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1. INTRODUCTION

Recent studies have shown evidence of an increase in global temperatures due to anthropogenic greenhouse gas forcing over the past century (Houghton et al. 2001). Such a change in global average temperatures could also lead to a larger proportion of rainfall derived from intense precipitation events, even though trends in globally averaged precipitation have been uncertain (Trenberth et al. 2003). Changes in the extremes of climate variations are likely to have larger societal impacts than changes in the mean climate. These impacts will be felt on regional scales, so it is prudent to investigate the effects of climate change on sub-global scales. The signal of temperature and precipitation trends on continental scales is still difficult to detect and hidden by variability from transient climate patterns. Some studies using climate indices have shown robust climate change signals at sub-global scales (IDAG 2005). This study focuses on the detection and attribution of an anthropogenic signal of the change in climate extremes over the contiguous United States using one such climate index.

The Climate Extremes Index (CEI) was designed to monitor the changes of occurrences of extreme climate events across the United States using an aggregate of conventional climate extreme indicators (Karl et al. 1996). The original definition of the index was given as the arithmetic average of the following indicators:

- 1) The sum of the percentage of the United States with maximum temperatures much below normal (below the 10th percentile) and the percentage of the United States with maximum temperatures much above normal (above the 10th percentile).
- 2) The sum of the percentage of the United States with minimum temperatures much below normal and the percentage of the United States with minimum temperatures much above normal.
- 3) The sum of the percentage of the United States in severe drought (equivalent to the lowest tenth percentile) based on Palmer Drought Severity Index (PDSI) and the percentage of the United States with severe moisture surplus (equivalent to the highest tenth percentile) based on the PDSI.
- 4) Twice the value of the percentage of the United States with a much greater than normal proportion of precipitation derived from extreme (more than 2 inches or 50.8 millimeters) one-day precipitation events.

- 5) The sum of the percentage of the United States with a much greater than normal number of days with precipitation and the percentage of the United States with a much greater than normal number of days without precipitation.

Each step of the index has an expected value of twenty percent, and so the total index has an expected value of about twenty percent. Each step can be considered its own climate index, as well as can the combined index. Essentially, the first two steps monitor temperature extremes, the fourth step monitors intense precipitation trends, and the third and fifth steps monitor average precipitation and/or precipitation anomalies.

The advantage of using an index like the CEI is that the raw values of the parameters considered are removed, since one is only concerned with the change of the relative frequency of that parameter. By using percentiles of any given location to calculate the index, this removes the spatial dependency of variability within the parameter considered. An observed change locally can be attributed to either a change in the mean, a change in the variability, or both (Meehl et al. 2000). The use of the index also tends to increase the signal-to-noise ratio, leading to the possibility of more robust results.

2. DATA AND METHODOLOGY

A number of problems can arise from the definitions as originally proposed. The definition for the fourth step has been changed operationally at the National Climatic Data Center to a definition that does not rely upon the threshold for two inches of daily rainfall. An upper tenth percentile threshold has been implemented for this step to allow for spatial variations in the frequency distributions of daily rainfall (Gleason et al. 2006). For the original definition of the CEI, a long-term increase in the mean of a variable would result in a decrease in the values much below normal and an increase in the values much above normal, leading to a U-shaped curve for the long-term variations. Figure 1 shows the problem arising by summing the upper and lower tenth percentile areas of the United States; it is not clear which tail of the distribution is contributing more to the index for different periods in the record. If one is to introduce a definition of the CEI by using differences of the areas of the United States with values outside the tenth and ninetieth percentiles, then a physical trend may become more easily understood. The proposed definition of a modified Climate Extremes Index (mCEI) used herein is the arithmetic average of the following indicators:

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- 1) The difference of the percentage of the United States with maximum temperatures much below normal from the percentage of the United States with maximum temperatures much above normal.
- 2) The difference of the percentage of the United States with minimum temperatures much below normal from the percentage of the United States with minimum temperatures much above normal.
- 3) The difference of the percentage of the United States with severe drought based on PDSI from the percentage of the United States in severe moisture surplus based on the PDSI.
- 4) Twice the value of the percentage of the United States with a much greater than normal proportion of precipitation derived from extreme (above the ninetieth percentile) one-day precipitation events.
- 5) The difference of the percentage of the United States with a much greater than normal number of days without precipitation from the percentage of the United States with a much greater than normal number of days with precipitation.

