2.3 DETECTABILITY OF ANTHROPOGENIC CHANGES IN TEMPERATURE AND PRECIPITATION EXTREMES

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1. INTRODUCTION

The goal of the detection of anthropogenic climate change is to establish if model simulated changes due to anthropogenic changes in the composition of the atmosphere can be found in observations, and if these changes in forcing provide a consistent explanation for the observed change. While changes in large scale and annual mean temperature are particularly suitable to detect and quantify anthropogenic climate change (Mitchell et al., 2001), changes in climate variability and extreme climatic events will have a stronger impact on society. Nevertheless, the detection of anthropogenic changes in climate extremes has not yet been accomplished.

This paper aims at setting the stage for a detection of anthropogenic climate changes in extremes by studying the detectability of simulated changes within data from climate models. We use indices for climate extremes that are particularly suitable for a direct comparison of results with indices for annual and seasonal changes. This can address several problems that are hampering the detection of climate change in extremes:

One problem is the limited availability of daily global-scale observations. This problem is improving recently (NCDC, pers. com.) and some indices of extremes have been collected that are readily available and are near-global in coverage (Frich et al., 2001) over land. We therefore restrict the present paper to the detection of climate change in simulated data over land. A further problem is that station data often have very small decorrelation scales, which cannot be readily compared with model gridbox values. Ideally, gridded data for useful indices of extremes are needed for a meaningful comparison with model data. This problem with the availability of suitable daily data could be circumvented if changes in some extremes would be driven only by a shift in the distribution without a change in shape. In that case, changes in extremes could be perfectly predicted by changes in the mean. We therefore investigate if changes in extreme precipitation and temperature are significantly different from seasonal and annual mean changes.

A second problem in the detection of changes in extremes is that the results will depend on the index which is used to describe climatic extremes. For a meaningful detection result it is necessary to decide beforehand which index should be suitable for an early detection of climate change, and when change should be detected. This question can be investigated by attempting to detect the model simulated change in model data itself. Such a study is called a "perfect model study", since it establishes an upper limit for the signal-to-noise ratio of climate change in

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a model that simulates the forced change perfectly well. Such a study is one of the goals of this paper. We scan indices that describe the transition from annual/seasonal mean data to averages of very few extreme days per year to determine at what level of extremeness changes are still suitable for an early detection of climate change.

A third problem is that despite models simulate some broadly similar changes in extremes (see Meehl et al., 2000; IPCC, 2001), changes particularly in precipitation tend to be very model dependent (see, for example, Allen and Ingram, 2002, IPCC, 2001). To address this issue, we study changes from two coupled climate models. It is desirable to establish the most important results from more than two models, but two models provide a first sense of model uncertainty (see Hegerl et al., 1997). They also allow to extend "perfect model studies" to studies where the climate change pattern ("fingerprint") from one model is used to detect climate change in data from the other model. The results will indicate how signal- to-noise ratios deteriorate given model differences from the results of the perfect model study, and hence help determine which indices of climate change should allow for an early *and* robust detection of changes in climate extremes. The resulting signal-to-noise from such "imperfect" model studies should be more realistic, since we expect that observations are at least as different from a model simulation as simulations are from each other.

2. DATA AND METHOD

a. Climate Model Data

We use daily minimum and maximum temperature ("T_{min}, T_{max}") and precipitation data from three anthropogenic climate change simulations each with two different coupled climate models:

- CCCma is the first version of the coupled climate model Climate Centre (Flato et al., 2000). The model has a resolution of 3.75^o latitude by 3.75^o longitude. We use data from simulations of 20^{th} and 21^{rst} century climate change due to greenhouse gas and direct aerosol forcing ("GS", Boer et al., 2000a,b). Our analysis is based on three segments of 21 years duration: Segment 1975-1995 ("$1xCO_2$"), which we use for defining climatology and as the base state relative which the climate change pattern is calculated; segment 2040-2060 ("$2xCO_2$"), which is approximately the time of CO_2 doubling relative to the base period, and segment 2080-2100 ("$3xCO_2$").

