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Version: Accepted Manuscript

Link(s) to article on publisher’s website:
http://dx.doi.org/doi:10.1029/2010GL045137

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Dimensionally reduced emulation of an AOGCM for application to Integrated Assessment Modelling

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Abstract

Integrated Assessment Models are widely used tools for the evaluation of environmental policy. In order to include uncertainty estimates or derive optimal policies, highly efficient calculations of global change are generally required, often using pattern scaling to derive spatial distributions of change. Here we develop an alternative to pattern scaling that allows for nonlinear spatio-temporal behaviour. We use an intermediate complexity AOGCM to perform an ensemble of simulations for a range of greenhouse gas concentration profiles and model parameters. We decompose climate change fields into a series of spatial patterns and then derive the functional dependence of the dominant patterns on model input. This allows us to rapidly reconstruct a good approximation to the simulated change from an arbitrary concentration profile (without the need for further simulation). The efficiency of the approach paves the way for incorporating improved calculations of climate change into integrated assessment, including location-dependent estimates of uncertainty.
1 Introduction

The selection of environmental policies which minimise the impacts of climate change must account for the joint uncertainty which exists in the complex interactions between the climate system and the global economy. The likely impacts of climate change vary greatly both between and within regions and individual countries. These regionally disparate impacts arise both from socio-economic factors and from different present-day climates and degrees of anticipated climate change [Mendelsohn et al., 2006]. Atmosphere-Ocean General Circulation Models (AOGCMs), and regional climate models (RCMs), represent the only tools available for dynamically justified predictions of climate change. Whilst AOGCMs have been successfully incorporated into Integrated Assessment Models (IAMs) for application to specific emissions scenarios [e.g. Voldoire et al. 2007] such coupled models stretch the limits of present-day computing power and accordingly are not well suited to uncertainty analysis. Furthermore, it has not been possible to incorporate AOGCMs into the framework of optimised IAMs (which attempt to optimise environmental policy within some set of constraints) because, in effect, the solution of the climate model to all possible emission scenarios must be known in advance or, more realistically, be rapidly computable. In fact, the coupling of an AOGCM to an IAM in an optimised framework has been described as infeasible [Nordhaus and Boyer, 2000]. Such IAMs, which typically group countries together into up to ~15 aggregated regions, are thus in general forced to rely upon greatly simplified climate models which calculate globally averaged warming as a function of radiative forcing. Regional impacts are then derived either from functions of global temperature which subsume interactions between climate and impacts at the (large-scale) regional level [Nordhaus and Boyer,
2000] or by using pattern scaling techniques to derive spatial distributions of climate change [Mitchell et al., 1999; Huntingford and Cox, 2000; Bruckner et al., 2003].

Although pattern scaling has proved invaluable in addressing the computational demands of making climate projections under uncertain future emissions scenarios, and indeed will remain central to future IPCC analysis [Moss et al., 2010], computing and modelling developments over the last decade now facilitate the development of new techniques to address the weaknesses inherent in such an approach. The principal weaknesses of pattern scaling are (i) it assumes that the climate response is spatially invariant (with respect to both time and forcing), (ii) it does not represent time varying covariances between surface climate variables and (iii) it does not readily account for spatial variability in the uncertainty, although patterns of spatial uncertainty can be separately estimated to address this [Harris et al., 2006; Murphy et al., 2007]. Accordingly, pattern scaling cannot capture those elements of the climate response which may be sensitive to the greenhouse gas concentration pathway [Stocker and Schmittner, 1997; O’Neill and Oppenheimer, 2004]. Furthermore, in order to evaluate the spatial distribution of uncertainty, it is necessary to perform sensitivity analyses applying scaling patterns from different models, or model realisations, [e.g. Füssel et al., 2003], an approach which is poorly suited to the application of robust statistical designs or the probabilistic analysis of modelling results.

We here propose a methodology to address the shortcomings of pattern scaling, using principal component analysis to project multivariate model output onto a lower dimensional space and then emulating the map from the input space to the lower dimensional space [Wilkinson, 2010]. The method combines elements of the pattern-
scaling approach developed in the ICLIPS model [Bruckner et al., 2003] with the technique of deterministic emulation [Draper and Smith, 1998; Holden et al., 2010] of a Perturbed Physics Ensemble (PPE) [Murphy et al., 2004]. ICLIPS applies global temperature scaling to the first Empirical Orthogonal Function (EOF), derived for a range of climate variables from a transient simulation of future climate. We extend this by deriving EOFs from an ensemble of AOGCM simulations which incorporates both parametric and forcing uncertainty, and then applying regression techniques to emulate the higher-order principal components (PCs) as polynomial functions of model input. We do not restrict analysis to the first EOF, thereby allowing for nonlinear spatio-temporal behaviour. We use the emulators to derive an emulated PPE from an arbitrary concentration profile, capturing the spatial variability of modelled variance, allowing for the possibility of modes of climate variability that are sensitive to the rate of emissions and deriving mutually consistent fields of surface climate variables; our projections only differ from the dynamical model projections insofar as the emulation of the climate model is not perfect prediction (we refer to this as “code error”). The emulated parametric uncertainty then provides an estimate of model error which can be used to generate a probability density function of regional-scale climate change, an essential step towards the robust quantification of climate change impacts.