The expected value of the mCEI is four percent, since all steps except the fourth step have a new expected value of zero. A long-term increase in the mean would result in an increasing trend in the mCEI. As shown in Figure 1, the contrast between the long-term variations of the CEI and the mCEI shows contributions mainly from much below normal extremes early in the century and mainly from much above normal extremes later in the century. Such a change in the index considered is mostly due to a change in the mean of the distribution considered, though a change in the variability is not out of the realm of possibilities.

The observational mCEI is calculated using the United States Historical Climatology Network (USHCN) (Karl et al. 1990) monthly surface data for the temperature steps, TD3200 and TD3206 daily precipitation data for the precipitation steps, and TD-9640 (Karl 1986) divisional PDSI values. A ninety percent completeness

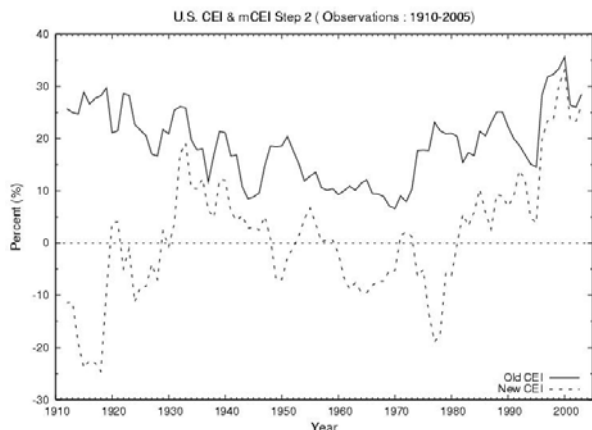


Figure 1. Observed values of Step 2 of the CEI's summation definition (solid) and mCEI's difference definition(dashed)

of record criterion was instituted with the temperature and precipitation data to remove any biases of increasing number of observations over the twentieth century. The year 1910 was used as a starting point because of the small number of stations that have records that go back earlier than 1910; which would affect the ninety percent completeness criterion across the time period interested. The data was then area-averaged onto a $1^\circ \times 1^\circ$ grid. Other grid resolutions were experimented with, but did not significantly affect the values of the index.

To attribute the trends in the index, a suite of coupled ocean-atmosphere global climate model data from the Program for Climate Model Diagnosis (PCMDI), which have been used in the Intergovernmental Panel on Climate Change's Fourth Assessment, are employed. The models were required to have relatively long pre-industrial control runs with no changes in external forcing parameters and to have daily precipitation, monthly mean surface temperature, and soil moisture data to be able to ascertain the variability of the pre-industrial climate. The models also had to have at least ninety years of a twentieth century run to compare to the observational record. It was also preferable to have as many ensemble members of each run as possible. The models that met these criterion were the National Center for Atmospheric Research Community Climate System Model (CCSM3.0) (Collins et al. 2006) and Parallel Climate Model (PCM) (Meehl et. al. 2004), Canadian Centre for Climate Modelling and Analysis Coupled Global Climate Model (CGCM3.1) T47 and T63 (similar to AGCM2 (McFarlane et al. 1992)), and Geophysical Fluid Dynamics Laboratory Climate Model 2.0 and 2.1 (Delworth et al. 2006). The models have variable horizontal resolutions from 1.5° to 3.75° . For the twentieth century runs, the models included time-dependent variations of greenhouse gas, anthropogenic aerosol and volcanic radiative forcings. Since the data is already provided from the models in gridded form, the mCEI can be calculated directly from the model output. However, since the mCEI is dependent upon the length of record used in the averages for each location, the length of the period taken in the model must be similar to the length available in observations.

A statistical analysis can be performed on the twentieth century model and observational data compared to the pre-industrial control runs to interpret the effect of increasing concentrations of greenhouse gasses over the twentieth century. The control runs must also be broken up into base periods that match the observed record due to the dependence on the length of period of the index. Thirty and fifty year trends of each step of the mCEI and total mCEI are calculated at the end of the 90-year period to compare with twentieth century values. To gather as many samples as possible without oversampling the control run data, the base period is shifted by fifteen years and recalculated to get control values of the index trends. Fifteen years was chosen because for a thirty year trend analysis, half of the data used would be new, independent values.

