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Earth's climate response to a changing Sun

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CHAPTER 3.9

DETECTION AND ATTRIBUTION: HOW IS THE SOLAR SIGNAL IDENTIFIED AND DISTINGUISHED FROM THE RESPONSE TO OTHER FORCINGS?

Kristoffer Rypdal[1], Martin Rypdal[1] and Sverre Holm[2]

1 Introduction

There will always be variability in the Earth's climate, even in the absence of external forcing, like variation in solar irradiance, volcanic eruptions, or human-induced changes. The nature of internal climate variability is analogous to the change of weather, just extrapolated to longer spatial and temporal scales. This "song of Nature" is comprised of a cacophony of frequencies corresponding to the natural modes of the climate system and forms a background spectrum with a pink-noise character. This means that the power spectral density of global temperature to a crude approximation has the form $S(f) \sim 1/f$, for frequencies f corresponding to periods from months to millennia. The shape of this spectrum implies that internal variability on low frequencies (long time scales) is strong. Another way to put this is that the climate exhibits correlations on long time scales; sometimes described as long-range memory. The variability created by these correlations constitutes a problem when we want to detect climate signals and trends with external causes.

Signal detection means to establish the statistical significance of a trend, an oscillation, or a spatiotemporal pattern. This is successfully done if we can establish that it is very unlikely that the pattern of interest has arisen by chance from the internal background noise. Once a pattern has been successfully detected, the next issue is to identify a cause, or more general, to identify and assess the relative weight of a number of causes. This process is what we call attribution.

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2 Detection

It is often claimed that the 11-year solar-cycle signal is detectable in global temperature. However, this statement is not precise, since the term "solar-cycle signal" refers to attribution, not to detection. Here, we shall illustrate how detection works by testing the hypothesis of a multidecadal oscillation in the global land temperature record. Numerous observational and some theoretical studies suggest that such an oscillation exists with main period around 70 years. The period is not sharp and fixed, but as a crude model, we can represent is as a sinusoid with this period. The hypothesis is then that the temperature time series can be written in the form;

$$T(t) = \delta + A_1 t + A_2 \sin(2\pi f t + \varphi) + \sigma w(t), \tag{2.1}$$

where f has been fixed to about 70 years and $w(t)$ is a random process with standard deviation σ. The parameter δ represents the background temperature level, ϕ the phase of the oscillation, while the interesting parameters are the trend coefficients A_1 and A_2 which represent the strengths of the linear and oscillatory trends. The parameters can be estimated to give the best least-square fit to the observed record. We shall assume here for simplicity that the linear trend is a physical reality and known. The method for testing whether the oscillation is real is to assume that the converse is true, i.e., to hypothesise that it can be described as a natural fluctuation of the internal noise. This *null hypothesis* takes the form $\delta + A_1\,t + \varepsilon(\theta;t)$, where $\varepsilon(\theta;t)$ represents a model for the internal noise depending on a set of parameters θ, which will be estimated by fitting to the observed data. When θ has been estimated, we can generate an ensemble of synthetic samples satisfying the null hypothesis and then fit the trend model Eq. (2.1) to each sample series. For each sample, we find estimates $(\hat{A}_1, \hat{A}_2)$ satisfying the null hypothesis, and we can build a probability density distribution (PDF) $P(\hat{A}_1, \hat{A}_2)$. In Figure 1a, we have plotted a contour of this joint PDF inside which the probability is 95%. Since (A_1, A_2) estimated from the observation data (red dot) is outside this contour, we may conclude that it is unlikely that it can occur by chance from the null hypothesis. In Figure 1b we have plotted the cumulative probability function (CDF) over the oscillation amplitude A_2. The dotted line marks the 95% cumulative probability and the full vertical line is A_2 estimated from the observed data. This means that the observed amplitude is outside the 95% confidence interval of the null hypothesis, and hence that the oscillation is statistically significant. We have *detected* an oscillatory trend, but we have not attributed it to any particular external cause.