2 Methods

The climate model applied here is the intermediate complexity AOGCM, GENIE-2 [Lenton et al., 2007], which couples the Intermediate General Circulation Model IGCM3.1 [Forster et al., 2000], a spectral model with intermediate complexity physics, to GOLDSTEIN [Edwards and Marsh, 2005], a 3D frictional geostrophic
ocean model with linear drag. GENIE-2 incorporates a basic land module, including a bucket representation of soil moisture and a simplified snow scheme, and a slab sea-ice module. The only change from the configuration used in Lenton et al. [2007] is to include the Tiedtke atmospheric convection scheme, described in Molteni [2003]. At the resolution applied here (T21 atmosphere with 7 vertical levels, 64x32 ocean with 8 vertical levels), GENIE-2 simulates ~10 years per CPU hour on a state-of-the-art 64-bit processor.

In order to restrict the number of simulations leading to implausible climate states, the technique of precalibration was applied [Edwards et al., submitted]. Firstly, a 200-member exploratory ensemble of 100-year pre-industrial spin-up simulations was performed, varying 15 atmospheric parameters. This initial ensemble serves to quantify uncertainty related to atmospheric processes, thus a 100-year simulation is sufficient. The mean globally-averaged Surface Air Temperature (SAT) in this exploratory ensemble was 8±11°C. The purpose of precalibration is to weakly constrain the model parameters by ruling out uncontroversially implausible values of model input, thus creating an ensemble approximately centred on observations. To achieve this, the exploratory ensemble was used to build a “quadratic emulator” of globally-averaged pre-industrial SAT, following the approach described in Holden et al. [2010]. Random samples of the 15 atmospheric parameters were then applied as inputs to the SAT emulator, with values for each parameter taken from uniform prior distributions across wide plausible ranges. Four hundred parameter combinations which produced an emulated SAT in the range 11 to 17°C were accepted as input for the precalibrated ensemble. These were combined with ocean parameters, using two (200x4, i.e. 200 members, 4 parameters) Maximin Latin Hypercube designs to create
the final 400x19 design. These parameterisations were applied to GENIE-2 to derive an ensemble of 2,000-year pre-industrial spin-up states. Of these, 264 simulations completed (mean SAT 16±7°C) with 124 simulations exhibiting plausible climates, as defined by a global temperature in the range 9.5 to 19.5°C. This weak plausibility constraint was applied to cover a wide range of possible climate-change responses [Holden et al., 2010].

The 2000-year spun-up states were then used to generate an ensemble of transient simulations from the year 1850. Historical radiative forcing (1850-2000) was taken from Nozawa et al. [2005], re-expressed as an equivalent CO$_2$ concentration (CO$_2$e). Future radiative forcing (2005-2105) was also expressed in terms of CO$_2$e, with a temporal profile described by a linear decomposition of the 1$^{st}$ three Chebyshev polynomials:

\[ CO_{2e} = C_0 + 0.5\left\{A_1 (t + 1) + A_2 \left(2t^2 - 2\right) + A_3 \left(4t^3 - 4t\right)\right\} \]

where $C_0$ is CO$_2$e in 2005 (393 ppm), $t$ is time (2005 to 2105) normalised onto the range (-1,1) and the three coefficients which describe the concentration profile ($A_1$, $A_2$ and $A_3$) take values which allow for a wide range of possible future emissions profiles. Each spun-up state was used twice (with different future greenhouse gas concentration profiles), with concentration coefficients following two 400x3 Maximin Latin Hypercube designs. The first design sampled concentration coefficients from uniform distributions in the ranges (100, 1000), (-200, 200) and (-100, 100), respectively. The second design used a narrowed range for $A_1$ (0, 400) in order to better sample input space that is consistent with likely greenhouse gas mitigation strategies. These ranges
encompass the range of SRES emissions scenarios (c.f Meinshausen et al 2009, Moss et al 2010) with a CO$_2$e concentration in 2105 ranging from 393 to 1,393 ppm. The 245 transient simulations which completed and which exhibited modern-plausible climates were considered in the analysis which follows.