3. RESULTS

The temperature related steps one and two showed the most significant thirty and fifty year trends. Figure 2 shows steps one and two averaged together along with a group of ensemble-mean twentieth century model runs. This average of the step one and two indices is closely related to the index based on mean temperature, which is what is used in most of the values shown for the twentieth century ensemble members. This does not significantly affect the behavior of the index. The heat waves of the 1930's and the 1950's can be seen, as well as the cool period of the 1960's through the early 1980's. Another interesting note is the drop in the early 1990's, which is most likely due to the eruption of Mount Pinatubo in 1991. All of the twentieth century runs capture this feature except for the CGCM3.1.

The twentieth century model runs capture the variability of the observed values of mCEI steps one and two relatively well. It should be noted that the ensemble averages for the multi-member ensembles of model runs show less shorter time scale variability than the observed index, as expected. All of the runs also capture the trend from negative values in the beginning of the period to positive values at the end of the period,

which can be interpreted as an increase in extremely warm mean temperatures and/or a decrease in extremely cold mean temperatures. From the data, both are observed. The control run confidence interval indicates that in an unforced climate, the mCEI for these steps has no trend expected. To get a conservative estimate of the significance of the trends in steps one and two, the pre-industrial control run that had the most variability is used. For the last thirty years, of the twenty-four twentieth century model ensemble members, 46% had trends that were above the 95% significance level, as was the observed trend. Only 2 members had decreasing trends over the last thirty years, and these trends were close to zero. The fifty year trends were slightly more significant, with 54% exceeding a 95% significance level, along with the observational record as well. The most sensitive models to the greenhouse gas forcing are the CGCM3.1 model runs, which every single ensemble member has a significant increasing trend. It is unlikely that these trends are caused by natural variability alone and the increase in warm extremes and decrease in cold extremes over the last thirty to fifty years is likely due to the increase of greenhouse gas forcing over the past century.

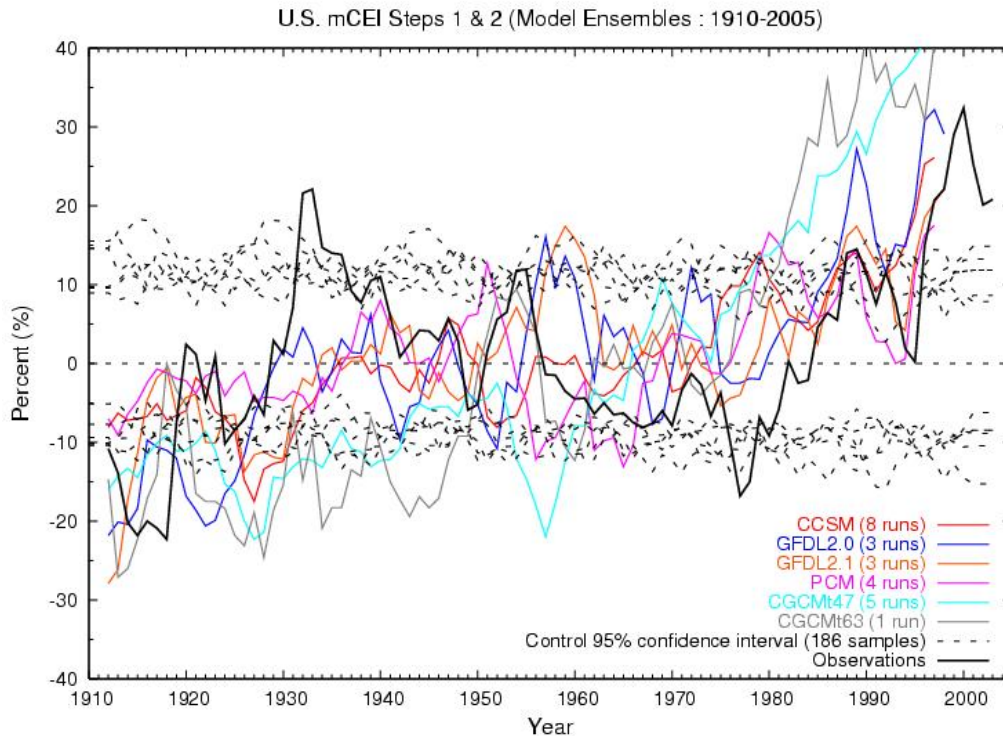


Figure 2. Five-year moving averages of model ensembles (color), observed values (bold), and pre-industrial control runs (dashed) of mCEI steps one and two. Each model's pre-industrial control run is plotted as a 95% confidence interval to show the approximate spread of control values of the mCEI in a 94 year period with no greenhouse gas forcing.

