COMMUNICATING GLOBAL CLIMATE CHANGE USING SIMPLE INDICES: AN UPDATE

Frank Drost¹, David Karoly¹ and Karl Braganza²

¹School of Earth Sciences, University of Melbourne, Melbourne, VIC 3010 Australia

²National Climate Centre, Bureau of Meteorology, Melbourne, VIC 3001 Australia

ABSTRACT

Previous studies have shown that there are several indices of global-scale temperature variations, in addition to global-mean surface air temperature, that are useful for distinguishing natural internal climate variations from anthropogenic climate change. Appropriately defined, such indices have the ability to capture spatio-temporal information in a similar manner to optimal fingerprints of climate change. These indices include the contrast between the average temperatures over land and over oceans, the meridional temperature gradient, the temperature contrast between the Northern and Southern Hemisphere and the magnitude of the annual cycle of average temperatures over land. They contain information independent of the global-mean temperature for internal climate variations at decadal time scales and represent different aspects of the climate system, yet they show common responses to anthropogenic climate change. In addition, the ratio of average temperature changes over land to those over the oceans should be nearly constant for transient climate change. Hence, supplementing analysis of global-mean surface temperature with analyses of these indices can strengthen results of attribution studies of causes of observed climate variations.

In this study, we extend the previous work by including the last ten years of observational data and the CMIP3 climate model simulations analysed for the IPCC AR4. We show that observed changes in these indices over the last ten years provide increased evidence of an anthropogenic influence on climate. We also show the usefulness of these indices for evaluating the performance of climate models in simulating large-scale variability of surface temperature.

1 **Introduction**

2 Earlier studies show that various surface temperature-based indices contain information
3 independent of the global-mean surface temperature for natural climate variations at decadal
4 time scales (Braganza et al. 2003; Karoly and Braganza 2001). The indices, the land-ocean
5 temperature contrast (LO), the Northern Hemisphere meridional temperature gradient (MTG),
6 the magnitude of the annual cycle of average temperatures over land (AC) and the
7 hemispheric temperature contrast (NS) are therefore, collectively, more useful in detecting
8 and attributing climate change than global-mean surface temperature (GM) alone. Also, the
9 indices are valuable tools for describing large scale patterns of surface temperature variability
10 and in evaluating climate models (e.g. Stott et al. 2006; Barnett et al. 2005; Hegerl et al.
11 2006). Braganza et al. (2004) show that observed linear trends in the indices during the
12 second half of the 20th century were significantly larger than climatic changes solely due to
13 natural forcings. These results indicate a likely significant anthropogenic influence on climate
14 during the latter half of the 20th century.

15
16 This study builds upon the previous work by Braganza et al. (2003; 2004) by extending the
17 analysis to include an additional ten years of observational data, by including two additional
18 observational datasets to estimate observation uncertainty, and the World Climate Research
19 Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3; Meehl et
20 al. 2007) climate model simulations analysed for the Intergovernmental Panel on Climate
21 Change (IPCC) Fourth Assessment Report (AR4). The question that we address is whether
22 observed changes in these indices over the last ten years provide increased evidence of an
23 anthropogenic influence on climate. We construct the indices using the CMIP3 model data
24 and investigate their temporal characteristics in an ensemble analysis. This approach provides
25 estimates of the magnitude of intrinsic variability and climate change signals in the various
26 indices for the recent past, the twentieth century, and the twenty-first century.

27
28 Furthermore, we consider an additional index in our analysis: the ratio of the global-mean
29 surface air temperature change over land and over ocean. This index has previously been
30 described and analysed by Sutton et al. (2007), Joshi and Gregory (2008) and Joshi et al.
31 (2008). Sutton et al. (2007) found that there was no simple relationship between this ratio and
32 global-mean temperature change among the 20 AR4 models analysed indicating that this ratio
33 contains independent information on inter-model variation. It was found that although the
34 difference in warming between land and ocean (LO) will increase under increasing radiative

forcing, all models showed that the ratio area-mean land to ocean warming remains relatively constant at a value around 1.5. This constant is a measure of the slower rate of warming in sea surface temperatures compared with terrestrial surface temperatures associated with the larger heat capacity and increased evaporative cooling for oceans. Given that the ratio varies independently of the global-mean and is robust and consistent among both model and observational data, this index presents additional information for investigating climate change.