- HadCM3 is the third cycle of the Hadley Centre climate model model. It has the same resolution longitudinally as CCCma, but a higher latitudinal resolution of 2.5^o latitude (Gordon et al., 2000, Pope et al., 2000). We use a three-member ensemble of climate change simulations forced with the IPCC scenario "sres2a"(Johns et al HCTN22: Anthropogenic climate change for 1860 to 2100 simulated with the HadCM3 model under updated emissions scenarios, available from www.metoffice.com /research/hadleycentre/pubs/HCTN/index.html) , which includes more forcing agents than "GS". We consider the difference as a crude representation of forcing uncertainty. We use data from 1959-1998, which include the segment $1xCO_2$ 1975-1995, and the same segment 2040-2060 ($2xCO_2$) as for CCCma1. Note that the total length of the chunks (40 + 21 yrs) is similar to that of the CCCMa chunks.

From these data, we have calculated a number of indices that sample the transition from climate means to extremes and allow for a comparison between changes in climate mean and extremes. For minimum and maximum temperature, we extracted the summer and winter season means: June - August ("JJA") and December through February ("DJF"), and calculated the average of the 30, 10, 5 and 1 hottest and coldest days for each year. For precipitation, we calculated the annual mean and the average of precipitation on the 30, 10, 5 and 1 wettest days per year, and the average accumulation per day on the 5 wettest consecutive days of a year. Note that these indices are less rare events than the 20-year return values studied for CCCma in Zwiers and Kharin (1998) and Kharin and Zwiers (2000). We chose weaker extremes since it is expected that very rare events take longer to sample than intermediately extreme events and therefore have smaller signal-to-noise ratio over a time period of several decades. Also, other indices that allow for use of statistical theory such as Peak over Threshold may be more suitable for a comparison with observation and an elegant treatment of statistics. We chose the present indices as averages over increasingly small amounts of data to document the transition from mean to extreme changes.

Note that these indices have been calculated without removing the seasonal cycle, therefore the indices should truly represent exceptionally hot / cold / wet days rather than days that are unusual for a season. The index data have been computed for both models independently and then transformed to the latitudinally coarser grid of the CCCma model prior to this analysis.

b. "Perfect" and "imperfect" model studies

The detection of anthropogenic climate change relies often on regression methods, where the observations are linearly composed from forced signal representing the expected climate change due to anthropogenic forcing (whose structure comes from a climate model simulation), its amplitude (which is estimated) and a noise residual (see Hasselmann, 1979, 1997; Allen and Tett, 1999; Mitchell et al., 2001). Since the present paper is a "perfect" and "imperfect" model study, we use model data from a single simulation (in the following referred to as "pseudo-observations") instead of observations.

The signal or "fingerprint" reflects the spatial pattern of change expected to occur in the observations. We use the difference between the average of the ensemble simulations at the $2xCO_2$ climate state and the $1xCO_2$ climate state for each index. Where detectability within a model is studied, only two simulations are averaged for the fingerprint while the third simulation is used as pseudo-observation. We attempt to detect a fingerprint of climate change in the spatial pattern of climate change between the $1xCO_2$ and $2xCO_2$ segment in the pseudo-observations to establish how well signals should be detectable by the middle of this century. We also use the trend over the $1xCO_2$ and $2xCO_2$ segments to determine if and when climate change should be detectable over shorter timespans.

The uncertainty in the estimate of the climate change signal is determined by applying the detection technique to samples of internal variability instead of the observations. If the estimated amplitude is significantly larger than zero, the model signal is detected in the pseudo-observations. We use the difference within the ensemble members as samples of internal climate variability. This yields (approximately for the case of HadCM2) 9 chunks of 20-year data, which are between 65 and 40 years separated (except for two adjacent chunks in HadCM3). Since the difference relative to the ensemble mean is studied, the estimate contains 6 degrees of freedom in our sample of internal variability. This is a quite small sample, results need therefore to be considered with caution. Also, such a small sample does not allow for using an "optimal" detection approach, since the covariance of climate variability cannot be reasonably estimated (see Hegerl et al., 1997; Allen and Tett, 1999).

