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

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Abstract

Pattern scaling methods are being widely applied to generate scenarios of climate change for quantification of their impacts on different systems. While generic limitations of this approach are well documented, the implications of the use of pattern scaling to inform adaptation decisions are not always made clear. The range of errors that are expected a priori are discussed and illustrated. Particular examples are used to demonstrate the extent to which pattern scaling is likely to be an unreliable tool for the quantification of the likely impacts of climate change. It is suggested that internal consistency tests are considered in any attempt to apply pattern scaling in practice.

1 Introduction

Global Climate models (GCMs) output interpreted through pattern scaling, change factors, and statistical and dynamical downscaling methodologies are frequently employed to quantify the impacts of climate change on water resources, food and energy production, biodiversity, and other sectors [1, 2, 3, 4]. Pattern scaling in particular is used to generate climate change scenarios under changes in anthropogenic forcings that have not been simulated by full GCMs, but can cheaply be "simulated" by simpler (and computationally faster to run) climate models. The main assumption of the pattern scaling approach is that the anthropogenic climate change signal at any region and/or time horizon (the response pattern) is linearly related with the global mean temperature change for the corresponding forcing scenario and period. The spatial pattern of change is also assumed to remain constant at any time horizon or forcing scenario [5, 6]. This approach assumes both spatial linear superposition and linear functional relationships within the climate system, therefore its application to non linear systems should be evaluated, and tests of internal consistency developed.

Pattern scaling is currently used to generate projections of climate change and to quantify their impacts. For instance the Australian climate change scenarios [7] and the UK Climate Projections UKCP09 [8] use this approach as part of their methodology to generate probabilistic projections of climate change. The technique is also being employed to evaluate the impacts of climate change on, for instance, ecosystems [3] and water resources [1, 2] , and the contribution of land use changes to climate change [4]. Within the framework of the Representative Concentration Pathways (RCPs), the next generation of scenarios for climate change research that constitute the basis of the IPCC Fifth Assessment Report, pattern scaling methods are being considered as a tool to generate climate projections not directly simulated by GCMs [9]. The assumption is that the climate projections obtained using pattern scaling will enlarge the ensemble of directly simulated projections that can provide information to evaluate the impacts, adaptation and vulnerabilities under climate change. In particular within the context of climate change impacts studies, it is argued that while pattern scaling will provide the large scale patterns of change, its use in combination with some downscaling/weather generator methods will generate the information needed at "decision relevant" scales [9].

Our work addresses directly some of the questions possed by Moss et al. [9, 10] in their work describing the Recommended Concentration Paths (RCP). Moss et al. [9, 10] state that it is necessary to evaluate "whether the results of scaling different atmosphere-ocean general circulation model (AOGCM) derived climate scenarios will be sufficiently comparable to full AOGCM runs designed to achieve similar outcomes". Understanding these issues is particularly important to evaluate whether the pattern scaling approach can actually provide robust and reliable decision making information for adaptation, vulnerability and policy analysis. If the assumptions underlying the approach are shown to fail and/or the method is not internally consistent, then its use to inform adaptation decisions is highly questionable.

We start in the following section by briefly describing the pattern scaling approach and its underlying assumptions .The three main assumptions are: first that local climate responses to changes in external forcing are linear functions of the induced global mean temperature changes; second that model simulated changes are robust independently of model biases; and third, that responses to external forcings and natural internal variability are independent, specifically that anthropogenic forcings do not modify the internal variability of the climate system. We argue that, in general, these assumptions can not be expected to hold at regional or local scales, and consequently evidence of their validity is required for each particular study.

We then evaluate the internal consistency of the approach. That is, assuming that there are scales at which the method can be used, we evaluate whether the decision relevant information generated by pattern scaling is internally consistent with the one provided by a full model simulation. In order to do so, in section 3 we apply this approach to a large ensemble of climate models and investigate if the errors of the pattern scaled projections are significant enough to affect estimates of climate change impacts. We show through specific examples that the original model information is highly distorted after pattern scaling; the approach changes the variability of the projections and estimates of warming and warming rates that are relevant for humans and ecosystems adaptation, with errors large enough to misled adaptation decisions. Pattern scaling is shown to be unfit for purpose in the cases analyzed here, suggesting that those who apply this method should establish if it is fit for purpose for the application of interest. Needless to say, in cases where climate model simulations do not have skillful information at the impacts relevant scales, neither pattern scaling nor any other approach used to generate new projections based on that data can possibly "create" skillful climate change projections.

Section 4 is devoted to the conclusions.