3 Attribution by multiple regression

A standard method in attribution studies is that of multiple linear regression. The idea is to separate the climate signal into a number of components assumed to represent the climate response to individual forcings. Each of these components have a certain characteristic shape (or fingerprint). In order to determine these

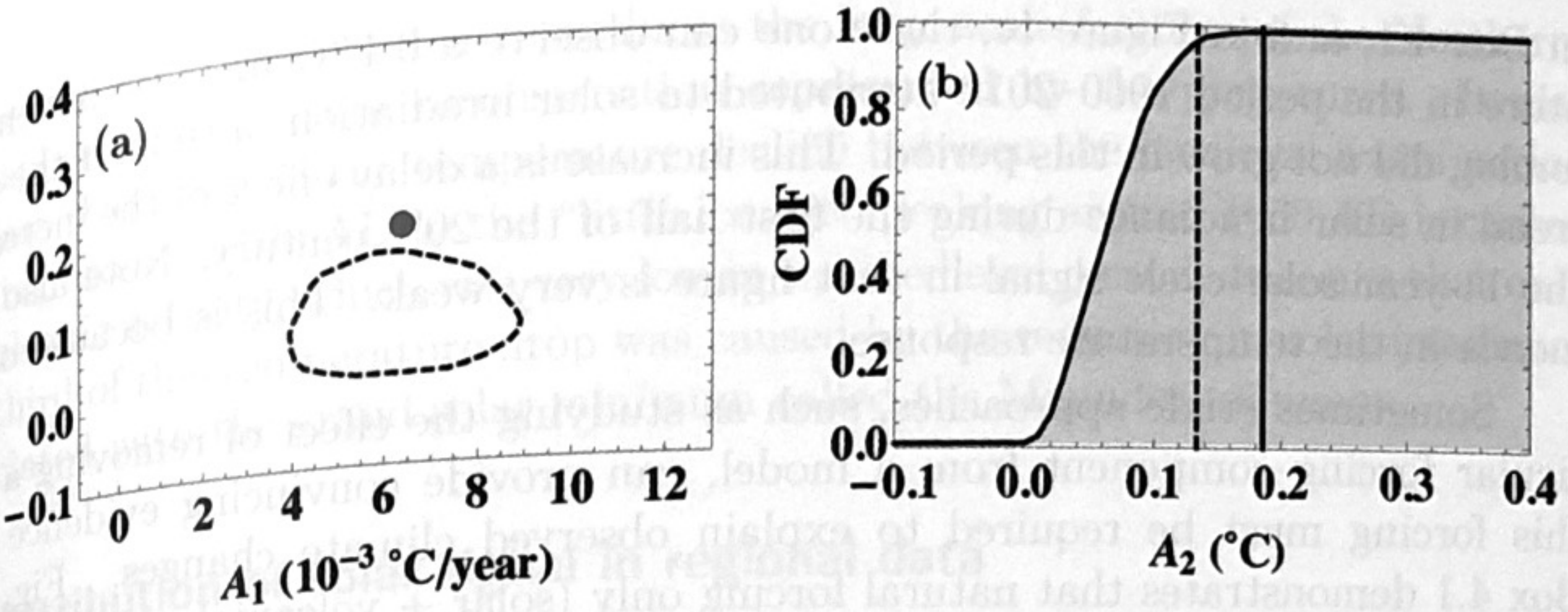

Fig. 1. (a): The 95% confidence contour (dashed) of the distribution $P(\hat{A}_1, \hat{A}_2)$ for global land temperature obtained by the null model where $\varepsilon(\theta; t)$ is assumed to be a pink-noise stochastic process. Observed trend coefficients are indicated by the red dot. (b): The CDF derived from $P(\hat{A}_2)$ for this null model, with upper 95% confidence limit as dotted vertical line and the A_2 estimated from observation as full vertical line.

fingerprints, we need models of some sort. Full-scale general circulation climate models can be used, but often also simpler, conceptual models are useful. The rationale for attribution studies is that even the most advanced climate models may estimate wrongly the magnitude of individual responses, even though they have got the fingerprints right. Hence, we may write the total climate signal $T(t)$ as a linear combination of the fingerprints. Consider, for instance, the global temperature $T(t)$ and the fingerprints of various forcings and an internal mode. Then we can write,

$$T(t) = c_S S(t) + c_V V(t) + c_A A(t) + c_I I(t) + \sigma w(t), \tag{3.1}$$

where $S(t)$, $V(t)$, and $A(t)$ are the fingerprints of solar, volcanic, and anthropogenic forcing, respectively, and $I(t)$ is the fingerprint of the internal mode. The fitting parameters c_S, c_V, c_A, and c_I translate each fingerprint into a temperature response, and can be estimated by minimizing the least square error with respect to the observed data. A measure of how successfully the method attributes variability to the various forcing components is to compute how much of the observed variance that is explained by the model.