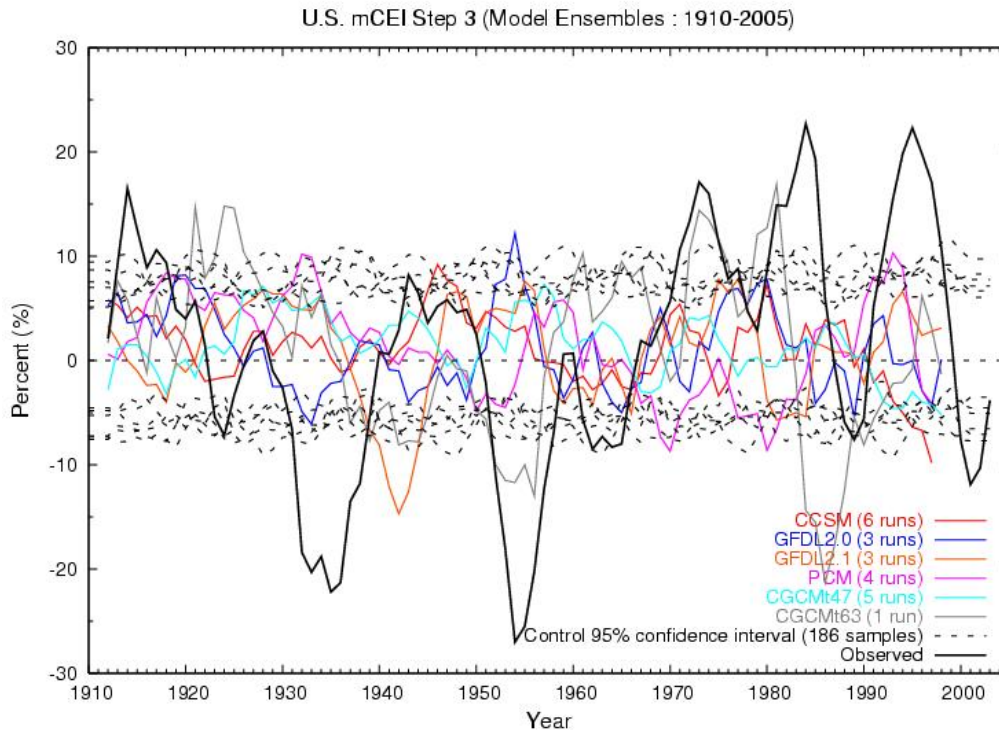


Figure 3. Five-year moving averages of model ensembles (color), observed values (bold), and pre-industrial control runs (dashed) of the mCEI step 3.

The third step in the mCEI based on the PDSI is an indicator of long term hydrological extremes, either meteorological drought; or prolonged wet spells across the country. Over the twentieth century, the trend in this step has remained close to zero with very large decadal variations. The first fifty years of the observational record show a tendency toward slightly negative values, with the droughts of the 1930's and 1950's indicated by the large negative values. However, the last thirty years have tended to be slightly wetter than average over the observational record. Overall trends change depending on the trend length specified, with an increase over the last 50 years, and a decrease over the last 30 years.

