate change signals. *J. Climate*, **25**, 7122–7137.

Zhang, X., F. W. Zwiers, and P. A. Stott, 2006: Multimodel multisignal climate change detection at regional scale. *J. Climate*, **19**, 4294–4307.

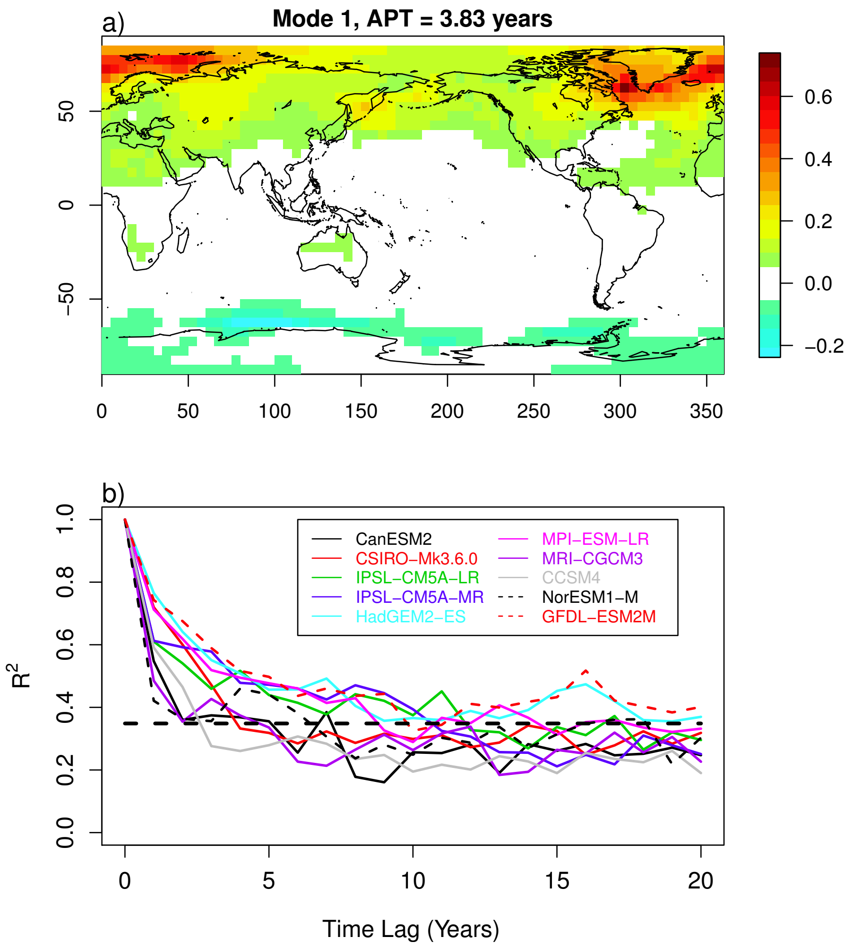

Figure 1: Most predictable component of annual mean surface air temperature derived from the pre-industrial control runs of the CMIP5 data set (top), and the squared correlation skill of this component in individual models when predicted from a linear regression model using forty principal components as predictors.

