GREENHOUSE CLIMATE CHANGE FINGERPRINT DETECTION

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1. INTRODUCTION

This paper provides a brief discussion of methods for detecting climate change associated with an enhanced greenhouse effect and presents an example of the fingerprint detection technique. Much of this discussion is taken from Section 8 "*Detection of the Greenhouse Effect in the Observations*" of the recent review on climate change by the Intergovernmental Panel on Climate Change [1] and from notes prepared by Professor Tom Wigley, Climate Research Unit, University of East Anglia for that Section.

There has been some controversy over the issue of greenhouse climate change detection. In some cases, detection has been considered to be the demonstration of a significant observed climate change consistent with model predictions of the enhanced greenhouse effect. In practice, detection also requires that the observed changes are in accord with detailed model predictions and not due to other causes. Thus, we must be able to attribute all or part of the observed climate change to the enhanced greenhouse effect alone (IPCC [1]).

Over the last hundred years, there has been a significant global-mean surface warming of about 0.5°C (Fig. 1, [1, 2]). At the same time, greenhouse gas concentrations in the atmosphere have increased substantially, with about 30% increase in CO_2 concentration. The long-term global warming is qualitatively consistent with an enhanced greenhouse effect. However, there are marked global temperature fluctuations on decadal time scales shown in Fig. 1 which are an indication of natural climate variability on these scales. Very little is known about climate variability on century

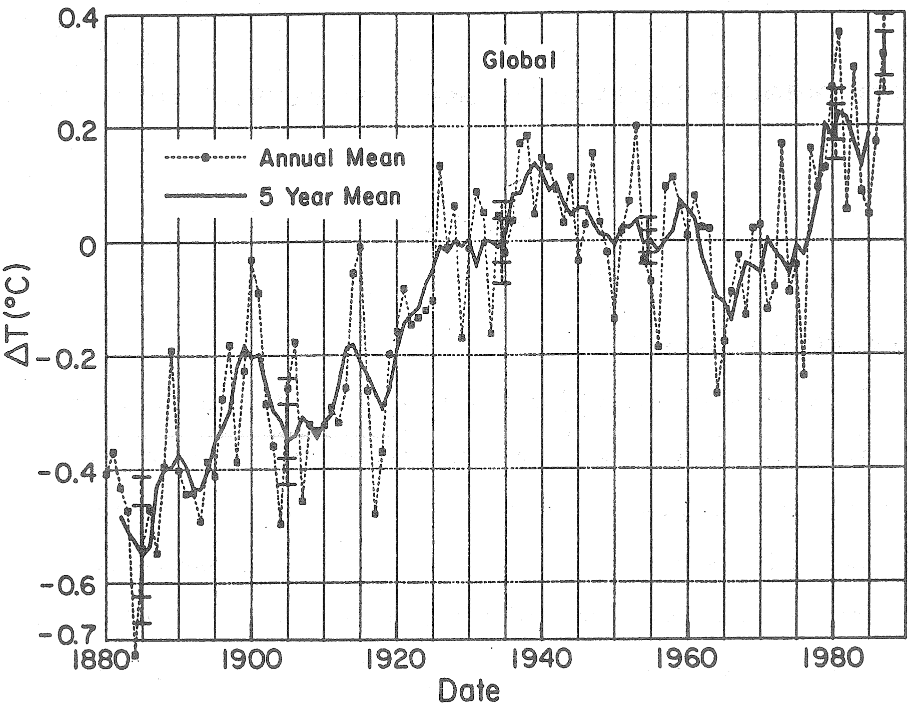

Figure 1. Global-mean surface air temperature variations prepared from land-based meteorological station data (from Hansen and Lebedeff [2]).

time scales and it is possible that the recent global warming is due just to climate variability. Global-mean warming is not a good signal to use for identifying an enhanced greenhouse effect because there are many possible causes of such a warming.

It is very difficult to demonstrate a causal relationship between climate change and an enhanced greenhouse effect using a single variable, such as global-mean surface temperature. The problem is to be able to attribute the observed change to the enhanced greenhouse effect with high confidence. The method which has been proposed to address this problem is the "fingerprint" method; identification of a multivariate signal that has a structure unique to the enhanced greenhouse effect and observation of a significant change in this signal (IPCC, [1]).