While data to calculate PDSI observationally are reasonably straightforward to do, such calculations are not available in most of the global climate model runs. However, a variable similar to PDSI, such as soil moisture is readily available and is used as a proxy. Since the calculations for PDSI are similar to the soil moisture budget, it is reasonable to expect that soil moisture can be used within the index for PDSI values. PDSI and soil moisture are well correlated, but the correlation decreases in magnitude the deeper the layer of soil considered and during cold seasons such as winter (Dai et al. 2004). Since this study is interested not in the mean values of PDSI or soil moisture, but rather the number of occurrences above or below the tenth and ninetieth percentiles on monthly time scales at each particular location, the approximation of PDSI by soil moisture anomalies is a reasonable one. Intense

droughts (or moisture surpluses) would be detectable using either variable, especially if it was below (above) the tenth (ninetieth) percentile. A comparison of the index calculated from soil moisture and area-averaged monthly precipitation data in the models yields similar correlations and trends obtained by comparisons between the index calculated from observational PDSI and area-averaged monthly precipitation data. The relationship between the third and fifth step also remains unchanged whether the index based on soil moisture data or monthly precipitation data. The third step of the mCEI was calculated for three drought indicators of different time scales (PDSI, Palmer Hydrological Drought Index, and Z-Index), only to show that the annual values of step three are insensitive to significantly different definitions of the drought index.

A relevant question is how well the models simulate the variability of PDSI using soil moisture. The ensemble-averaged models used do relatively poorly, as shown in figure 3, failing to represent the spread of the observed twentieth century extreme values. The inter-annual variability for the model calculated Step 3 is about the same amount as is seen in the observed variability in the index, however, the five-year variability in the model index values is less than that of observed values. Thus this brings into question how well the models are able to resolve long-lasting droughts or wet periods, such as those observed in the 1930's, mid 1950's, and the early 1990's. As pointed out by the model ninety-five percent confidence interval, as well as the twentieth century

ensembles, the models underestimate the magnitude of extreme conditions in long-term moisture deficiencies or surpluses. Another effect that leads to a decrease in the variability of the twentieth century model runs would be the effect of ensemble averaging. It is likely that each ensemble member may have an extreme drought or moisture surplus when the other ensemble members are relatively normal or are experiencing the opposite conditions. Thus droughts or moisture surpluses with a similar magnitude of the observed extreme periods are not as likely from an ensemble-averaged model. This point may be observed with the CGCM3.1 t63 resolution run, which only has one member and mimics the variability quite well. The effect of ensemble averaging is not seen in the temperature steps because extreme warm or cold periods are more common than extreme droughts or wet spells, thus are not averaged out in the total ensemble. The individual ensemble members of the CGCM3.1 T47 do simulate the variability of the third step in the observations well, but the ensemble average of these model runs do not.

Overall, the twentieth century models stay within the 95% confidence interval provided by the control runs. It does not appear that there are any large trends in the third step over the twentieth century for either the observed record or the models. Of the twenty-two available ensemble members for this step, only two show thirty year trends or fifty year trends that exceed the 95% significance level, while the observed do not even exceed the 90% significance level. The two members that do exceed the 95% threshold both have negative trends in soil moisture. However, the larger in magnitude the model ensemble is with increase trends in temperature steps, the more likely that the third step's trend will tend to be negative. This is intuitive, as increased temperatures would lead to more evaporation from the soil, and a tendency towards negative PDSI values. The CCSM3.0, CGCMt47, and CGCMt63 exhibit such trends.

The fourth step of the mCEI, shown in Figure 4 (below), has been steadily increasing over the last twenty-five years. This is consistent with the expectation that an increase in intense rainfall in the United States is likely with increasing global greenhouse gas concentrations (Groisman et al. 2004). The twentieth century model ensembles capture the trend of the fourth step over the last twenty years quite well, except for the CCSM3.0. The observed trend over the last thirty to fifty years is significant at the 90% confidence level when using the total ensemble control run variability, but fails to exceed this threshold if the most variable control run is used. Of the sixteen individual ensemble members used to calculate the fourth step, only one had a thirty and fifty year trend above the 95% significance level. The average values of the fourth step are slightly higher than the expected value of twenty percent for the pre-industrial control runs. The average values were about 21 – 23%, with the standard deviation of about 2 – 3%, probably due to fact that the distribution for the proportion of rainfall derived from extreme one-day

precipitation events is not necessarily normally distributed. However, trends across time in the values of the index should be normally distributed around the mean.

Results from the fifth step (Figure 5) are similar to those of the third step. The decadal variations of the third and fifth step of the mCEI are positively correlated, though not as strong as that of the temperature steps. Periods with extreme drought based on PDSI also tend to have a much larger number of days without precipitation. The same features in the observational record can be seen as in the third step, only slightly less in magnitude. However, the models capture the five-year variability much better than in the third step, with the observational record exceeding the control 95% confidence interval less frequently. Observational trends are close to zero and not significant, while most of the CCSM3.0 ensemble members show significant drying trends over the last thirty years.