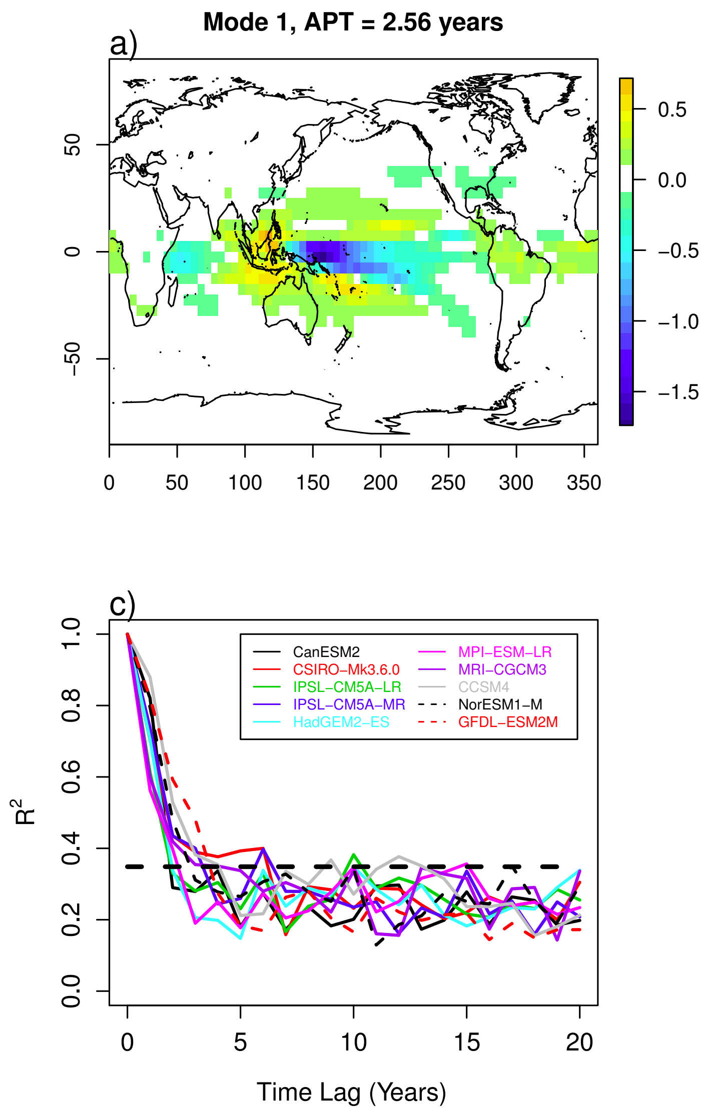

Figure 2: Most predictable component of annual mean precipitation derived from the pre-industrial control runs of the CMIP5 data set (top), and the squared correlation skill of this component in individual models when predicted from a linear regression model using forty principal components as predictors.