Datasets

The climate indices were derived from monthly mean global surface temperature data and were determined from 3 different observational datasets and data from simulations with 8 CMIP3 coupled atmosphere-ocean-sea-ice climate models (Meehl et al. 2007). We apply the analysis of the climate indices on various datasets, to determine the consistency/sensitivity of the findings, noting that the underlying data in each set are not truly independent.

Global monthly temperature anomalies were obtained from the Goddard Institute for Space Studies (GISS: Hansen et al. 2001; Hansen et al. 2010), 1880-2010; the National Climatic Data Centre (NCDC; Smith and Reynolds 2005; Smith et al. 2008), 1880-2010; and the Hadley Centre Climate Research Unit version 3, variance adjusted (HadCRUT3v; Brohan et al. 2006), 1850-2010 datasets. Anomalies in the GISS dataset were computed against the period 1951-1980, those of the NCDC and HadCRUT3v datasets against the period 1961-1990. Although these datasets have combined data from various sources differently, their global-scale time series are very similar, especially on decadal timescales (See figure 3.1 in Trenberth et al. (2007)). Jones and Wigley (2010) discuss that the three different datasets agree better at large spatial and temporal scales.

Although over 20 climate models have submitted data for the IPCC AR4 analysis, for this project we use data from those models that had submitted at least one simulation for the Pre-Industrial Control scenario (PICNTRL) and multiple simulations for the 20th century (20C3M) and emission scenario A1B (SRESA1B), a mid-range future emission scenario. The reason for restricting the analysis to data only from models that fit these criteria is that multiple output from the same model for the 20C3M and A1B scenario will provide an indication of the model's internal variability.

There are 2 exceptions to this approach. Firstly, A1B simulations of model ncar_pcm1 were started from anthropogenic-forced only simulations and not from 20C3M simulations. However, as anthropogenic forcings at the end of 1999 are much larger than those of natural origin, any possible ‘discontinuity’ in global mean surface temperature when linking up 20C3M simulations with those of SRESA1B at the start of 2000 were found to be within the range of variability of global mean surface temperature (for simulation 1-3 less than 0.3*std and for simulation 4 1.6*std of the 20C3M annual variability). For that reason, we feel justified to use the ncar_pcm1 simulation data in a similar manner to the other models for our analysis. Secondly, we have also used data from Australia’s Commonwealth Scientific and Industrial Research Organisation’s (CSIRO) Mark3.0 model. This model has 3 simulations for 20C3M, but only a single simulation for future emission scenario A1B. An overview of the models and their number of simulations used in this study are given in table 1.

NR	MODEL	PICNTRL	20C3M	A1B	REFERENCE
1	cccma_cgcm3_1	1	5	5	(McFarlane et al. 1992; Scinocca et al. 2008)
2	miub_echo_g	1	5	3	(Roeckner et al. 1996)
3	miroc3_2_medres	1	3	3	(K-1 model developers 2004)
4	mpi_echam5	1	4	4	(Roeckner et al. 2003)
5	mri_cgcm2_3_2a	1	5	5	(Yukimoto and Noda 2002; Yukimoto et al. 2001)
6	ncar_ccsm3_0	2	9	9	(Collins et al. 2006)
7	ncar_pcm1	1	4	4	(Washington et al. 2000)
8	csiro_mk3_0	2	3	1	(Gordon et al. 2002)

Table 1: An overview of the models, scenarios and the number of simulations used in this analysis.

Braganza et al. (2003) noted that observations do not cover all parts of the world evenly, with large areas having none or very sparse data coverage. Incomplete global data coverage was particular prominent in the early part of the record. Since a mismatch in data coverage between observations and model data could potentially affect the outcome of the analysis, Braganza et al. (2003) used a data mask to exclude regions where the observations were sparse or non-existent. The data mask excludes those regions that have less than 40 years of data since 1900. The choice of 40 years of data was chosen such that in their trend analysis on surface temperature data from the last 50 years, those regions with data coverage solely during the second half of the twentieth century had to have a minimum temporal coverage of 80%. This criterion therefore excluded regions with short time records that would not have been sufficiently long for their analysis. The description of the construction and the use of the data mask was presented in Braganza et al. (2003).