Combining all of the steps and averaging to form the mCEI, one can get an overall sense of the climate in the United States over the past century. From the definition of the mCEI, positive values tend toward warmer and wetter conditions, whereas negative values tend towards cooler and drier conditions. Figure 6 shows the relationship between the individual steps of the combined mCEI values over 1910 to 2005. The only time frame that the third and fifth steps do not match is early in the observational period, due to the fact that the PDSI values start at zero by definition. The recent increasing trends are mostly due to the trends in the temperature and intense rainfall steps.

Comparing the model runs to the observed mCEI shows that even all the twentieth century ensemble models show relatively large trends in the last fifty years. As far as the individual models, seven of the individual ensemble members show positive fifty year trends that exceed the 90% significance threshold. Only one ensemble member had a decreasing trend, which was close to zero. The trends in the CCSM3.0 are much less significant than the other models because of the strong drought at the end of the period, which tends to average out the strong warming signal in the temperature steps. The observed trends are statistically significant at the 95% confidence interval, even if the control model with the largest variability is used to compare as natural variability. The largest contributors to this significant increase are the temperature steps, and to a lesser degree, the intense precipitation step of the index. There are trends toward a slightly more frequent wet extreme periods, though these trends could be due to natural variability.

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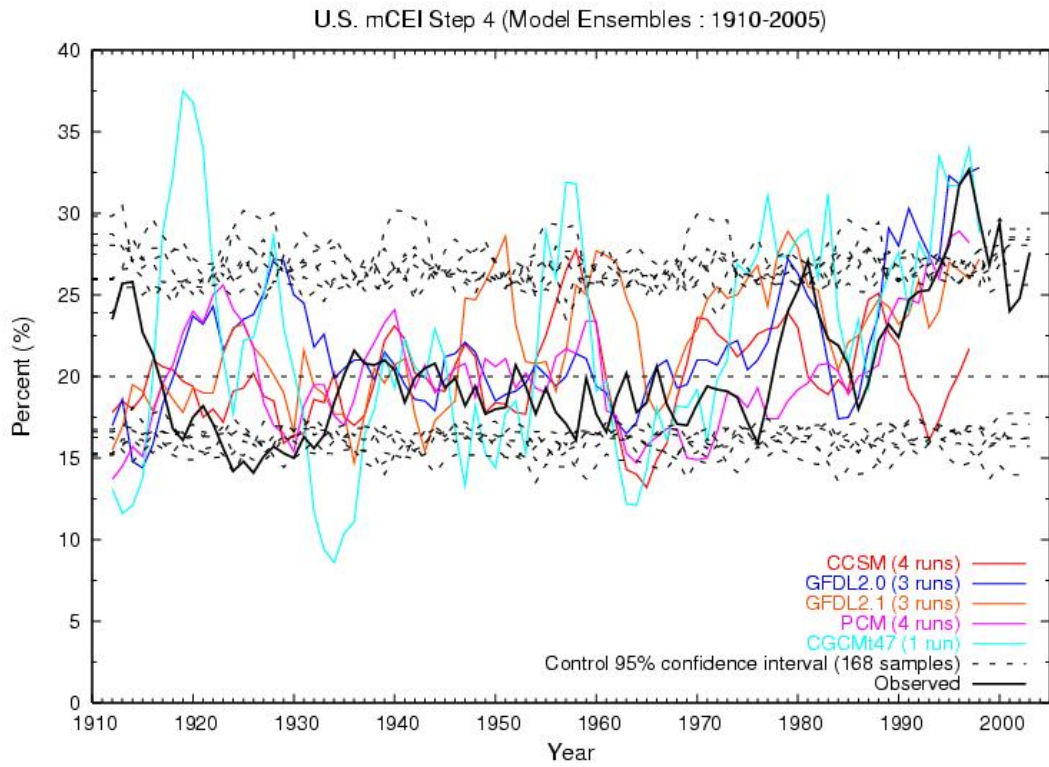


Figure 4. Five-year moving averages of model ensembles (color), observed values (bold), and pre-industrial control runs (dashed) of the mCEI step 4.