3. RESULTS

a. Climate change signals

Both models were found to simulate quite similar climatologies of mean and extreme maximum and minimum temperature. Climate change patterns at the time of CO_2 doubling for both minimum and maximum temperatures show overall warming for both seasonal mean and extreme changes. Changes are larger for cold than warm means/extremes, and cold extremes change particularly strongly over NH mid- and high latitudes (not shown). If the changes in T_{min} and T_{max} extremes were solely due to a shift in the distribution due to global warming, changes in extremes would change by the same amount as changes in seasonal means. Therefore we computed the difference between the warm season mean (JJA for the Northern Hemisphere, NH and DJF for the Southern Hemisphere, SH) and the warmest day and night per year, and between the cold season mean and the coldest day/night per year. A simple nonparametric Mann-Whitney test can assess at which gridpoints extremes change significantly (at the 10% risk level) different from seasonal means. Figure 1 shows the result for the change in warmest nights per year relative to seasonal means from CCCma. 68% of land gridpoints show changes in warm extremes that are significantly different from the change in seasonal mean, indicating that seasonal mean changes in that model are a poor proxy for changes in extremes. Note that the distribution tends to become generally narrower (blue colors) over the NH mid- to high latitudes, but extremes grow more than the mean over the SE United States and parts of South America and Western Europe. The respective plot for HadCM3 (not shown) shows similar changes over South America and parts of the NH high latitudes, but the correlation between both patterns is poor (indicating that changes in tail width is subject to model uncertainty). Results for changes in extremely warm summer days, and extremely cold winter days and nights are qualitatively similar, in all cases seasonal means change differently from extremes over large fractions of the globe, with changes towards narrower and wider distributions over different regions of the globe.

Climatologies and climate change patterns are substantially more different between models for precipitation than for temperature. Although global annual mean precipitation is similar between both models (2.8 and 2.9 mm/day), the pattern of annual mean precipitation in both models shows peak precipitation over different areas of the globe, with a more pronounced ITCZ in HadCM3 than CCCMA, and marked differences in the location of wet areas particularly over Africa (not shown). Global mean 5-day accumulation is higher in CCCma (22mm/day) than HadCM3 (15mm/day), and the spatial distribution of climatological extreme precipitation differs between models, although overall impressions of patterns are similar.

We express climate change patterns in percent of climatological precipitation (or extreme precipitation respectively) since this magnitude is more relevant for impact studies and yields a less pronounced focus on the tropics than changes in absolute values (note that detection results proved to be moderately sensitive to this, with a tendency for more robust detectability if percent changes are used).

In both models, global annual mean precipitation increases by a similar amount (1.1% in CCCma and 1.4% in HadCM3), since this increase is driven by basic physics (see discussion in Allen and Ingram, 2002). In both models, the climate change pattern (fig. 2) changes substantially from mean to extremes, with extreme precipitation showing stronger and more positive changes. The difference between the climate change pattern of annual mean precipitation and the wettest day per year is significant over large fractions of the globe in both models and indicates a general widening of the tail as also expected from observations (Groisman et al., 1999). Climate change patterns for both mean and extreme changes are not very similar between models (correlations of 0.09 between fingerprints for annual mean changes vs 0.17 for fingerprints for the wettest day per year). Climate Change patterns correlate somewhat better between models and between indices if only gridpoints are considered where changes are significant at the 10% risk according to a non-parametric Mann-Whitney test (0.27 for annual to 0.35 for wettest day/yr) indicating that climate change patterns for precipitation show contributions from climate variability even at the time of CO_2 doubling and if three simulations are averaged. All correlations discussed above include the spatial mean, if the spatial mean is subtracted, they become very small.

b. Detectability of changes

We base a simple estimate of signal-to-noise ratio on the ratio of the amplitude of the climate change signal at the time of CO_2 doubling in a single simulation to an estimate of the variability of that amplitude due to internal climate variability. Note that the estimate of the level of natural variability is based on only 6 samples of internal variability that are sampled similarly, but not exactly in the same way as the pseudo-observations: The 20-year averages are not always the same distance apart as the signal, and autocorrelation within the long chunk of HadCM3 data should play a role. Therefore the exact values of signal-to-noise ratios need to be considered with caution. The estimate also assumes that the variance of climate variability remains the same in a warmer climate, which may not be the case, interannual variability of signal amplitude timeseries appears to increase in a warmer climate.