At this stage, we have an ensemble of 245 transient simulations of future climate, incorporating both parametric and forcing uncertainty. Singular vector decomposition was performed on the ensemble of temperature anomaly fields (2100-2000, centred decadal averages). The first EOF describes 84.8% of the total variance (Table 1), indicating that a single EOF (i.e. pattern scaling) is sufficient to generate a reasonable approximation to the simulated SAT response at 2100 under a wide range of parameter inputs and greenhouse forcing scenarios. We here retain the first five EOFs, which together describe 91.4% of the simulated variance. Each individual simulated field can thus be approximated as a linear combination of the first five EOFs, scaled by their respective PCs. As each simulated field is a function of the input parameters, so are the PCs which hence are scalar quantities that can be emulated as a function of the input parameters. PC emulators of the 1st five EOFs were derived as functions of the 19 AOGCM parameters and the 3 concentration profile coefficients. The emulators were built in R (R development core team 2004), using the stepAIC function [Venables and Ripley, 2002], following a similar procedure to that described in Holden et al. [2010]. For each PC emulator, we first build a linear model, progressively adding linear terms to minimise the Akaike Information Criterion, and then successively removing terms according to the more stringent Bayes Information Criterion (which penalises free parameters more strongly). This procedure was then repeated twice, first allowing the addition of second-order (quadratic and cross) terms,
then allowing the addition of third-order terms, in both cases building upon the model that was derived at the previous step. A maximum of 30 third-order terms were allowed in order to reduce the risk of over-fitting given the relatively small ensemble size. The high correlation (“Model Fit” $R^2$) between emulated and simulated PCs (Table 1) is in part a consequence of over-fitting; the degree of over-fitting was quantified by a cross-validation of the emulators, described in the following section.

3 Emulator validation

Two strategies were applied to validate the emulators. Firstly, an ensemble of transient GENIE-2 simulations was performed with 122 of the modern-plausible 19-parameter vectors. In each case the same greenhouse gas concentration profile was applied by fitting the output of the integrated assessment model TIAM [Loulou and Labriet, 2008] to the polynomial (Eq. 1). This scenario was preliminary output of the SynsCOP15 project [SynsCOP15, 2009], reflecting a globally cooperative climate strategy which limits post-industrial global warming during this century to 2°C and under which simulated CO$_2$e stabilises at ~530 ppm towards the end of the century. The ensemble mean and standard deviation of the temperature anomaly simulated in GENIE-2 (2100–2000, centred decadal averages) are plotted in Fig.1a and Fig. 1b, respectively. Although a detailed validation of the simulations is beyond the scope of this paper, we note that the pattern of warming is consistent with IPCC projections under a range of SRES scenarios [Meehl et al., 2007], although the degree of warming is likely to be understated as the equilibrium climate sensitivity of the IGCM (1.74°C) [Forster et al., 2000] is at the low end of IPCC estimates. Emulated fields derived from the same concentration profile are also plotted in Fig. 1, together with the
differences (emulated – simulated). The emulated ensemble provides a good approximation to the spatial distribution of simulated warming and the associated uncertainty. Globally averaged warming is 1.02ºC (simulated) and 1.01ºC (emulated), whilst globally averaged uncertainty is 1.08ºC (simulated) and 0.91ºC (emulated). The emulator slightly underestimates the simulated uncertainty due to in part to the inclusion of only the first 5 EOFs and in part due to the difficulties in reproducing extreme simulations with deterministic polynomial emulators. The emulated ensemble was calculated in 0.06 s, in stark contrast to the ~1,000 CPU hours required to perform the transient simulations.

To further investigate the performance of the emulators, leave-one-out cross-validations were performed for each of the five PC emulators. The cross-validation was performed on all 245 simulations, each time building five PC emulators from the (1st five) PCs of the other 244 transient simulations, and then emulating the PCs from the omitted simulation. Table 1 compares the means and standard deviations of the cross-validated emulated PCs with the simulated PCs, distributions which describe the combined parametric and forcing uncertainty. The “Cross Validation” $R^2$ between simulated and emulated coefficients of ~20 to 60% demonstrates that individual emulations cannot be regarded as robust. However, as the emulated fields are described by linear combinations of the EOFs, the necessary condition for the emulated ensemble to provide a good approximation to the simulated ensemble is that the distributions (mean and variance) of the emulated PCs are well reproduced. Table 1 illustrates that this is indeed the case, explaining the good agreement demonstrated in Fig 1. A similar analysis is provided for decadally-averaged annual precipitation in Table 2. This analysis again demonstrates that the ensemble mean and variance are
well reproduced by the emulator, although revealing that the first five EOFs are insufficient to provide an adequate representation of simulated variance of precipitation. The implications of this complication are discussed in the following section.