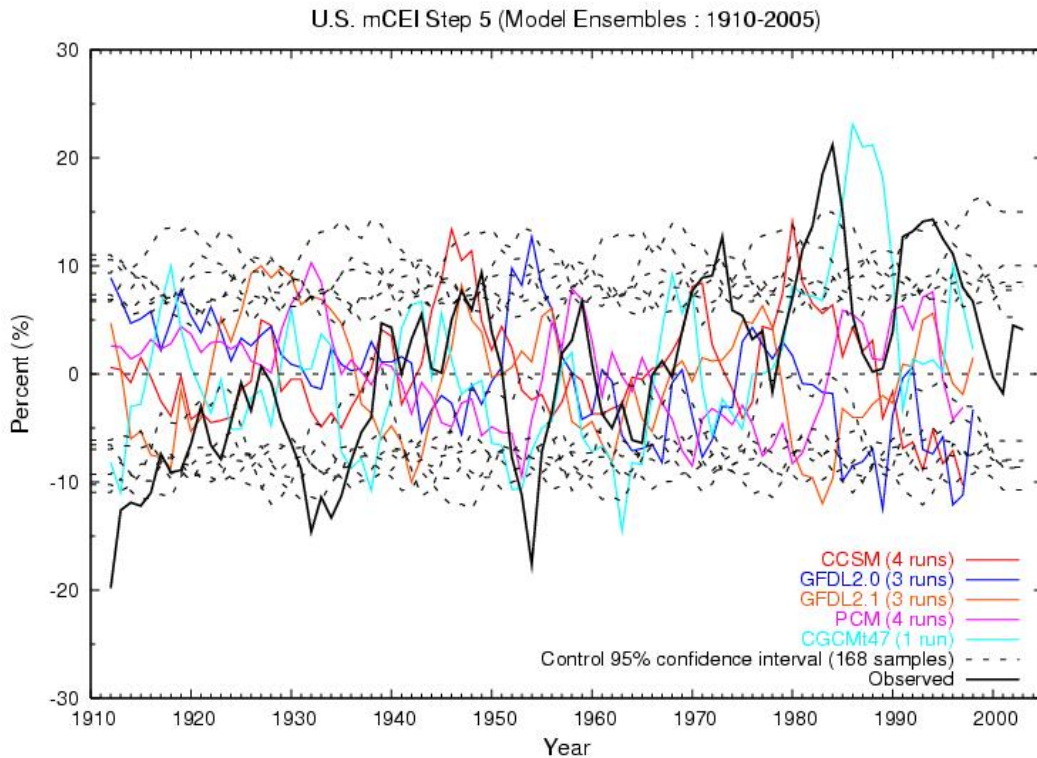


Figure 5. Five-year moving averages of model ensembles (color), observed values (bold), and pre-industrial control runs (dashed) of the mCEI step 5.

