The Probability of Rapid Climate Change

Peter Challenor, Robin Hankin, Robert Marsh
Southampton Oceanography Centre and the Tyndall Centre for Climate Change Research

Abstract

Western Europe's climate is warmer than would be expected because of heat transported by the thermohaline circulation in the North Atlantic Ocean. Model simulations and paleoclimate data show that it is possible for this circulation to shut down leading to rapid cooling in European climate. We investigate the probability of this occurring using the intermediate complexity climate model, C-GOLDSTEIN, under various CO_2 emissions scenarios. We use modern Bayesian statistical methods to speed up the computation of Monte Carlo simulations allowing us to investigate not only the probabilities, but also sensitivity to our initial conditions.

1. Introduction

The climate of Western Europe is kept mild by heat transported by the North Atlantic. The mechanism is as follows. Cooling and brine rejection forms cold, salty ---and hence dense ---water in the Arctic. This water then sinks and warm surface waters are then pulled north to replace this dense water. The heat transported North by this mechanism gives North West Europe a much milder climate than equivalent latitudes on the Pacific coast of North America. Because it is driven by differences in density caused by changes in temperature and salinity this circulation is known as the Thermohaline circulation (THC). At present the THC has a strength of about 20 Sv (1Sv=10^6 m^3s^{-1}). In simple models of the THC [1] there are two possible states of the ocean. One state has a strong THC, as at present, and another that has either a very weak THC or none at all. Even these simple models exhibit catastrophic switches from the strong state to the other; it is then very difficult to get back. Such a rapid climate change could have a dramatic effect on the climate of Western Europe (a fall in winter temperatures of a few degrees). At the end of the last ice age a collapse in the THC is believed to have produced the Younger Dryas where Europe saw temperatures about 9° lower than today. In this paper we address the probability of such events happening due to increasing greenhouse gases, and whether there is a safe level at which we can stabilise gases.

2. Forecasting low probability events

The standard method for carrying out climate forecasts is to run a climate model (of whatever complexity) for a hundred or so years and use that run as the prediction of the future state of the climate. Such a run does not give us any measure of the uncertainty in the prediction and only gives a prediction of the mean (expected) state of the climate. Low probability events such as a THC collapse are often referred to as "low probability, high impact events" in the language of risk assessment. To predict such occurrences we need to adopt another approach and use probabilistic methods. The climate system is complex and non-linear so it is unlikely that we will be able to solve these problems analytically; conventionally, methods such as Monte Carlo simulations are used, in which large ensembles of climate forecasts are run. For our case of THC collapse, we run an ensemble of models and estimate the probability of THC collapse by determining the fraction of the ensemble in which the THC collapses. In principle this is very easy to carry out. However the complexity of climate models (including intermediate complexity models such as the one we are using) means that the computer time to carry out such an estimation with any reasonable degree of accuracy would be beyond the reach of existing or foreseeable computers. If we are to investigate low probability climate impacts we need to find more efficient techniques than Monte Carlo simulation.

There are two possible solutions to this problem. The method being used by climateprediction.net [2] is to use spare cycles on very large numbers of non-dedicated computers that are often in people's homes to carry out the calculations (An additional benefit of this approach is that it involves the general public in climate research in a very direct way). Using such methods they have successfully run many thousands of years of simulation. The current model they are using is a 32-bit version HADAM3 which does not include an ocean and hence no THC so there is nothing to collapse. Our approach is different. Rather than find extra computer cycles to run a full size model we build a statistical approximation to the model known as an emulator. The emulator includes a measure of its own uncertainty so we know where the approximation is good and where it is less good. Emulators are much faster to run than the original model; the example given later runs five orders of magnitude faster than the climate model.

Our emulators are based on the work by Tony O'Hagan and co-workers at the University of Sheffield [3], [4] and [5]. The method uses Bayesian statistics. We set up a prior model for our emulator, based on beliefs about the physical climate system and then the model to modify those beliefs and hence produce an emulator for the climate model. The form of the emulator we use is a Gaussian process. This is a stochastic process that can be considered as the extension of the multivariate Gaussian distribution. At any point (**x**) the mean is given by a mean function $\mu(\mathbf{x})$ and its variance by a variance function $\sigma^2(\mathbf{x})$, the correlation between two points ($\mathbf{x}_1$ and $\mathbf{x}_2$) is given by a correlation function $C(\mathbf{x}_1,\mathbf{x}_2)$. Gaussian processes are very adaptable and it can be shown that they can fit any smooth function. In fitting a Gaussian process there is a trade-off between the complexity of the mean function and the proportion of the variation absorbed by the covariance function. We fit a relatively simple mean function. Our prior is that it is a linear function about whose parameters we know nothing. Our correlation function has a Gaussian shape

$$C\left(x_1, x_2\right) = \exp\left(-c\left(x_1 - x_2\right)^2\right)$$

where c is a roughness scale. One advantage of a Gaussian correlation function is that it guarantees that the resulting Gaussian process is differentiable.

Our procedure to build the emulator is as follows: we run the full climate model at a number of points in parameter space according to a designed experiment, we then use these runs to estimate the parameters of the Gaussian process using the methods in [3] and [4]. The design we use is a Latin hypercube [6]. Latin hypercubes are widely used in computer experimentation as they allow us to span multidimensional spaces with a small number of points. Once we have built the emulator we can ascribe probability distributions to the uncertainty on model inputs, sample from these distributions, run the emulator at these sampled points and hence derive the probability densities of the model outputs. To speed up the sampling process we use sampling design points introduced by Oakley and O'Hagan in [4]. Using the strength of the THC as our output parameter we can estimate the probability of THC collapse by simply taking the proportion of runs that have a collapsed THC.