4 Discussion

We have demonstrated that the characteristics of the simulated PPE are well reproduced by the emulated PPE, with the caveat that the polynomial emulators tend to understate extreme simulated responses. In principle the approach can be applied to any simulated output, although more EOFs are required to describe the variance of less well constrained fields such as precipitation (Table 2), which are strongly influenced by internal variability [Murphy et al., 2004]. The first EOF describes 85% of SAT variance, but only 28% of the variance in precipitation. The spatial distribution of precipitation is known to be highly sensitive to parametric uncertainty and thus poorly suited to pattern scaling [Murphy et al., 2004].

The essential requirement for applying the technique of dimensional reduction is that there is a consistent covariance structure amongst the outputs (here the values of a climate variable at different spatial positions); the physical constraints imposed on the climate system are in general sufficient to satisfy this requirement, despite the internal variability. Internal variability may explain why these emulators perform less well than the scalar emulators derived for the deterministic GENIE-1 model [Holden et al., 2010]. Although it is likely that some EOFs, especially those of lower order, cannot be emulated, this failure would suggest that such modes of variability are dominantly
stochastic and hence that it is reasonable to incorporate this missing information by adding random multiples of the EOFs, taking zero-mean Gaussian distributions with appropriate variance [Wilkinson, in press].

The analysis here applies logistic regression to derive the emulators and thus does not quantify the additional uncertainty introduced by the emulator. However, as the simulated variance is well approximated by the emulation we infer that parametric uncertainty generally dominates. However, especially in view of the difficulties in emulating extreme responses, the approach would benefit from the use of more sophisticated Gaussian process emulation techniques [Kennedy and O’Hagan, 2001] which quantify the code error due to additional uncertainty in poorly sampled regions of input space.

5 Conclusions

We have demonstrated that dimensionally reduced emulators of an ensemble of transient AOGCM simulations provide a good approximation to ensemble-averaged fields of warming together with the associated uncertainty. Whilst a 100-year, 100-member transient ensemble of GENIE-2 requires ~1,000 CPU hours, the emulation of this ensemble is performed in a fraction of a second. We have chosen not to present a full emulation of precipitation, primarily reflecting concerns relating to the robustness of simulated precipitation in this model [Annan et al. 2005]. However, the successful decomposition and cross-validation of the first five PC emulators (Table 2) illustrates that an emulation of GENIE-2 precipitation is achievable, although it would be necessary to include 25 principal components to capture just
75% of the simulated variance in this ensemble. The approach is, in principle at least, applicable to any output field with a consistent covariance structure. Notwithstanding the aforementioned complications, it is likely to be especially useful for outputs such as precipitation that exhibit complex spatial variability and are hence not well suited to pattern-scaling techniques.

This paper proposes a methodology for deriving computationally efficient projections of climate change which addresses a number of the problems inherent in pattern scaling. It may also be possible to apply the technique to regional, rather than global, projections, as a hybrid approach combining the benefits of dynamical and statistical downscaling. Application of the approach to impact analyses and integrated assessment will require the use of a higher resolution climate model, providing more robust estimates of hydrological changes and incorporating, most notably, a model of dynamic vegetation. Feedbacks between climate and land surface changes are central to climate impact analysis [Voldaire et al. 2007] and are associated with substantial uncertainty [Friedlingstein et al., 2006] which can, at least in principle, be addressed through this approach which allows for complex spatial dependencies on model inputs.

Acknowledgements

We would like to thank Richard Wilkinson for a number of very useful discussions and are also grateful to Chris Huntingford and an anonymous referee for their insightful reviews. This work was funded by the U.K. Natural Environmental Research Council through QUEST-DESIRE (NE/E007600/1) and the French
Ministère de l’Écologie, de l’Énergie, du Développement durable et de la Mer through the Programme Gestion et Impacts du Changement Climatique (G.3-0006032).

References


Figure 1: Comparison of simulated and emulated SAT anomaly (2100–2000, centred decadal averages) for an emissions scenario (see section 3) described by the coefficients $A_1 = 135$ ppm, $A_2 = -63$ ppm, $A_3 = -1$ ppm.
### Table 1: SAT EOFs, emulators and cross-validation

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<tr>
<th>EOFs</th>
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<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
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<tr>
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<td>256</td>
<td>224</td>
<td>198</td>
<td>182</td>
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<tr>
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<td>1.4%</td>
<td>1.2%</td>
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<td>$R^2$</td>
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<td>41%</td>
<td>88%</td>
<td>54%</td>
<td>96%</td>
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<td>16</td>
<td>73</td>
<td>32</td>
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<th>Emulated PC Average</th>
<th>Simulated PC St. Deviation</th>
<th>Emulated PC St. Deviation</th>
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</table>

| $R^2$ | 62% | 18% | 17% | 18% | 28% |

### Table 2: Precipitation EOFs, emulators and cross-validation

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<td>91</td>
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| $R^2$ | 28% | 44% | 44% | 34% | 64% |