Signal-to-noise ratios for temperature evolve quite differently between the models and the warm / cold extremes of T_{min} and T_{max}, peaking for example for one model in seasonal means while in the average of the 30 hottest / coldest days in the other. However, in both models signal-to-noise ratios decay by no less than a factor of two in the transition from mean to extreme changes, and are in several cases similar to that of seasonal mean changes. This indicates that changes in temperature extremes that occur on average once or several times per year should still be easily detectable. In both models, signal-to-noise ratios for warm means/xtremes are generally higher than for cold means/extremes despite the stronger change in cold extremes. This is probably due to the natural variability being stronger in the cold season. In all cases, the signals of both models are similar enough that the signal-to-noise ratio using the other model's fingerprint is similar to that using fingerprint from the same model. There is some suggestion that changes in temperature extremes might be detectable at the present time in trends over 20 years.

Signal-to-noise ratios for precipitation are generally lower than for temperature (figure 3). Changes can be detected best within a model ("perfect model study") if annual mean or the average of 30/10 wettest days are used, with peak detectability varying between models. In both models, detectability decreases towards events that occur only once per year (1 day wettest and 5 day accumulation, the decrease is more pronounced for CCCma data, not shown). However, if the fingerprint from the other model is used to detect changes within a model (dashed line in fig. 3), signal-to-noise ratios are very low for annual mean changes and peak at the wettest day per year, which is shown in fig. 3 and even more pronounced for CCCma data. This is related to the above discussed increase in correlations between climate change patterns towards more extreme changes and suggests that climate change may be more robustly detectable in moderately extreme precipitation than in annual mean precipitation, where the pattern of change differs stronger between the two models. It needs to be investigated if this effect carries over if more models are used. However, the tendency for an overall increase in extreme precipitation seems to occur in other models as well (IPCC, 2001), suggesting that this result may be robust.

4. CONCLUSIONS

For both precipitation and temperature extremes we find evidence that seasonal and annual mean changes are significantly different from changes in extremes over large fractions of the globe. A similar significant difference was found between very moderate extremes (change in 30 most extreme days) and the most extreme day per year. This suggests that seasonal mean values are not sufficient to describe changes in extremes, and that the tail of the distribution changes in both variables in a warmer world. For precipitation, the distribution generally becomes wider, increasing extreme precipitation more than the mean, while temperature extremes become milder in some regions of the globe and extremer in others relative to the change in seasonal means. Changes in temperature extremes appear robust and similar between models, although the changes in the tail of the distribution are model sensitive. Therefore, changes in moderately extreme temperature should be rather easily and robustly detectable.

Changes in precipitation are very model sensitive, with small correlations between model climate change patterns. If the spatial mean is included, correlations are somewhat larger for extreme than mean precipitation. This is reflected in a better detectability of changes between models for extreme than mean precipitation, indicating that moderately extreme precipitation might be better suitable for an early detection of climate change given the uncertainty in fingerprints for climate change.

A full publication of this material is in preparation and will be available under
www.env.duke.edu/faculty/bios/hegerl.html,
click publications.

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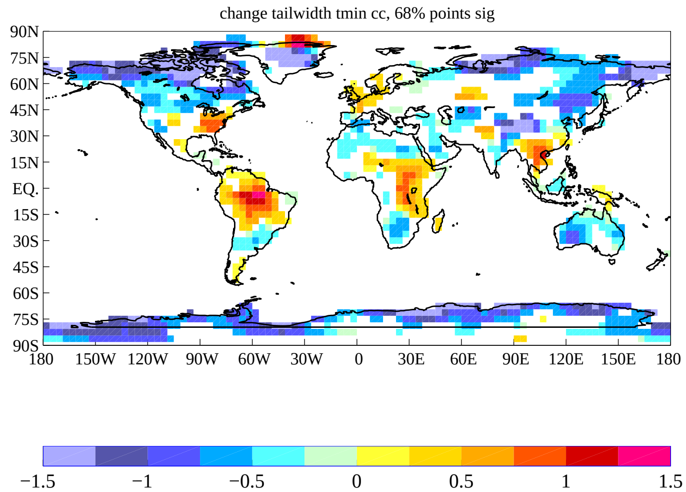

Figure 1: Change in the warmest minimum temperature per year (warmest night) at the time of CO_2 doubling relative to the change in the warm season mean (JJA for the Northern Hemisphere, DJF for the Southern Hemisphere) for CCCma. Changes are only shown where significant according to a Mann-Whitney test. 68% of the gridpoints show changes that are significant at the 10% level, indicating that seasonal mean temperature is a poor proxy for changes in extreme minimum temperatures.