One common problem with this approach is that if there are many causal factors to consider, and hence many parameters to fit, there is a risk of overfitting. This means that a good fit can be obtained even though the result is unphysical. Another problem is that the fingerprints of forcing in general are distorted and delayed by inertia in the climate response caused by slow heat exchange between the ocean surface layer and the deep ocean, sea ice, and ice sheets. This inertia may, for instance, lead to a small response to the relatively fast solar cycle forcing, while the response to slow trends in solar irradiance may be stronger, but considerably delayed. Delay effects are not accounted for in the regression model (3.1) if the model defining the fingerprint does not involve a dynamic response to forcing. A conceptual model of such a dynamic response is described in Box 4.1, and in Figure 1c, there one can observe a 0.1 °C increase in temperature in the period 1960–2010 attributed to solar irradiation, although the solar forcing did not grow in this period. This increase is a delay effect of the increasing trend in solar irradiance during the first half of the 20th century. Note also that the 11-year solar-cycle signal in that figure is very weak. This is because of the inertia in the temperature response.

Sometimes crude approaches, such as studying the effect of removing a particular forcing component from a model, can provide convincing evidence that this forcing must be required to explain observed climate changes. Fig 1 in Box 4.1 demonstrates that natural forcing only (solar + volcanic) cannot explain the warming trend in global temperature over the last 50 years.