In the next section, some general comments on detection strategies are presented and in Section 3, multivariate or fingerprint methods are described in more detail. In Section 4, an example of greenhouse climate change fingerprint detection is demonstrated by comparing the vertical and meridional structure of atmospheric temperature changes from greenhouse climate model simulations with the observed changes over the last three decades.

2. DETECTION STRATEGIES

In seeking to identify an enhanced greenhouse effect in the observational record, the following issues must be considered (IPCC,[1]):

- The strength of the predicted signal relative to the noise, the signal-to-noise ratio.
- Uncertainties in the predicted signal and in the noise.
- Availability and quality of suitable data.
- Statistical methods for testing the similarity of signal and observations.

Each of these issues will be considered briefly in turn.

Signal-to-noise ratio

The signal-to-noise ratio (S/N) provides a convenient criterion for ranking different possible detection variables. Detection will be easier for variables with larger S/N. An indicator of the strength of the signal can be obtained using the change of a variable between control and double CO_2 concentration experiments with climate models. The noise can be estimated from observations or from model results, generally by using interannual variability to estimate climate noise at longer time scales. Model studies (Barnett and Schlesinger [3]) have shown the highest S/N ratios for tropospheric and surface temperatures and lower tropospheric water vapour content and lowest S/N ratios for precipitation and surface pressure.

For multivariate signals involving spatial patterns, ideally the signal pattern should be distinctly different from the pattern of natural variability (noise), ensuring a high S/N. However, it is likely that there will be some similarity between the large-scale patterns for the signal and climate variability because the same feedback mechanisms associated with snow and ice extent, water vapour and cloudiness, soil moisture and sea surface temperature are common to both natural variability and the greenhouse effect.

Signal and noise uncertainties

In general, the enhanced greenhouse signal is derived from climate model simulations and there must be great uncertainties about signals for which there are large model-to-model differences. Some model intercomparisons have been made for double CO_2 equilibrium climate simulations and the most consistent results between the models are for the vertical and meridional pattern of atmospheric temperature change (Schlesinger and Mitchell [4]). The consistent features of the atmospheric temperature change are warming of the troposphere, cooling in the stratosphere, enhanced warming in the tropical upper troposphere and enhanced warming in the high latitude lower troposphere in the winter hemisphere.

Another difficulty with defining the signal is associated with differences between the results of equilibrium and transient greenhouse climate model simulations. The slow increase of greenhouse gas concentrations and the inclusion of ocean dynamics in the transient model simulations leads to slower signal definition and greater variability within and between the transient model simulations (Stouffer et al. [5]). Hence the results from equilibrium simulations must be considered only as a guide to possible signal structure.

Since the expected climate changes due to the enhanced greenhouse effect will occur on decadal time scales and longer, it is only the low-frequency characteristics of natural climate variability which are important in defining the noise. However, these characteristics cannot be quantified accurately from observational data because of the shortness of the record. Statistical methods may be used to estimate the low-frequency variability from interannual variability but this will lead to uncertainties arising from any assumptions made in applying a statistical model. Alternatively, extended climate model simulations may be used to estimate the low-frequency variability but such experiments have not been carried out yet with complex climate models.

Data availability

The availability of observational data imposes important limitations through two aspects; the definition of an evolving signal in the data and the quantification of the low-frequency noise. Both require long record lengths and adequate spatial coverage. Reliable upper air data suitable for defining the three-dimensional thermal structure of the atmosphere are available only from the late 1950's and extend up to the lower stratosphere only. This period of data is probably too short for adequately resolving climate change but it is the longest record available for defining the three-dimensional structure of any atmospheric parameter. This record is definitely too short for estimating the low-frequency natural variability.

Statistical testing methods

In statistical terms, detection studies have generally been phrased in terms of testing hypotheses. The possible null hypotheses can be grouped into two types: that there is no enhanced greenhouse effect (more commonly, that there has been no change in climate); or that observed changes of climate are the same as predicted by model simulations of an enhanced greenhouse effect. It is only with the second type of null hypothesis that the problem of attribution can be considered. Rejection of this second type of null hypothesis could arise because of differences between the observed and model climate change due to either the absence of real greenhouse climate change in the observations or poor simulation of the greenhouse effect by the model.

For many of the possible detection statistics which could be used for testing these hypotheses, the sampling distribution is unknown because of temporal and spatial correlations in the data fields. Thus, non-parametric methods must be use to assess significance. These usually involve the generation of a sampling distribution for testing the hypothesis by Monte-Carlo or permutation techniques.