C-GOLDSTEIN

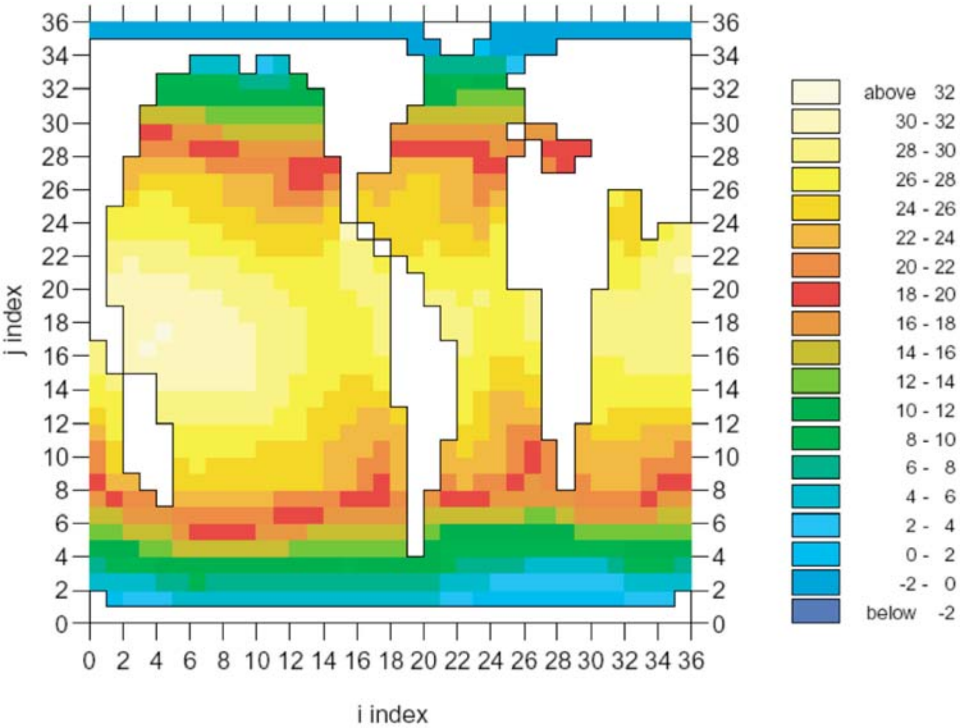

Figure 1 Sea surface temperature from C-GOLDSTEIN.

The model we use is C-GOLDSTEIN: a coupled ocean-atmosphere climate model,. It is described in detail in [7]. In the configuration we use the resolution is 36 x 36 giving 10° resolution in longitude and 3° to 20° in latitude depending on the latitude. There are 8 depth levels in the ocean. The ocean is dynamic and the atmosphere is represented by an energy balance model [8]. The zonal wind field is prescribed and some corrections are made to the fresh water fluxes. The Atlantic/Pacific freshwater flux is controlled by two parameters. The first of these is the ratio of the freshwater flux to the Equator-North Pole temperature difference, the second is the ratio to the Equator-North Pole humidity difference. An example of the model grid is shown in figure 1

There are 16 parameters in the model that we do not know. We use these to put uncertainty into the system and hence to generate our probabilities. These are listed in table 1 along with our initial estimates of their uncertainty.

Parameter (non-dimensional unless otherwise stated)	Mean	Standard deviation
Windstress scaling factor	1.7	0.4
Ocean horiz. diffusivity (m^2s^{-1})	4100	1600
Ocean vertical diffusivity (m^2s^{-1})	1.8×10^{-5}	1.3×10^{-5}
Ocean drag coefficient (10^{-5} s^{-1})	3.4	1.4
Atmos. heat diffusivity (m^2s^{-1})	3.8×10^{6}	1.0×10^{6}
Atmos. moisture diffusivity (m^2s^{-1})	1.59×10^{5}	0.27×10^{5}
"Width" of atmos. heat diffusivity profile (radians)	1.3	0.4
"Slope" of atmos. heat diffusivity profile (radians)	0.069	0.052
Zonal heat advection factor	0.06	0.06
Zonal moisture advection factor	0.14	0.08
CO2 scaling factor (x350 ppmv)	1.00	0.06
Climate sensitivity (Wm^{-2})	5.77	0.72
Threshold humidity (for pptn.)	0.85	0.10
Sea ice diffusivity (m^2s^{-1})	6200	3000
Scaling factor for Atlantic-to-Pacific moisture flux (x 0.32 Sv)	0.91	0.10
Solar constant (Wm^{-2})	1354	14

Table 1 The uncertain parameters in C-GOLDSTEIN

We run C-GOLDSTEIN 100 times in a 16 dimensional Latin hypercube. We then use the methods in [3] to calibrate the model with data. This calibration reduces the uncertainty on the parameters by removing those values that are not consistent with the data. The data we use for this calibration step are part of the observational dataset used for physical calibration of Goldstein. Once we have carried out the calibration step we can use the emulator to estimate the probabilities as described above,

CO_2 Scenarios

We are interested in the probability of THC collapse given a particular CO_2 emissions scenario. We therefore do not include any uncertainty on the CO_2 concentrations but work with conditional probabilities. To obtain a realistic spread of future emissions we look at the four main SRES scenarios and calculate their conditional probability of THC collapse. In addition we investigate the sensitivity of our results to our initial uncertainty distributions given in table 1. One interesting question is whether there is a safe level of CO_2 concentration. If we define "safe" as a level which gives zero probability of THC collapse the answer is probably no, but if we define a safe level of risk as, say, one in a thousand, or even one in a million, then we are able to define corresponding acceptable concentrations of CO_2.

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