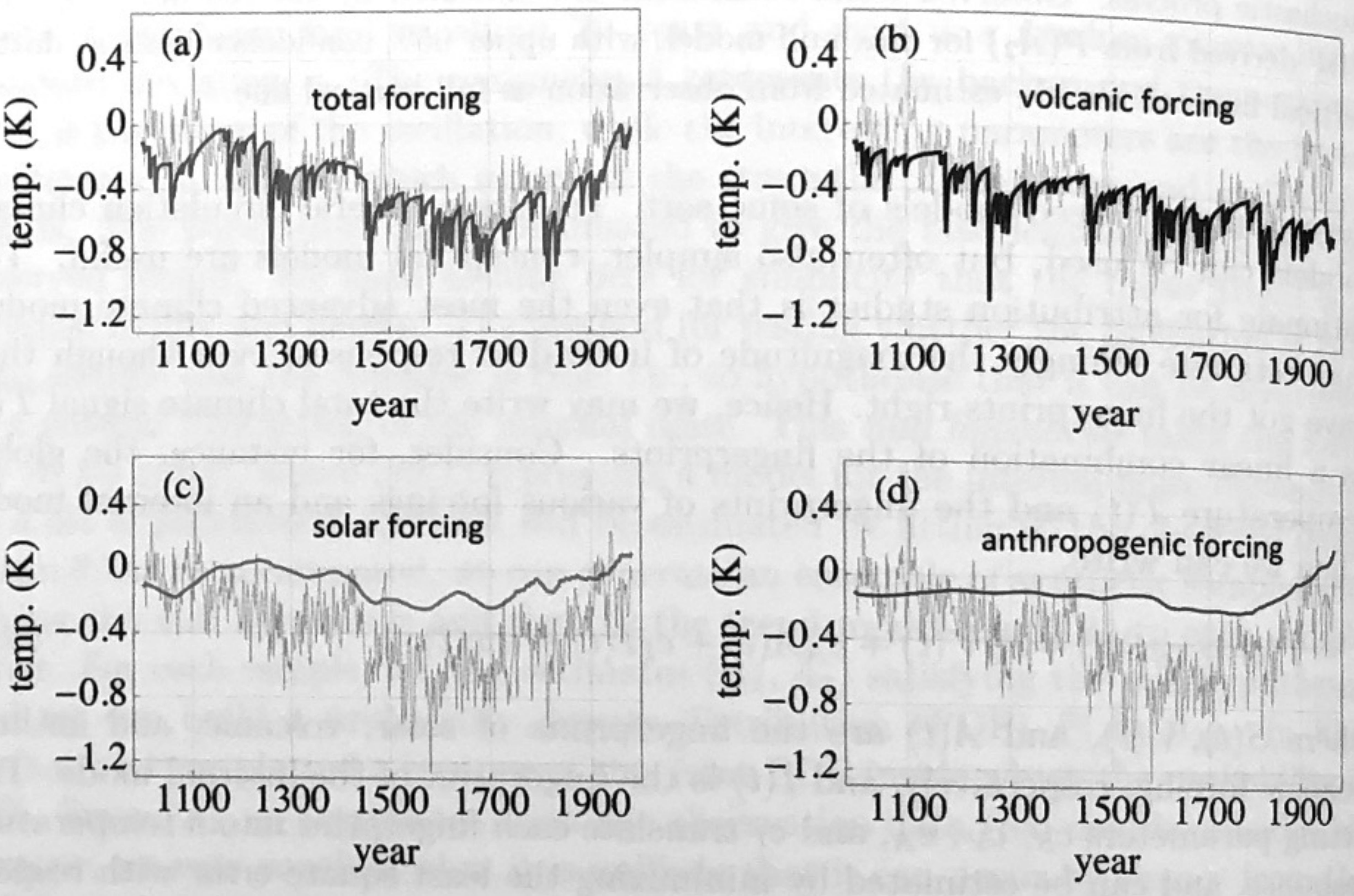

Fig. 2. Forced temperature change 1000–1979 AD according to the conceptual response model. Grey curve is the observed temperature record as reconstructed from paleoproxies. (a) From total forcing. (b) From volcanic forcing. (c) From solar forcing. (d) From anthropogenic forcing.

4 Attribution example using a conceptual model

Even though the natural forcing, including solar, seems unable to explain recent global warming, it could have played a significant role in the near pre-industrial past. In Figure 1 we have applied the same conceptual model as in Box 4.1, with the same model parameters as computed for the instrumental 20th century data, to the forcing reconstructed for the period 1000–1979 AD. We observe that the response to the total forcing reproduces the large-scale features of the Northern-hemisphere temperature reconstruction represented by the grey curve. It also appears that most of the temperature decline between the medieval warm period peaking around 1100 AD to the "little ice age" peaking around 1650 AD is caused by volcanic activity, which was very low in the medieval period. It seems that only one third of this temperature drop was caused by the reduction in solar irradiance associated with the grand solar minimum called the Maunder minimum.

5 Attribution of solar signal in regional data

The solar signal in global temperature appears to be weak throughout the 20th century, but it may be stronger in regional and seasonal climate variability. Such variability, associated with the 11-year cycle has been studied in some models, and several physical mechanisms of amplification of the solar forcing have been proposed. For such signals, the attribution issue is mathematically complicated since the fingerprints now depend both on space and time coordinates. One technique used for such studies is to decompose the spatial temperature field into patterns called empirical orthogonal functions (EOFs), and these patterns are ranked according to how much of the total variance they explain. Each EOF is multiplied by a time-dependent coefficient, which is called the principal component of that EOF. Often a few of these EOFs with their principal components explain most of the variability and in some cases a particular principal component has a temporal fingerprint that matches the solar forcing signal. In such cases, the principal component time series can be analysed by a multiple, linear regression model and one can investigate how much of the variability of the climate mode corresponding to the particular EOF can be attributed to solar forcing.

6 Attribution of cycles

It has been suggested that the multidecadal oscillation, whose significance was studied in Section 2, can be attributed to cycles in the motion of the sun caused by the giant planets. The rationale for such a proposal is that some spectral analyses of the climate time series and time series for planetary motions show some spectral lines at the same frequencies. Two properties can be used to test such a hypothesis. The first is to compare the stationarity of the spectral lines in question, in particular those at around 20 and 60 years. Lack of stationarity means that what appears as a sharp frequency and phase of an oscillation really changes with time, and can be investigated by different techniques classified as time-frequency analysis. Another technique is test for coherence using the well established magnitude squared coherence function. Application of these kinds of tests demonstrate very clearly that the climate signal lacks the stationarity and the coherence required to explain the spectral lines as oscillation driven by the planetary motions. There are some more substantiated studies based on spectral analysis that suggest a connection between planetary motions and solar activity reconstructed from radio-isotope proxies over the last ten millennia. These results are also controversial, however, and they do not imply that the corresponding spectral lines detected in solar activity have a discernible effect on the climate.

