Pattern scaled climate change scenarios: are these useful for adaptation?

Ana Lopez, Leonard A. Smith

Centre for Climate Change Economics and Policy, Centre for the Analysis of Time Series, LSE.

I. Introduction:

Pattern scaling methods are commonly used to generate scenarios of climate change for the quantification of its potential impacts on different subsystems. While generic limitations of the pattern scaling approach are well documented [1], the implications these hold for adaptation decision making are not always made clear. The goal of this work is to discuss the errors that are expected a priori and the extent to which pattern scaling is a reliable tool for the quantification of the likely impacts of climate change.

II. Pattern scaling

Pattern scaling is used to generate climate change scenarios under changes in anthropogenic forcings that have not been simulated by full GCMs, but can be simulated quickly and cheaply by simpler energy balance climate models. It assumes that the anthropogenic climate change signal at any region and/or time horizon $T^*(x,y,t)$, is linearly related with the change in global mean temperature for the corresponding forcing scenario and period $T(t)$, and that the spatial pattern of change $P(x,y)$ remains constant at any time horizon or forcing scenario. That is:

$$T^*(x,y,t) = \hat{T}(t) + P(x,y)\hat{T}(t), \qquad (1)$$

$P(x,y)$ is obtained using a full GCM run under a particular forcing, as the pattern that minimizes the distance between the simulated change $T(x,y,t)$ and the pattern scaled change $T^*(x,y,t)$. Thus $P(x,y)$ is the pattern that minimizes :

$$\int dt [T(x,y,t) - T^*(x,y,t)]^2$$

Pattern scaled changes for other forcings are generated using eq(1), where $P(X,Y)$ is the previously calculated pattern, and the scaler $T(t)$ is computed using for instance and energy balance model that can quickly generate global mean temperature changes for multiple forcing scenarios.

The basic assumptions underlying this approach are:
i. Local climate responses to changes in external forcing are linear in global mean temperature changes.
ii. Model simulated changes are robust.
iii. Responses to external forcing and natural internal variability are independent of each other, so that changes in anthropogenic forcing do not change the internal dynamics of the climate system.

If these assumptions do not hold, then the approach is fundamentally flawed and its use to project changes at regional/local scales for decision support is called into question.

The first assumption fails when regional/local climate is determined by processes other than radiative transfer, for instance, if changes in hydrological cycle or atmospheric circulation are relevant [2].
The second assumption is clearly questionable for processes where changes in regional/local climate variables depend on initial state such as sea-ice and snow-albedo feedback and changes in circulation patterns [3]. More generally, it is not clear why, for a highly non-linear system, simulated changes could be robust in spite of model biases [4].
The third assumption is known to fail for simpler non-linear dynamical models than GCMs [5].

But even if we ignore the fact that regional/local changes are not necessarily linear with external forcings, we can still ask: does pattern scaling preserve the model information potentially useful/relevant to adaptation decision making? We discuss this question in the rest of the poster.

III. Model Data:

We use ensembles of climate models generated by the climateprediction.net (CPDN) experiment [6].
A 67 member initial condition (IC) ensemble is used to analyse whether pattern scaling preserves information about internal variability. A perturbed physics ensemble (PPE) is used to analyse how pattern scaling performs depending on the rate of global warming of the models explored. The PPE explores 26 parameter perturbations (radiation, large scale cloud, ocean, sulphate cycle, sea ice, convection) and perturbed initial conditions of the HADCM3L climate model.
Monthly means for: Global , Giorgi regions and the nine UK grid boxes are available for a series of variables. In this work we analyse monthly mean temperature time series at for Giorgi regions.

References:
[1] J.F.B. Mitchell et al (1999), Climatic Change 41, 547; T.D. Mitchell(2003) Climatic Change 60, 217.
[2] Lawrence et al (2010), Int.J. Climol. ; V. Petoukhov et al (2010) J. Geophys. Res. 115.
[3] Hall et al (2008), GRL; Holland et al (2003), Clim. Dyn.; Fletcher et al (2009) GRL.
[4] Smith,L.A (2002),PNAS99
[5] Knopft et al (2005), Nonlinear Proc. Geophys.
[6] Frame, D.J. et al, 2009, Philosophical Transactions of The Royal Society A, 367, 855; http://climateprediction.net/

IV. Results

To find out whether the pattern scaling technique preserves potentially useful climate model information, we calculate the spatial pattern $P(x,y)$ using the ensemble mean for each ensemble. We then compute the "pattern scaled model run" (PSR) using eq(1) taking as $T(t)$ the global mean temperature for each particular model run (MR), and compare the information provided by the PSR ensemble versus the MR ensemble.