Braganza et al. (2003) used the HadCRUT2 dataset for determining an appropriate data mask. This project uses the HadCRUT3v dataset which at the time of this study extends till the end of 2010. We have therefore created a new data mask for this study as this study has 10 years more data. Our data mask was created under the same criteria used by Braganza et al. (2003). Although more observational data were available, only 2 regions in the mask created by Braganza et al. (2003) are included now as they contain sufficient observational data: the south-east Pacific, roughly between 20°S-40°S, 220°E-270°E and at 2 grid points in the central Pacific at 0°, 220°E and 0, 240°E (see their Figure 1). The main regions that remain masked are the high latitudes and parts of the Amazon and inner Africa. The same data mask was applied to both the observational and modelling data, with corresponding changes in the resolution of the mask.

All the six indices used in this study are based on surface temperature anomalies. For the observational datasets, seasonal surface temperature anomalies were determined at each grid point if data were available for at least 2 months within that season, and annual anomalies were determined if at least 2 seasons had data present. A year in this study is regarded as the period December-November. The indices are constructed identically for each dataset.

Global Indices

A detailed description of the construction and the meaning of the climate indices and their context in the detection and attribution of climate change was presented in Braganza et al. (2003; 2004). Sutton et al. (2007) present a description on the ratio of the global-mean surface air temperature change over land and over ocean. Only a short overview of the indices is presented here.

The global indices examined are:

- 1) Global-mean surface temperature (GM): The area-weighted global average of surface temperature. The calculation is slightly different to that done in Braganza et al. (2003) as the global-mean is determined from the mean of the NH and SH in order to stop the better sampled Northern Hemisphere from dominating the average (Brohan et al. 2006).
- 2) Land-Ocean surface temperature contrast (LO): The difference between mean surface temperature over land and mean surface temperature over sea. Changes in this index

reflect particularly the greater warming that takes place over land than over ocean (e.g. Jain et al. 1999; Thompson et al. 2009).

- 3) Northern-Southern Hemisphere temperature contrast (NS). Warming in the Northern Hemisphere is potentially larger than in the Southern Hemisphere as it contains a larger landmass. However, the larger loading of anthropogenic sulphate aerosols in the Northern Hemisphere contributes to a relative cooling at mid to low tropospheric latitudes (e.g. Santer et al. 1996), thereby affecting the difference in warming between the two hemispheres.
- 4) The mean magnitude of the Annual Cycle in temperature over land (AC). This index is determined by subtracting mean winter from mean summer temperatures over land for both hemispheres. After weighting these values by the fraction of global land surface area in each hemisphere they were combined into a single index. This index reflects the greater warming that occurs over land during winter than during summer.
- 5) The mean Meridional Temperature Gradient (MTG) in the Northern Hemisphere between 52.5°N-67.5°N and 22.5°N-37.5°N. The observed trend in this index reflects the greater warming that occurs at higher latitudes (Gitelman et al. 1997, 1999).
- 6) The Ratio between changes in Land and Ocean temperatures (RLO) was described earlier. We have extended the earlier analysis from Sutton et al. (2007) by increasing the number of observational datasets and extending the period of analysis.

Climate variability

Prior to investigating possible trends in any of the indices, it is important that we evaluate the intrinsic variability of those indices. In order to verify whether the models are capable of simulating the variability of the indices in observations, the standard deviation of the control (unforced) and twentieth century (forced) climate model simulations on interannual and decadal time scales is determined and compared to those of the observational data. We undertake this analysis on five of the six defined indices. As the index RLO is defined as a ratio between two indices, any variation in the very small value of the denominator will lead to a large change in the index itself. The index RLO is a special case which will be analysed in a different manner later. The variability analysis is similar to that employed by Braganza et al. (2003). In that study, variability was compared between indices derived from palaeo climate indicators, instrumental observations and control and transient model simulations; with the aim of reasonably estimating intrinsic variability against which the significance of

forced trends can be compared. We follow from that work in using variance to estimate intrinsic variability and present only a general overview of the variability calculation here.