In describing the tests that have been used, it is convenient to introduce some simple notation, following Wigley and Santer [6]. Let the detection parameter be $T_{xt}, x = 1, n_x, t = 1, n_t$. The subscript t denotes time while x denotes a spatial co-ordinate or different variable so that in the univariate case, $n_x = 1$. Although the time and space variations of T are continuous, in practice T is defined only at discrete points and times. To distinguish observed data values from model-generated values, T is replaced by D (data) or M (model). Also, T_{xt} may be either an instantaneous value at t or a time mean over some interval centred on t.

The two types of hypotheses above can be expressed as two types of statements; there has been no change in D_{xt}, or changes in D_{xt} are similar to model predictions M_{xt}. To define changes, we need a reference level, which is usually a time mean over an interval centred on $t = 0$ so that changes are denoted by $\delta T_{xt} = T_{xt} - T_{x0}$.

Testing of the first type of hypothesis involves questions like: Is δD_{xt} significantly different from zero? or is there a trend in δD_{xt}? The second type of hypothesis involves questions like: Does δD_{xt} differ significantly from δM_{xt}? or is there a trend in the pattern correlation between δD_{xt} and δM_{xt}?

3. FINGERPRINT METHODS

The fingerprint method involves the identification of a multivariate signal unique to the enhanced greenhouse effect and observation of a significant change in this signal. The key aspect of this method is that it involves time series of more than one variable or a single variable at more than one location. One might consider the time evolution of a set of three-dimensional spatial fields and compare model results with observations. This is the only way that the attribution problem is likely to be solved. However, there are many difficulties both in applying the method and interpreting the results. Both signal and noise uncertainties are larger for spatial fields, there are statistical problems in using multivariate tests, there is a large number of characteristics of spatial fields or evolving spatial patterns that may be compared and there have been few studies in this area (IPCC, [1]).

One type of multivariate detection would be to compare changes in mean fields or variability between observations and those predicted by climate models. Tests for changes in the mean fields involve comparison of δD_{xt} with δM_{xt}, where δM_{xt} might be the scaled difference between 10-year averages from double CO_2 and control equilibrium model simulations and δD_{xt} the difference of the same variable between two 10-year averages from observational data.

Pattern correlation methods have been used to compare evolving changes, either by correlation of observed and modelled patterns of change or by the changing correlation of observed and modelled patterns. This method has been used by Barnett and Schlesinger [3], who considered the correlation C_t as a function of time between δD_{xt} and $\delta M_x = M2_x - M1_x$, where M2 and M1 are the mean values from $2\times CO_2$ and $1\times CO_2$ model simulations. Thus C_t tends to 1 as δD_{xt} tends to δM_x. However, no noticeable trend was found in C_t, which could be interpreted as non-detection or as due to model errors.

4. A FINGERPRINT EXAMPLE

The fingerprint used in this example is the zonal mean atmospheric temperature difference as a function of height and latitude between double CO_2 and control climate model simulations. This signal is the most consistent pattern of greenhouse climate change for different models. Here, the results from an improved version of the model of Manabe and Wetherald [7] are used to define the signal. This climate model consists of a spectral atmospheric general circulation model with rhomboidal wavenumber 15 truncation and 9 levels in the vertical. The changes from the earlier version of the model involve explicit cloud prediction based on a relative humidity threshold, rather than specified cloud amounts used earlier. This atmospheric model is coupled to a mixed layer ocean model. The climate model was run to equilibrium with normal CO_2 concentrations and with double CO_2 concentrations. The difference between the 10-year mean zonal mean temperature from these equilibrium simulations defines the