If the temporal scale in eq.(1) corresponds to underlined decadal means, our results are broadly consistent with [1]. For instance the r.m.s error between PSR and MR spatial patterns is relatively small (less than 0.3°C). However, an evaluation based on r.m.s misses significant differences in the range of the PSR and MR projections, as illustrated in fig.1.

If the temporal scale considered in eq.(1) corresponds to monthly means, the reduction in variability of the MR ensemble with respect to the PSR ensemble is exacerbated (fig 2). Therefore, potentially relevant information such as extremes (see V), is modified drastical
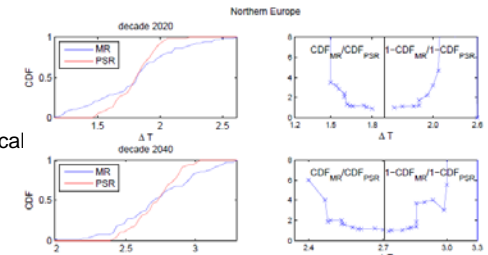

Figure 1: Relative probabilities of exceeding a temperature change threshold. The panels on the left hand side show cumulative distribution functions (CDFs) for the MR and PSR ensembles for two different decades. The panels on the right hand side show the relative probability of the change in temperature being smaller than a given value)(left side) , and the relative probability of the temperature change being larger than a given value (right side). The vertical line indicates the temperature change for which CDFmr = 0.5. Top panels show that probability of exceeding 2° C is more than three times larger in the MR ensemble than in the PSR ensemble.
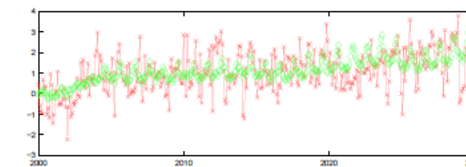

Fig 2: example of a temperature time series 2000-2030, arbitrary model, SEU. Green PSR, red MR.

V. Implications for impacts and adaptation.

Would the information provided by the PSR ensemble lead to decisions similar to the ones we would have made using the original climate MR ensemble? As an example we discuss how the estimation of the changes in occurrence of a heat wave would change depending on whether we use the PSR ensemble or the MR ensemble. Taking as a threshold the Southern Europe temperature anomaly in the boreal 2003 summer 2.3° C, the fraction of simulations in the IC ensemble overcoming this threshold as a function of time depends **strongly** on whether we evaluate the PSR or the MR ensemble.
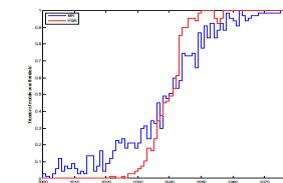

Fig5: Change in annual risk of heat wave occurrence as quantified by the MR (blue) and the PSR(red) ensembles.
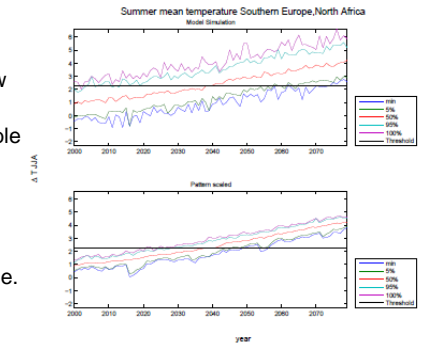

Fig 4: change in JJA SEU temperature as a function of time for the MR ensemble (top) and the PSR ensemble (bottom). Black horizontal line indicates 2.3 C threshold.

Using the pattern scaling approach to estimate changes in occurrence of heat waves would presuppose that the top and bottom panels in figs. 4 and 5 are equivalent.

VI. Conclusions

• Critical assumptions about the linearity of the local response with external forcing **fail** at the scales relevant for adaptation decision making.
• The pattern scaling approach is **not internally consistent** for the particular context examined here.
• Deploying pattern scaling as a quick (and cheap) way to generate scenarios for impacts is problematic. Before using pattern scaling for making real adaptation decisions one might want to verify the linearity and internal consistency in that particular context.