The interannual and decadal variability of the three observational datasets is determined over the last 131 years of the data, i.e. 1880-2010. Anomalies in all indices were determined relative to the period 1890-1920. This period was chosen as it was the earliest period covered by all models in their 20C3M climate integrations. In order to remove trends in the observational data, a fourth-order polynomial was fitted to their time series and subsequently removed from the data. The residual data represents an estimate of the internal variability of the indices and its variability is represented by its standard deviation.

A similar approach was applied to the calculation of the indices from the twentieth century climate integrations, 20C3M. As the 20C3M simulations end eleven years earlier than the observational data used in this study (1999 versus 2010), the 20C3M datasets were extended till 2010 by adding the data from the appropriate model with its corresponding future climate simulation under emission scenario SRESA1B. The only exception to this approach is for the data of the CSIRO MK3.0 model. As only 1 climate integration for scenario SRESA1B was undertaken with the CSIRO MK3.0 model, each of its three twentieth century climate integrations were extended with data from this future climate simulation. In general, since the first ten years of the climate simulations under the various future emission scenarios, A1B, B1 and A2, do not differ significantly, data from any future emission scenario could have been chosen for extending the twentieth century climate integrations. Unlike some of the 20C3M simulations, the future emissions scenarios do not include observed (known) natural forcings, which have been shown to improve comparisons with observed changes in climate indices (Christensen et al. 2007). Extending the 20C3M data to 2010 allows us to compare model data with recent observations. After extending the dataset, a fitted fourth order polynomial was removed from the data and the interannual and decadal variability of the 20C3M climate integrations were determined.

All PICNTRL integrations analysed in this study were considerably longer than the length of observational data, with a few models having integrations for 1000 model years. Rather than obtaining a single value for the standard deviation taken over the whole integration, we determined the standard deviation of the indices using 120-year samples, where each period had a 60-year overlap with its adjacent periods. The period of 60-year overlap was chosen

chosen because it is half the length of the sample period considered. This is long enough to lead to small correlations between independent samples for variations with periods up century time scales and short enough to allow us to obtain multiple estimates of the internal variability of the indices representing century time-scale variability. Trends were removed from each 120-year period prior to the calculation of the standard deviation. Comparing the standard deviation of the indices derived from the observational data against the spread and the mean of the standard deviations of the indices from the PICNTRL integrations indicates how well the models can simulate the interannual and decadal variability of the climate.

Comparing the standard deviations of the detrended 20C3M climate integrations to those of the 120-year periods in the PICNTRL integrations for all models shows that they all span a nearly identical and narrow range (not shown). In other words, the detrended interannual and decadal variability in twentieth century climate simulations is similar to variability in the control in each model. This finding confirms that of Braganza et al. (2003). As the simulated intrinsic variability in each model is virtually the same for the forced and unforced climate integrations, we test the capability of the models in simulating the climate's variability by comparing only the variability in the PICNTRL climate integrations against those in the observational data. Figure 1 presents the interannual and decadal variability of the indices of PICNTRL simulations with those from the observations.

Variability in each of the observational datasets is quite similar. In comparison to the observations, it is apparent that most models capture the variability in the indices quite well, particularly at decadal timescales. Although some models exhibit variability that is either slightly too low or too high for some of the indices, a very good approximation of the amount of variance is obtained when the mean of all simulations is taken. An example of this is for the multi-model ensemble global-mean surface temperature, GM, where the relatively low interannual variability of model `cccma_cgcm3_1` is offset against the relatively high interannual variability of model `mpi_echam5`. Hence figure 1 supports the case for using multi-model ensembles for this analysis. It should also be noted that the variability of the actual observations over the 20th century is effectively a single realisation of, potentially, a range of possible outcomes given the same climate forcing. Since the models, and the indices used here in particular, are not explicitly tuned to 20th century observed changes, it should not necessarily be expected that model performance is effectively evaluated by the mean model variance corresponding to the instrumental observations.

As in Braganza et al. (2003; 2004), we now restrict the analysis mainly to decadal periods as any sign of anthropogenic influence on climate is clearer at longer timescales. Braganza et al. (2003) and Sutton et al. (2007) had already shown that the climate change indices vary independently from the global-mean, and are therefore additional indices that can be used to analyse climate change. We have performed the same analysis and we obtain similar results. Figure 2 presents the correlations of the indices determined over the various 120 year periods in the control simulations versus their respective values for the global-mean, GM. Although there is quite a spread in the correlation values, which is an indication of the inter-model and temporal variations in the various indices, the range covers the spread in the correlation values of the three observational datasets. Mean values for the correlations are 0.46, 0.41, 0.44 and -0.30 for the correlations of GM with LO, NS, MTG and AC respectively. Those values are similar to those found by Braganza et al. (2003).