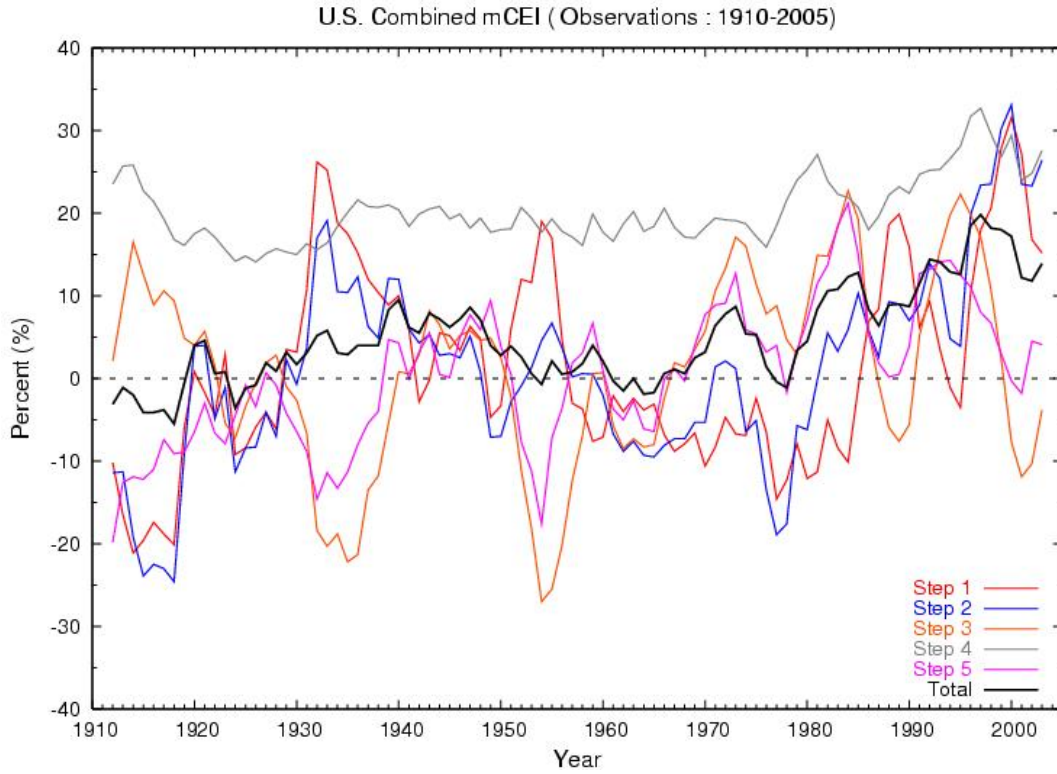


Figure 6. Observed values of each step of the mCEI (thin) and the total mCEI.

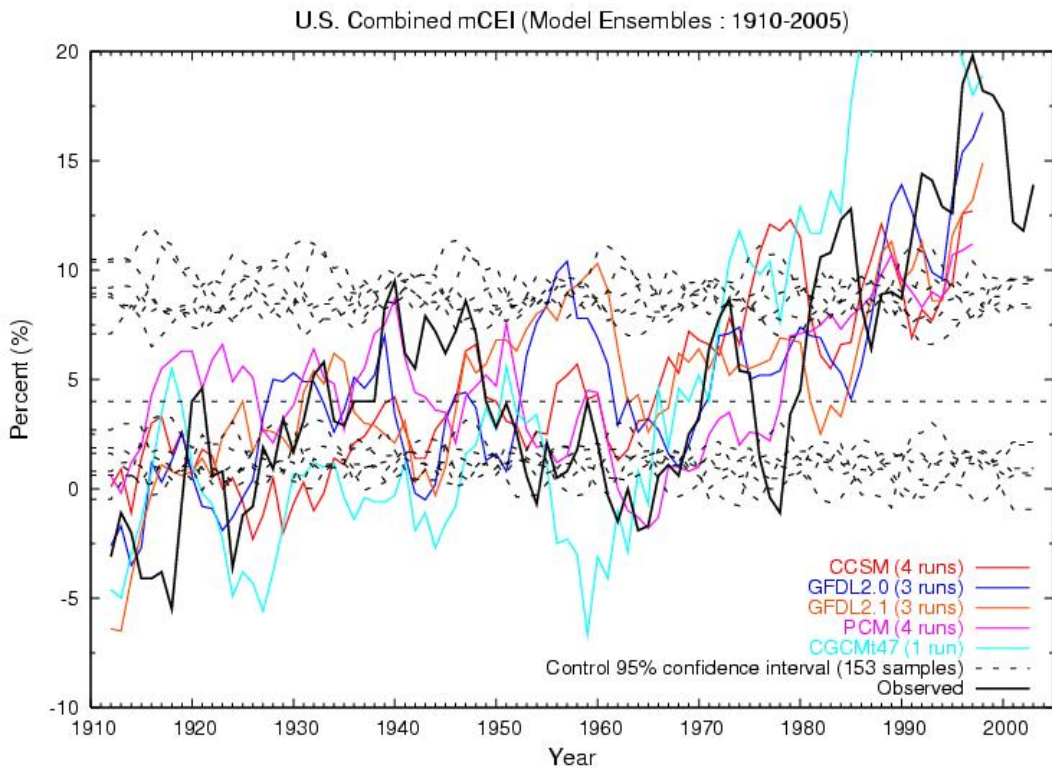


Figure 7. Five-year moving averages of model ensembles (color), observed values (bold), and pre-industrial control runs (dashed) of the total mCEI.