In general, the detection and attribution of cycles remains a topic of much controversy. It is known that there are cycles in the solar forcing due to variations in the orbit of the Earth around the Sun, and in the tilt and precession of the Earth's rotation axis. These so-called Milanković cycles have periods of thousands of years and are thought to act as pacemakers of ice ages. The attribution of ice ages and variability within ice ages to this orbital forcing, however, is not trivial, and a number of unsolved issues remain.

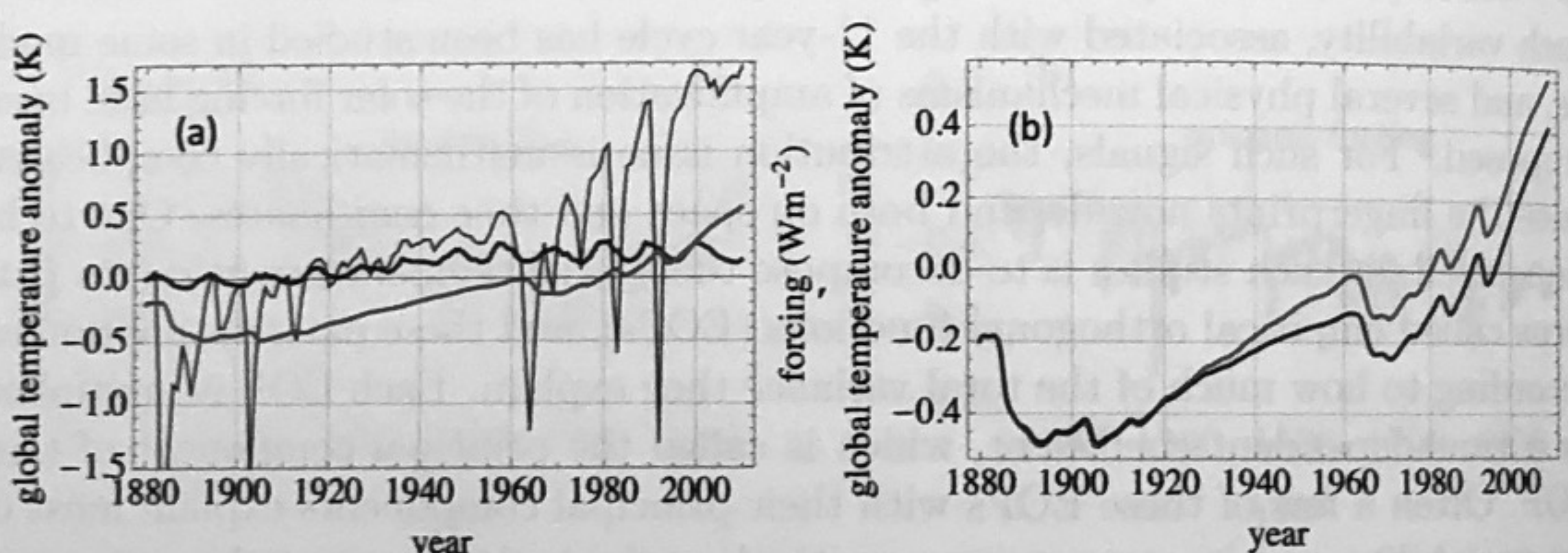

Fig. 3. (a): shows total forcing (blue), where the negative dips are due to volcanic eruptions, and forcing from total solar irradiance (magenta). The red curve is the temperature response to the total forcing. Note that the three last dips due to eruptions nearly coincide with solar minima. (b): shows the response to the total forcing (red) and the response to the forcing where the solar forcing has been subtracted.

What about the temperature response to the 11-year solar cycle? As discussed in Section 3, the inertia in the climate response gives reason to believe that this response is rather weak, and it is very difficult to detect such a signal in the noisy temperature signal. Nevertheless, claims have been made that a solar cycle is visible in temperature records over the last 4-5 cycles. We find such oscillatory structures with peak-to-peak amplitude of almost 0.1 K in the temperature response to total forcing and they seem to be in phase with the solar cycle. However, their real cause becomes apparent when looking at the total and solar forcing signals in Figure 3a, and at the response to forcing with, and without, the solar component, as shown in Figure 3b. Surprisingly, the oscillatory response remains unaltered after the solar forcing has been eliminated. It turns out that this strong oscillation is caused exclusively by a few volcanic eruptions incidentally taking place just prior to solar minima (Figure 3a), and hence demonstrates the necessity of careful attribution studies.

Further reading

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