Trends

In order to investigate the extent and range of trends in the indices, we have extended the twentieth century simulation data from the various models with data from their SRESA1B climate change scenario simulations till the year 2100. Figure 3 presents ensemble plots of the time series of 5 indices from all of the SRESA1B simulations. As the main period of interest is the period 1900-2010 and because the forced changes from the model runs are apparent by 2050, only the period 1900-2050 is plotted in figure 3. The projected rise in the global-mean is matched by a significant positive trend in all the indices except for AC, which shows a significant negative trend.

The global-mean temperature exceeded its pre-industrial or long-term mean during the latter stages of the twentieth century. The indices are also projected to deviate from their long-term mean during the twentieth-first century under the SRESA1B emission scenario. Braganza et al. (2004) was able to detect statistically significant trends in their analysis of the indices over the period 1950-1999 in both observations and model data. With ten more years of observational data available, we investigate whether the trends over the last 50 years are more significant than over the period 1950-1999.

From the control simulations, we have determined the 5%-95% confidence interval for natural variability of 50-year trends for each index for a single climate realisation. If observational trends in the indices are outside this interval then it is most likely that they can not be attributable to natural variability. Figure 4 shows the trend in each of the indices over the last 50 years in the observations, 1961-2010, and for all simulations of all eight models. All three observational datasets clearly indicate that the trend in GM and LO exceed the 5%-95% confidence interval determined from the control simulations (shaded region). A similar statement holds for MTG and AC albeit that not all observational trends exceed the 5%-95% confidence interval. However, the mean value of the three observational trends in the indices MTG and AC does exceed the 95% significance level. Two out of three observational datasets show a trend in NS that does not exceed the 5%-95% confidence interval. However, the 95% significance level lies within the margin of error of the mean value of the three observational trends in NS and the observational ensemble mean trend in NS is therefore either significant at, or very near the 95% significance level. Although the presentation of our results is different to those in Braganza et al. (2004), these results indicate that the observational trends in the indices have gained significance over the last decade. Furthermore, as this analysis uses three observational datasets, our results have higher confidence as our findings are in general robust across the three datasets.

Although the range of trends as simulated by the models cover the range of possible trends as indicated by the observational data quite well, there is a tendency for some models to overestimate the trend in GM and underestimate the trend in LO. In particular, the trend in GM as determined in model cccma-cgcm3-1 is double the observed, and the trend in LO in model mri-cgcm2-3-2a is less than half of those found in the observations. With the exception of 2 simulations of the mri-cgcm2-3-2a model, all simulated trends are outside the 5%-95% confidence interval determined from the control simulations. The average value of all the trends in GM and LO in the simulations is $1.67 \pm 0.06^\circ\text{C}/100\text{yr}$ and $0.90 \pm 0.05^\circ\text{C}/100\text{yr}$ respectively.

Although the spread of the simulated trends in MTG and AC in the simulations cover the range of trends determined from the observational data, a number of model simulations indicate that these trends fall within the 5%-95% confidence interval. However, the 95% significance level for these indices lies within the margin of error of the multi-model ensemble mean trends in MTG ($1.04 \pm 0.13^\circ\text{C}/100\text{yr}$) and AC ($-0.44 \pm 0.07^\circ\text{C}/100\text{yr}$) so the multi-model ensemble mean trends in these indices are either significant at, or very near the

95% significance level. On the other hand, the mean value of all the trends in NS in the simulations is $0.46 \pm 0.05^\circ\text{C}/100\text{yr}$ which means that the multi-model ensemble mean trend in NS is significant at the 95% level.