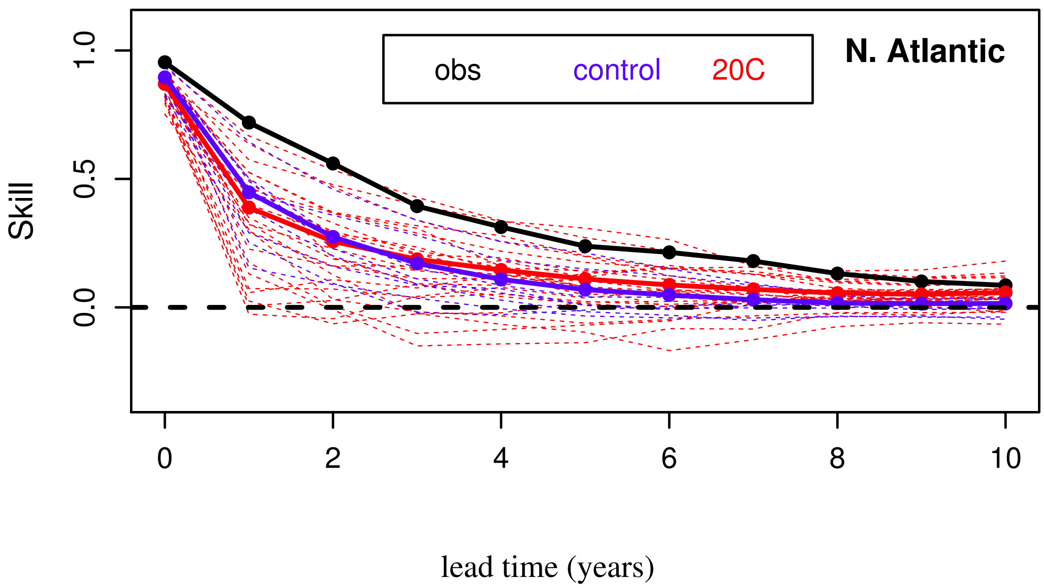

Figure 3: Skill of predicting observed annual mean, North Atlantic, unforced sea surface temperature anomalies during 1976-2010 (black curve). Skill is measured by one minus the mean square error divided by the total variance. The predictions were generated by a linear regression model trained on CMIP3 pre-industrial control simulations. The unforced SST field is calculated by regressing out the forced response pattern. Also shown is the skill in control simulations (blue) and forced simulations during 1860-1999 (red) for both multi-model (solid) and individual models (dashed). The horizontal dashed line indicates zero skill.

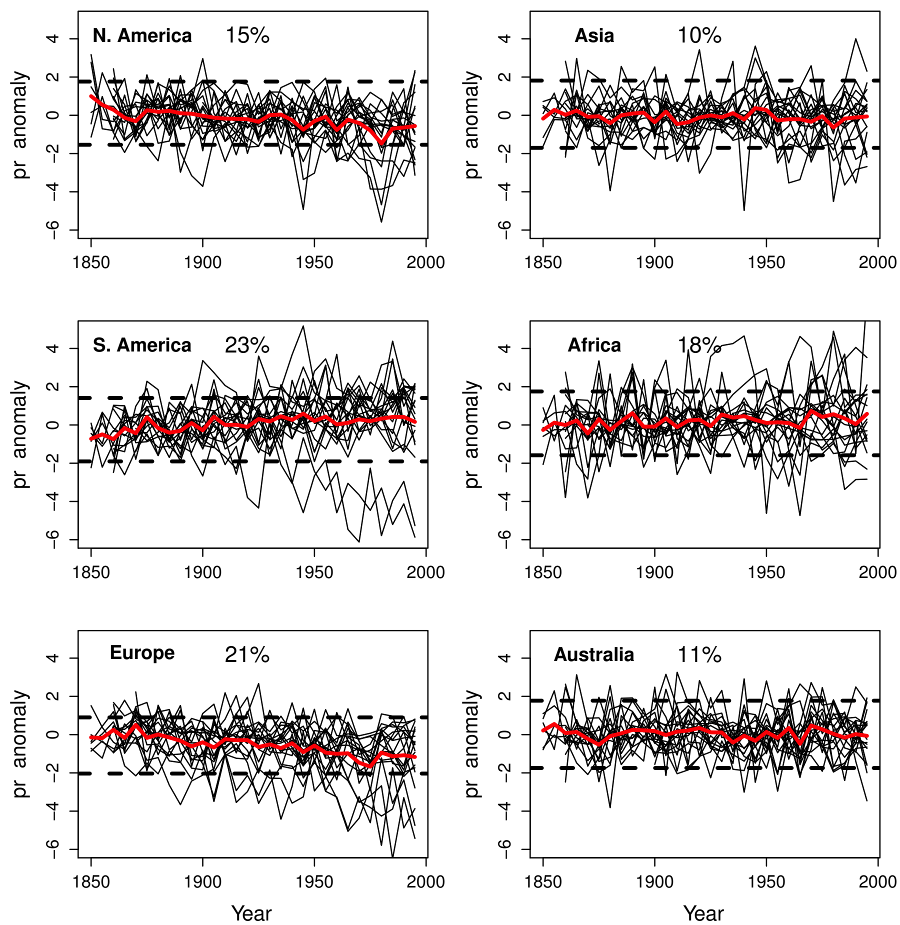

Figure 4: Time series of the most detectable component, on average, of JAS mean precipitation over six continents. Individual twentieth century runs are shown as thin black lines, and the ensemble mean is shown as the thick red curve. The time series were calculated from 19 independent twentieth century runs. The horizontal dashed lines indicate the 5th and 95th percentiles estimated from independent control runs. The percentages in each panel gives the percent of twentieth century realizations that fall outside the 5th and 95th percentiles of the control run. The pre-industrial control mean of each respective model has been removed from the time series.