2 Methods and data

2.1 Pattern Scaling approach and underlying assumptions

Mitchell [5] defines pattern scaling as follows. Suppose that $T(x, y, t)$ is the actual pattern of change in the variable T at (x, y, t), as simulated by a full GCM. Then, an *approximate* pattern of change $T^*(x, y, t)$ for this variable can be obtained in terms of a spatial pattern $P(x, y)$, and the global mean change $\hat{T}$ as follows

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

where $P(x, y)$ is the pattern that minimizes the distance between T and T^*, i.e., it minimizes $\int dt[T(x, y, t) - T^*(x, y, t)]^2$ [1]. This approximation encapsulates the assumption that the spatial pattern of change P is constant in time, and the only effect of the transient forcing will be to scale the pattern up or down following the trajectory of the global mean temperature change. Hence "pattern scaling".

The spatial pattern derived in this way using the information from a full GCM, can then be used to generate time and space dependent patterns of change for other forcing scenarios that have not been simulated by any full GCM. Simple fast climate models (such as energy balance models) can be run cheaply under various forcing scenarios to provide the global mean temperature changes $\hat{T}$. The attraction of pattern scaling is that it allows these inexpensive runs to provide "spatial" information simply by multiplying $\hat{T}$ by $P(x, y)$, as in equation (1), generating time and space dependent changes under these new forcing scenarios. Mitchell et al [5] show that for the forcing scenarios they consider, the error in annual mean temperature when using T^* instead of T is smaller than the sampling error due to the model's internal variability (as defined by an initial conditions (I.C.) ensemble), where the error as a function of time is defined as the rms distance $\sum_{x,y}[(T^* - T)\delta x \delta y]^2$. Our results confirm this observation, however we note that this is not a desirable property of the methodology if it is to be used to evaluate impacts, since it only means that the approach reduces the variability of the full GCM ensemble.

The main characteristics of the projections obtained using this approach and its limitations when applied to decadal annual or seasonal means have been discussed previously [5, 6]. For instance it was shown that: the pattern scaled projections fall within the range of the internal model variability as defined by the initial conditions ensemble; patterns derived using transient simulations do not have skill to project long term effects of stabilization scenarios; and a pattern derived with a given concentration of greenhouse gases fits a scenario with reduced greenhouse gases well, but a scenario with greenhouse gases and aerosols poorly (due to the fact that aerosols remain

[1]The first EOF derived from the time series $[T(x, y, t) - T^*(x, y, t)]$ gives the same pattern as $P(x, y)$ [5].

more localized)[5]. In [6] it was shown that the technique works better for temperature than precipitation, due to the fact that the signal of change is not very strong for precipitation. Pattern scaled projections fail to reproduce extremes; it has been argued that in this case a non linear relationship should be considered [11]. An analysis for South America has also shown that errors in pattern scaled projections are smaller than GCM biases [12], though as we will see this result does not imply that the use of pattern scaling is well justified.

Equation (1) implies that for the pattern scaled field T^* to be a good approximation to the fully simulated field T it is required that:

1. Local climate responses to changes in external forcing are linear in global mean temperature changes.

2. Model simulated changes are robust.

3. Responses to external forcing and natural internal variability are independent of each other, i.e., changes in anthropogenic forcing do not change the internal dynamics of the climate system.

To clarify whether or not the pattern scaling approach may prove able to generate decision relevant information, we discuss the likely validity of these assumptions individually.

1. Local climate responses to changes in external forcing are linear in global mean temperature changes. This assumption implies that, for instance, the warming pattern for a 4^o global warming is the same as for a 2^o global warming, but twice as big. Pattern scaling is only viable if local temperatures scale linearly with global mean surface temperature. In addition, the simple energy balance models used to simulate global mean surface temperature assume that their changes are linear with changes in radiative forcing (net forcing downwards at the top of the atmosphere). Therefore, the pattern scaling approach must presuppose that local surface temperatures scale linearly with radiative forcing.

At regional/local spatial scales however, processes other than radiative transfer are important in determining local climate. For instance Lawrence et al [13] show that even though land cover changes in the comunity climate system model (CCSM) do not result in very significant global changes, larger regional and seasonal changes are observed mostly driven by changes in surface hydrology, with radiative forcing playing a less important role (for instance less water available in the soil for evapotraspiration will change the relative importance of latent heat and sensible heat). Changes in atmospheric circulation that play an important role for regional climates can have a non linear relationship with large scale warming, as discussed by Petoukov et al [14] in relation with recent cold winter extremes over northern continents. These results bring the linearity assumption into question.

2. Model simulated changes are robust.

Climate models have large biases when compared with present climate [15, 16]. In spite of their lack of skill in reproducing many aspects of present climate, it is assumed that climate models' simulated changes over the next century or so are robust. While this hypothesis can not be verified, some modeling studies indicate a strong connection between larger biases in simulated current climate with higher climate sensitivity [17], suggesting that larger simulated warming might be related to the presence of model biases.

Of course when non-linear physical processes are invoked, this assumption is a nonsense. Such phenomena include snow-albedo feedback [18], sea-ice feedback [19], [20], and possibly changes in circulation patterns that could be altered under climate change [21].