Ratio of land and ocean temperature changes: RLO

As mentioned earlier, the ratio of the global-mean surface air temperature change over land and over ocean, RLO, has been discussed as a suitable index for investigating climate change (e.g. Sutton et al. 2007). At equilibrium, when there is no change in radiative forcing, this ratio should be close to one. During periods of transient radiative forcing however, the ratio can be expected to differ from unity. Under global warming scenarios (increasing radiative forcing), with the land warming faster than the ocean, this index should be greater than one. Due to limits in evaporation over land and heat uptake by the oceans, continued positive radiative forcing will not lead to continued increases in RLO. Hence this index will not continue to increase under increasing warming but will eventually asymptote to a constant larger than 1. Importantly, Joshi and Gregory (2008) showed that this index varies significantly depending on whether changes in radiative forcings were due to CO_2 changes or to natural changes. Therefore RLO is a suitable index for indicating anthropogenic climate change.

The construction of RLO is analogous to that of LO with the temperature change over land being divided by the change over the ocean. Due to the construction of this index, its temporal evolution is different from the other indices, and hence is discussed here separately. Note that changes are used relative to the 1890-1920 average.

Due to the fact that temperature changes over the ocean are very small, particularly during the early part of the observational period, the time series of RLO can be very noisy. It is not until the second half of the twentieth century that the signal in ocean warming starts to stabilise the signal in RLO. For that reason, we restrict ourselves in the analysis of RLO to the latter part of the observational period, namely 1980-2010. Figure 5A presents the temporal evolution of RLO determined from the 3 observational datasets used in this study. From 1980 onwards there is a clear tendency for RLO to stabilize and approach a value larger than 1. The mean values for RLO over the period 1990-2010 in the observational datasets are 1.69 (GISS), 1.40 (NCDC) and 1.39 (HadCRUT3v). Occasionally values for RLO appear larger in the

1 observational data, particularly in the GISS data, than in any of the model data (see Figure
2 5B). The high values for RLO in GISS could possibly be associated with how the GISS data
3 has been constructed (Hansen et al. 2010) and to the sensitivity of RLO to the extent of the
4 data mask. As the data mask was initially determined for the lower resolution data of
5 HadCRUT3v and was subsequently interpolated onto the higher resolution grid of GISS,
6 varying the cut-off value for masking a grid point alters the number of land and ocean grid
7 points. In this study we used a cut-off value of 0.5. A higher value would mask more land at
8 high latitudes in the Northern Hemisphere, a region that particularly experiences increasing
9 temperatures. Reducing the number of land points exhibiting strong temperature increases
10 would subsequently lower the value for RLO.

11
12 Figure 5B shows the plot of RLO determined from all simulations and from all models
13 analysed in this study. Presented are the RLO mean, standard deviation and minimum and
14 maximum values of RLO across all the simulations for each year. Similar to RLO determined
15 from the observational data, it is not until the end of the twentieth century that the simulated
16 RLO values stabilize. As demonstrated by Sutton et al. (2007) and Joshi et al. (2008), RLO
17 from the models settles around a value of roughly 1.5°C. Figure 5B shows that RLO for all
18 simulations for all models also converges to a similar value. The mean value for RLO at 2010
19 is 1.54 ± 0.04 which sits well within the range of values determined from the observational
20 data.

21
22 Sutton et al. (2007) commented that there seems to be some discrepancy between RLO values
23 determined from observed and simulated data, as they found a ratio of nearly two for the
24 observational data. Sutton et al. (2007) suggested that the relative high warming ratio in the
25 observations at the end of the twentieth century might partly be due to natural variability.
26 Initially we obtained similar large values for RLO when we used datasets constructed prior to
27 2010. But upon using the latest observational datasets, (Hansen et al. 2010; Smith et al. 2008)
28 most of the very high values disappeared. Although naturally variability is likely to affect the
29 value for RLO, we suggest that at least some of the initial high values for RLO might be
30 explained by previous inadequacies in the observational data. Using the latest observational
31 data results in values for RLO that are more in line with those determined from model data.
32 Strong declines in the value of observational RLO in 1982, 1985 and 1991 are perhaps
33 suggestive of a possible signal of volcanic aerosols in RLO that warrants further study.