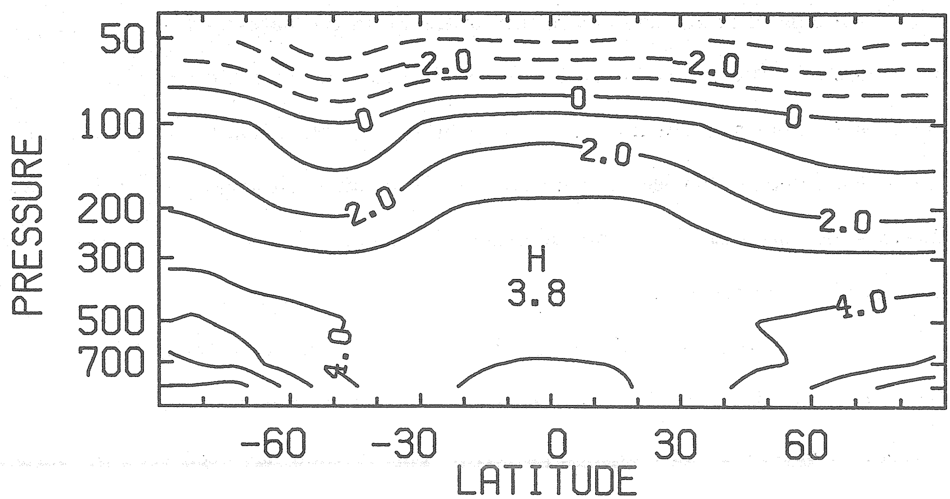

Figure 2. Zonal mean atmospheric temperature difference between 10-year averages from double CO_2 and control equilibrium simulations of the GFDL climate model (Manabe and Wetherald [7]). The contour interval is 1° C and negative contours are dashed.

greenhouse fingerprint for this example, δM_x, and is shown in Fig. 2. Note the features of these temperature differences consistent between models, including warming of the troposphere and cooling of the stratosphere.

There is a relatively short period of observations of atmospheric temperature above the surface as reliable radiosonde data with reasonable global coverage are available from the late 1950's only. In addition, these data have usually been used for weather analysis and forecasting. Changes in analysis methods and inclusion of different sources of temperature observations, including satellite-derived temperature soundings, have lead to an analysis record which is inappropriate for investigation of climate change. Recently, Oort has updated his global analyses of atmospheric temperature prepared from radiosonde data alone from the original period, 1963 to 1973 (Oort [8]), to include an additional 15 years up to 1988. These global analyses have been prepared using the same analysis technique for the whole period. Problems with these analyses may arise through changes in the spatial coverage of the radiosonde network and less than adequate coverage over ocean areas, particularly in the Southern Hemisphere.

These analyses are used to define the evolving thermal structure of the atmosphere over the period 1963 to 1988. The zonal mean temperature is used at seven pressure levels; 850, 700, 500, 300, 200, 100 and 50 hPa, and at 5° latitude intervals to be compatible with the model resolution. The difference between the 10-year averages for the last 10 years (1978-88) and first 10 years (1963-73) of these analyses is shown in Fig. 3, with stippling showing differences which are locally significant at the 5% level using a t-statistic test. Note the general warming in the lower troposphere and cooling in the stratosphere over this period. A Monte-Carlo field significance test shows that this difference field is significantly different from zero at more than the 1% level, supporting rejection of the type one hypothesis that there has been no climate change over this period.

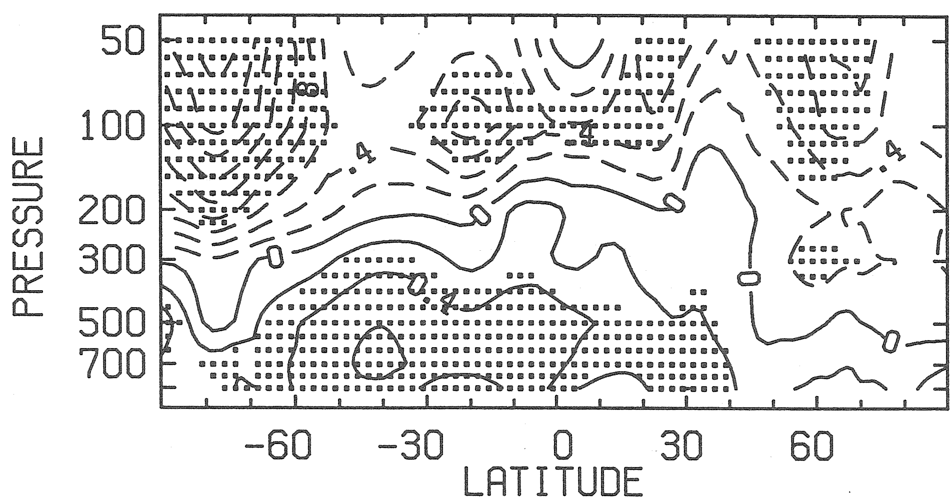

Figure 3. Observed zonal mean temperature difference between 10-year averages for periods 1978-88 minus 1963-73 from the global analysis dataset of Oort [8]. The contour interval is 0.2° C and negative contours are dashed. Stippling indicates differences locally significant at the 5% level using a t-statistic test.

