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## 1. INTRODUCTION

In this study, we use some simple indices of surface temperature patterns, including the global-mean temperature, the land-ocean temperature contrast, the meridional temperature gradient, and the magnitude of the annual cycle, to describe global climate variability and change. These indices are expected to contain information independent of the global-mean temperature for natural climate variations. They also represent the main features of the modelled surface temperature response to increasing greenhouse gases in the atmosphere. Hence, they should have a coherent response for greenhouse climate change.

Preliminary results from this study were presented by Karoly and Braganza (2001) but they are extended here. We use global instrumental observations for 1881-1999 (Jones, 1994; Parker et al., 1995), paleoclimate reconstructions from proxy data for 1700-1900 (Mann et al., 1998), and simulations from 5 different coupled ocean-atmosphere climate models (CSIRO9, HadCM2, HadCM3, GFDL R30, ECHAM4) to investigate the variability and correlation structure of these indices. The indices are used to evaluate the performance of control climate model simulations of natural climate variability. As the indices are expected to contain independent information for natural climate variations but show a coherent response to greenhouse forcing, the observed correlation structure of the indices is compared with forced and unforced model simulations. The forced model simulations include increasing greenhouse gases and increasing sulphate aerosols from about 1860 (GS cases).

## 2. DEFINING THE GLOBAL INDICES

Four simple indices based on surface temperature patterns are used. All the indices have been identified previously in studies of climate variability and change, although they have not been considered together, apart from in Karoly and Braganza (2001).

- Global-mean surface temperature (GM): The area-weighted global average of surface temperature. This has been used in many climate change detection studies.
- The contrast between land and ocean surface temperature (LO): The difference between mean surface temperature over land and mean sea surface temperature. This index has been chosen to capture the pattern of greater warming over land than ocean
- The magnitude of the annual cycle over land (AC):

Calculated for each hemisphere by subtracting mean winter from mean summer temperature over land, then weighted by the fraction of land area in each hemisphere and combined into a single index.

- The mean meridional temperature gradient (MTG): Difference between two zonal bands representing the NH extra-tropics (22.5°N-37.5°N) and the NH mid to high latitudes (52.5°N-67.5°N). MTG has been chosen to represent the recent observed pattern of greater warming in high latitudes compared to the tropics

A data mask was created to exclude regions where the observations were sparse or non-existent. This mask was applied to both observations and model data. As a result of applying the mask, large regions of the Southern Ocean and Antarctica, as well as smaller regions in the high northern latitudes and over the interior of the southern continents have been omitted from the analysis.

## 3. CLIMATE VARIABILITY

The observed variability of the indices on decadal timescales is compared with the variability in control climate model simulations to evaluate the quality of the simulations of natural climate variability. The standard deviation of the indices is used as a simple measure of the variability. To estimate the variability on decadal timescales, the time series of the annual values of the indices are filtered with a 21 point binomial filter. As there are significant observed trends in the indices over the 20<sup>th</sup> century (Karoly and Braganza, 2001), these trends were removed to obtain an estimate of the natural climate variability from the observational data.

Table 1 shows the decadal standard deviations of the indices for the detrended observations, control climate model simulations and proxy data. Standard deviations of the long control model runs were estimated using the mean of the standard deviations for 120-year samples taken at 50-year intervals. Also shown are the estimated 90% confidence intervals for the standard deviation, based on the multiple samples from the long control simulations or the range of variability in the case of the proxy data and ECHAM4.

The variability of the detrended observations compares very well with the control climate simulations and proxy climate data for each of the indices. In general, the standard deviation of the detrended observations is within the 90% confidence interval of the control run standard deviation for all the models at both interannual and decadal timescales. There are a small number of exceptions, such as the models generally overestimating the variability of the meridional temperature gradient. For some of the indices, the

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standard deviation from the proxy data underestimates the variability in the detrended observations and the control model simulations eg for AC and MTG. This could be anticipated from the limited coverage and resolution of the proxy data

#### 4. CORRELATION STRUCTURE

Next, we consider the correlation structure of the indices. Table 2 shows the decadal timescale correlations of the indices with the global-mean temperature (GM) for the detrended observations, proxy data, and control climate model simulations. It is notable how well the models do in simulating the magnitude or at least *relative* strengths of the correlations with GM. While the components of the indices, such as land temperature alone, are highly correlated with GM, the indices have smaller correlations and therefore contain information independent of GM.

As a further test of the correlation structure of the indices, we consider the determinant of the correlation matrix of the indices GM, LO, AC and MTG on decadal timescales. The value of the determinant gives an

estimate of the relative strength of the association between the indices. By definition, if all the indices are totally independent, the determinant equals unity while if any one of the indices is linearly dependent (highly correlated) with any other, the determinant falls to zero. Table 3 shows the determinant of the correlation matrix on decadal timescales under natural variability (control integrations, proxy data 1700-1900 and detrended observations), and GS forcing over the last 120 years (1881-1999) as simulated by the models. For almost all the natural variability cases, we see that the determinant is significantly higher than zero (the exception being the ECHAM4 simulation). More importantly, there is a significant reduction in the magnitude of the determinant and hence much stronger coherence between the indices in the observations and GS runs over the last century.

The change in the correlation structure of the indices over the recent period and consistency with the coherent response to anthropogenic forcing is another indication that recent observed climate change is likely to be due to anthropogenic forcing. Further comparison of the recent observed trends in the indices is given in a companion paper in this conference and in Karoly and Braganza (2001).

Index	Obs (det)	Proxy	CSIRO9	HadCM2	HadCM3	GFDL-R30	ECHAM4
GM	0.06	0.05	0.05 ±0.01	0.07 ±0.02	0.06 ±0.01	0.07 ±0.02	0.06
LO	0.05	0.06	0.06 ±0.01	0.06 ±0.02	0.06 ±0.02	0.06 ±0.02	0.07
AC	0.13	0.02	0.09 ±0.02	0.12 ±0.04	0.12 ±0.04	0.12 ±0.03	0.12
MTG	0.09	0.06	0.16 ±0.04	0.14 ±0.04	0.15 ±0.03	0.14 ±0.02	0.16

**TABLE 1.** Standard deviations of decadal variations of the indices for natural climate variations from detrended observations, proxy data for 1700-1900 and control climate model simulations.

Index	Obs (det)	Proxy	CSIRO9	HadCM2	HadCM3	GFDL-R30	ECHAM4
LO	0.12	0.34	0.51 ±0.24	0.50 ±0.27	0.50 ±0.27	0.45 ±0.22	0.42
AC	-0.06	-0.03	-0.04 ±0.26	-0.07 ±0.58	-0.21 ±0.30	-0.18 ±0.14	-0.46
MTG	0.24	0.42	0.35 ±0.28	0.34 ±0.34	0.46 ±0.25	0.26 ±0.31	0.39

**TABLE 2.** Correlation of decadal variations of the indices with global-mean temperature (GM) for natural climate variations from detrended observations, proxy data for 1700-1900 and control climate model simulations.

	Natural Variability	1881-1999 GS Forced
Obs	0.39	0.04
Proxy	0.28	
CSIRO9	0.49 ± 0.22	0.09
HadCM2	0.53 ± 0.27	0.09 ± 0.03
HadCM3	0.37 ± 0.18	0.06 ± 0.03
GFDL-R30	0.62 ± 0.34	0.21 ± 0.11
ECHAM4	0.13	0.04

**TABLE 3.** Determinants of the correlation matrices of GM, LO, AC and MTG on decadal timescales for natural variations (detrended observations or control model simulations) or the recent period 1881-1999 (observations or GS forced simulations).

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