1 Although Figure 5 seems to indicate that the value for RLO determined from observational
2 and model data are converging, we can not be certain yet that they indeed converge to the
3 same stable value for RLO. With ocean temperatures being the denominator in RLO, any
4 small discrepancy in ocean temperature will have a large affect on the value for RLO. There
5 are still uncertainties in the amount of heat uptake by the ocean, and hence about ocean heat
6 content and surface temperatures (e.g. Levitus et al. 2005; Domingues et al. 2008; Levitus et
7 al. 2009; Urban and Keller 2009) and modelling ocean heat uptake is still one of the main
8 difficulties for coupled climate models. For instance, uncertainties and limitations in
9 simulating ocean diffusivity affects the amount of heat transported to the deep ocean, thereby
10 affecting ocean surface temperatures (e.g. Schmittner et al. 2009; Dalan et al. 2005).

11
12 Further analysis of RLO constructed from model data shows that the distribution of RLO
13 values determined from all SRESA1B simulations used in this study becomes more Gaussian
14 in time with decreasing standard deviation. The ensemble mean value of RLO determined
15 over the model years of 2080-2100 is 1.55 ± 0.01 . Under emission scenarios SRESB1 and
16 SRESA2, the values are respectively 1.54 ± 0.01 and 1.55 ± 0.01 . This evolution of the
17 variability in RLO is opposite to the other indices discussed earlier. As with the other indices,
18 the case for this index to clearly identify anthropogenic global warming becomes more robust
19 in the twentieth-first century. Unlike the other indices, the value for RLO for each model
20 converges in time to a constant value. The spread of values for RLO during the latter part of
21 the twenty-first century mainly reflects the differences in RLO between the various models. A
22 constant value for RLO is consistent with physical arguments that suggest that the ratio of
23 temperature changes over land and over the ocean is restricted (e.g. Joshi and Gregory 2008;
24 Joshi et al. 2008). Limits in evaporation controls the temperature changes over land and limits
25 in ocean heat uptake restrict the rate of warming of the ocean (e.g. Manabe et al. 1991; Sutton
26 et al. 2007). Hence, the ratio of average temperature changes over land to those over the
27 oceans should be nearly constant for transient climate change.

30 Discussion

31 We have revisited previous work by Braganza et al. (2003; 2004) and Joshi et al. (2008), who
32 have looked at various indices based on surface temperature changes that are suitable for
33 detection and attribution of recent, observed climate change; global-mean surface
34 temperature, the contrast between the average temperatures over land and over oceans, the

meridional temperature gradient, the temperature contrast between Northern and Southern Hemisphere, the magnitude of the annual cycle of average temperatures over land and the ratio of warming over land to that over the oceans. The purpose of this study was to investigate whether, with ten more years of observational data, there was increased evidence of anthropogenic warming of our climate. This question has extra relevance since the influence of intrinsic natural variability, for example through the exchange of heat between atmosphere and ocean (ENSO; Fawcett 2007) or decadal variations in stratospheric water vapor (Solomon et al. 2010) may have slowed the rate of warming due to increasing greenhouse gases in the last decade. The influence of such transient changes underscores the need to use multiple indicators of change when estimating the strength of climate signals. Since the indices used here contain information independent from the global-mean (e.g. Braganza et al. 2003; Sutton et al. 2007) they potentially contribute to a clearer representation of the underlying climate signal. Particularly for ENSO, correlations of the SOI with the indices are, in general, smaller than those with global-mean temperature, and in fact are even smaller over the last 50 years than when determined over the last century. Therefore recent trends in the indices are less affected by ENSO variations. Similar comparisons can be drawn when accounting for changes in stratospheric water vapor. As stratospheric water vapor can be regarded as an ‘external’ forcing affecting GM directly, its variations are less correlated to those in the indices than to those in GM. We have used data from 3 different observational datasets and from 8 climate models which had submitted data to CMIP3. We applied our analysis on multiple datasets as that strengthens the findings.

This study has shown that the evidence for anthropogenic climate change has increased since a similar study by Braganza et al. (2004) on data for the twentieth century. This increased evidence can be described in two ways. Qualitatively we see increased evidence as the multi-observational mean trend in the indices GM, LO, MTG, and AC are all outside the 5%-95% confidence interval for natural variability of 50 year trends. The same statement can nearly be said of NS as well, except that the uncertainty estimate of the multi-observational mean trend in NS overlaps with our estimate of the range of intrinsic variability in the index. The fact that the trends in these observational indices have higher significance than in Braganza et al. (2004) reflects increased evidence for anthropogenic climate change.