To test the type two hypothesis, the observed temperature changes are compared with the modelled greenhouse signal. The temperature differences in Fig. 3 have a pattern correlation of 0.39 with the greenhouse fingerprint in Fig. 2, which is significant at the 10% level using a permutation (Monte-Carlo) test. The two patterns have some features in common, including warming in the lower troposphere and cooling in the stratosphere. The largest difference is that the observed level at which the warming changes to cooling in the observations is much lower than in the model simulations. Other details such as the enhanced warming at high latitudes and in the tropical upper troposphere in the model results are not apparent in the observations.

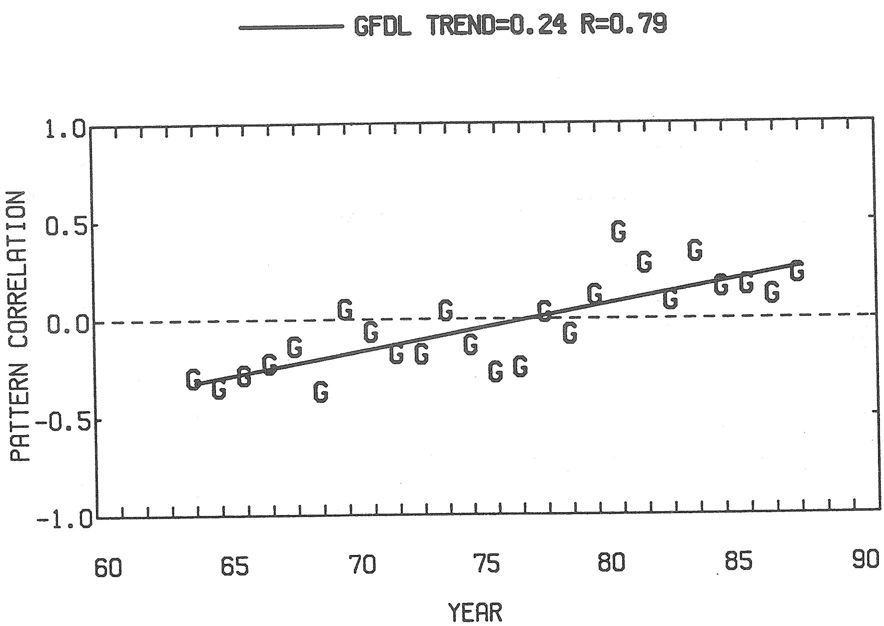

Figure 4. Time series of the pattern correlation between the annual anomalies of observed zonal mean temperature and the GFDL model greenhouse fingerprint shown in Fig. 2. Each annual pattern correlation is shown by a G, as well as the least-squares straight line fitted to these values.

The time series of the pattern correlation, C_t, between the observed annual temperature anomalies, δD_{xt}, and the model fingerprint, δM_x, is shown in Fig. 4. There is a trend in the pattern correlations which is significant at more than the 1% level using a non-parametric rank test. This trend indicates that there is an increasing manifestation of the greenhouse fingerprint in the observations, *apparently* a successful detection example.

5. CONCLUSIONS

A strategy for the detection of an enhanced greenhouse effect in observational data has been described, based on the recent IPCC review [1]. This has involved the definition of a multivariate signal of greenhouse climate change, a greenhouse fingerprint, from model simulations and the observation of a significant change in this signal using atmospheric data. An example of this method was presented, using the zonal mean temperature difference between double CO_2 and control equilibrium climate model simulations as the greenhouse fingerprint and comparing this fingerprint with observed atmospheric temperature variations over the last three decades. There was shown to be a significant increase in the greenhouse signal in the observational data over the period of analysis, 1963 to 1988. This *appears* to be a successful exercise in detection of an enhanced greenhouse effect.

However, a number of cautions have to be placed on these results. Upper air data is available for a very short period, probably too short to resolve a real greenhouse climate change. It is possible that the multivariate greenhouse signal used here is not unique to the greenhouse effect and may be due to other forcing mechanisms, including decreases in stratospheric ozone concentrations or increases in sea surface temperatures. There are important differences between the greenhouse signal shown in Fig. 2 and the observed pattern of temperature differences in Fig. 3. These may indicate that different forcing mechanisms are responsible for the two patterns, that natural variability is confusing the observed pattern or that the model is not simulating the greenhouse signal correctly. These problems show that much more study is required in this area of greenhouse climate change fingerprint detection.

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