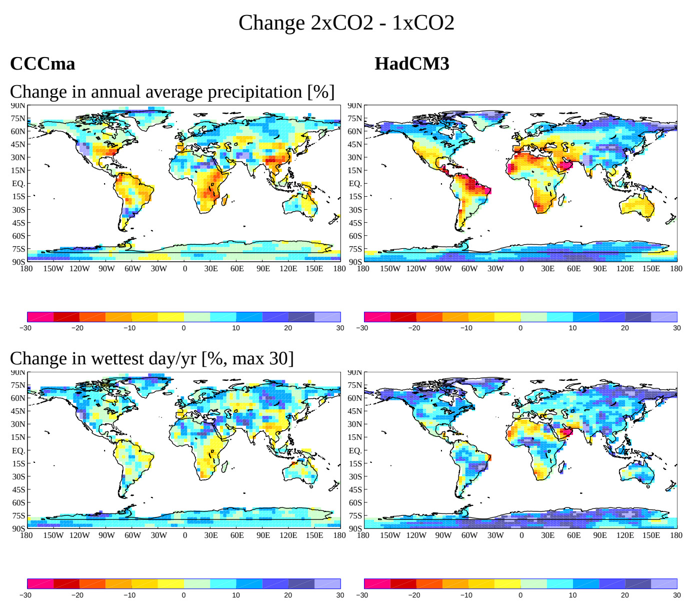

Figure 2: Change in annual mean precipitation (top two panels) and the wettest day per year (bottom two panels) in CCCma (left) and HadCM3 (right) at the time of CO_2 doubling. Changes are expressed in percent of the present day climatological value, the scale ranges from -30% to +30%. Changes in both variables correlate poorly. However, correlations increase from 0.27 for annual mean changes (only gridpoints with significant changes considered) to 0.35 for the wettest day per year (correlations computed with spatial mean included).

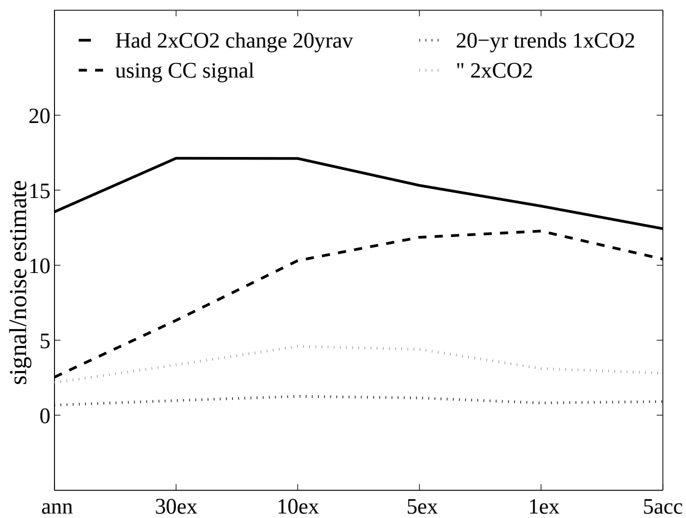

Figure 3: An estimate of the signal-to-noise ratio of precipitation changes based on simulations with HadCM3. The horizontal axis shows the signal-to-noise ratio for the transition from annual mean ("ann") to the wettest day per year ("1ex", and the average accumulation of the 5 wettest days per year ("5acc"). The through line shows the results of a "perfect model study" using data from HadCM3 only (and is based on the average of three cases using one simulation as pseudo-observations and the other two as fingerprint); the dashed line results of an "imperfect model study" using a fingerprint from CCCma to detect changes in HadCM3. Note that while the changes in the wettest 30 and 10 days per year show the highest signal-to-noise ratio within the model, changes in the wettest day per year become more detectable when the other model's fingerprint is used. Results using CCCma data and HadCM3 fingerprints are qualitatively similar. The black dotted line shows the signal-to-noise ratio for trends over 20 years at the present and at the time of CO_2 doubling, indicating that it is not expected that short trends in precipitation can be detected at the present time, but they might become detectable in the future".