Similar to Braganza et al. (2004), we also find the range of values for the trends in the indices determined from the models is quite large, with trends often being smaller than those

determined from the observational data. The multi-model ensemble mean trend in GM and LO lies clearly outside the 5%-95% confidence interval for natural variability, but, unlike in Braganza et al. (2004), the multi-model ensemble mean trend in NS also exceeds the 95% significance level. Furthermore, the 95% significance level for MTG and AC lies within their margin of error of their multi-model ensemble mean trend, indicating that their trends are also virtually significant at the 95% confidence level. We can therefore state that there is also increased evidence for anthropogenic climate change from a quantitatively point of view as we have greatly increased the amount of data on which we have applied the analysis and we find consistently similar results among all observational and model data. Evaluating all results together has increased our confidence that changes in the climate indices are statistically significant and, following from the attribution studies of Braganza et al. (2003; 2004), that such changes are very likely caused by anthropogenic gas emissions.

This finding is further supported by the analysis of the sixth index, the ratio of warming over land to that over the oceans which, due to its construction, exhibits different characteristics to the other indices. The ratio of warming over land and oceans is not characterised by a continual rate of change proportional to climate forcing, but rather converges towards a constant value. Previous studies had indicated that this ratio stabilizes at a value near 1.5. We find a similar value in our analysis of the simulation data and we find it to be independent of model or emission scenario. Although Sutton et al. (2007) had found that the value for this ratio in the observational data was larger than in twentieth century simulations, using the latest datasets we find that the observational value is in line with those determined from the model data. As the ratio is sensitive to natural variability and because there are still uncertainties in both observational and model sea surface temperatures, we can not be more conclusive than previous studies (e.g. Joshi et al. 2008; Sutton et al. 2007) in stating that the stable RLO factor is close to 1.5.

While competing natural variability and anthropogenic forcing may have recently reduced the rate of warming in global-mean temperature due to increasing greenhouse gases; this study indicates that when taking multiple climate change indices there is increased evidence of anthropogenic climate change. As such, future updates of this study should consider the option of investigating whether the trends in the indices achieve higher levels of significance. Further, as this study has also shown the usefulness of these indices for evaluating the

performance of climate models in simulating large-scale variability of surface temperature, it would be useful to include them in analysing output of future CMIP simulations.

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Figure captions

Figure 1: Standard deviation of the indices for detrended observational (A, B, C) and model PICNTRL data (1-8) at annual (open circles and squares) and decadal time scales (grey circles and squares) determined over periods of 120 years. Listed along the x-axis are: Observations: A = NCDC, B = HadCRUT3v, C = GISS. Models: The numbers refer to the models as listed in table 1. The black dots indicate the standard deviation determined over the full length of the PICNTRL simulation.

Figure 2: Distribution of the correlations of the indices with global-mean temperature GM determined over various 120-year periods from control (PICNTRL) model simulations. The correlations are for detrended decadal-averaged data. Superimposed onto this distribution are the respective correlation values for the observational data. There is only one correlation value for each observational dataset but they are printed higher up on the vertical axes solely to improve the visual comparison.

Figure 3: The temporal evolution of the mean (dash-dot line), one standard deviation (dark grey shaded area), and the minimum and maximum range (light grey shaded area) of the indices determined for all historical simulations for the 8 models (see main text). The 3 thin light-grey lines in each graph are the values for the indices derived from the 3 observational datasets used in this study. The twentieth century simulation data were extended with data from the SRESA1B simulations.

Figure 4: Trends in the indices in the observations (A, B, C) and in all the historical simulations of the model data (1-8) for the period 1961-2010 at annual time scales. Listed along the x-axis are: Observations (black squares): A = NCDC, B = HadCRUT3v, C = GISS. Models (grey circles): The numbers refer to the models as listed in table 1. The shaded area marks the 5% to 95% confidence interval for no trend in each index.

Figure 5: A: Temporal evolution of annual-mean RLO for the period 1980-2010 relative to 1890-1920 determined from the observational datasets.

B: Temporal evolution of annual-mean for the period 1980-2010 from the model historical simulations. Dashed line is the mean value; dark grey shaded area is at one standard deviation; light grey shaded area is minimum/maximum value.

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