Models with significant biases can not be expected to perform linearly. An example of this is the snow-albedo feedback at high latitudes. If the simulated temperature has a large positive bias, then there is no snow to be melted in spring/summer. Consequently the amount of water that can be stored in the soil decreases, reducing evapotranspiration that in turn results in a relative increase in sensible over latent heat (a decrease in soil moisture content is related with the occurrence of heat waves [22]). Therefore, it is reasonable to expect that for models with large temperature biases, the occurrence of temperature extremes can be a spurious result due to the model bias.

Similarly, models that simulate smaller ice extent in the Arctic at present, show a more pronounced sea-ice albedo feedback, simulating larger warming in this region [23].

Changes in circulation patterns can also occur as a consequence of model biases: with a large positive bias in surface temperature, snow cover decreases and the land surface warms (through reduced albedo) faster than the ocean. This can induce changes in the local atmospheric circulation pattern (surface convergence over the land and divergence over the ocean) [21].

3. 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.

The underlying assumption here is that changes in anthropogenic forcing do not change the internal dynamics of the climate system. Therefore a static spatial pattern of change can be obtained from a given GCM run under a particular forcing, and the only effect of any other transient forcing will be to scale up or down that given pattern by the new global mean temperature change. It is well known however, that for non-linear systems, in general changes in forcings are expected to affect the internal dynamics of the system [24].There is no obvious reason to think that this result will not hold for the climate system. Ignoring the possibility of runaway changes induced by internal feedbacks, it could perhaps be argued that induced changes to internal variability can be neglected when focusing on long term global mean temperature changes to inform mitigation policies. On short time scales this approximation must be justified in a case by case basis at the smaller spatial scales relevant for impacts and vulnerability studies. On long time scales however, when the local forest may have become a local desert, the assumption is dubious even for large scale averages.

The previous discussion raises serious doubts as to whether the pattern scaling technique is fit for purpose at regional or local scales; evidence is required that each of these assumptions are met in each study. Otherwise the information generated to be used for adaptation and vulnerability studies is fundamentally flawed.

Independently of the fact that regional and local changes are not well approximated linearly, one can determine whether (or not) the pattern scaling approach preserves model information relevant for adaptation decision making. In the rest of this paper we show, through some particular examples, that pattern scaled projections are inconsistent with the model runs from which they are derived. Taking as illustrative examples occurrence of heat waves in Europe, and changes in decadal rates of warming at subcontinental scales, we show that the pattern scaling approximation destroys potentially relevant information contained in the model simulations, in particular information about temporal variability. In this work, it is not our goal to evaluate the decision relevance of the models, rather given the model simulation, our aim is to evaluate whether the model information is conserved by the pattern scaling approach, effectively providing a test of internal consistency for the pattern scaling approach.

2.2 Model data

We analyze data generated by the climateprediction.net (cpdn) experiment [25], an ongoing experiment in which individual model simulations are carried out using idle processing capacity on personal computers volunteered by members of the general public.

The climate model used is HADCM3L, a version of the UK Met Office Unified Model consisting of the atmospheric model at standard resolution (2.5^0 latitude, 3.75^0 longitude) including nineteen vertical layers coupled an ocean with twenty levels. The experiment intends to explore the effects of both, initial conditions and model parameter perturbations. Each simulation involves a 160-year transient run that includes two phases. In the historical phase, from 1920 until 2000 the experiment is forced with historical records of CO_2, volcanic emissions, and solar forcings. In the second phase, the SRESA1B scenario is used to force the model response between 2000 and 2080.

In this work we concentrate on two subsets of simulations.

Set A consists of a 67 member initial conditions ensemble of the HADCM3L model run with standard values of the physical parameters, but different initial conditions. In section 3.1 we use set A to evaluate whether the pattern scaling approach preserves the internal variability of the model ensemble.

Set B is a set of 1476 transient simulations that were completed by June 2009, and constitute a perturbed physics ensemble. This ensemble explores the uncertainty associated to perturbing 26 model parameters that are relevant to model simulation of radiation, large scale clouds formation, ocean circulation, sulphate cycle, sea ice formation, and convection in the atmosphere. In section 3.2 we use set B as a proxy to evaluate the performance of the pattern scaling approach when using the pattern extracted from a model ensemble forced by a given emissions scenario, to approximate projections of GCMs under a different emissions scenario.

A variety of climate variables at different temporal (monthly to decadal means), and spatial scales (grid points to continental averages) are being stored by this experiment. Monthly time series are available for the Global mean, the area average over 22 continental to subcontinental regions similar to the Giorgi regions [26][2], eight grid boxes covering the United Kingdom,

[2]These regions are defined as rectangles covering the same land area as the Giorgi regions but including the adjacent oceans,and follow the naming convention of the IPCC 4AR [27]

and six other areas spanning part of the oceans. Seasonal decadal means are stored for gridded data for sixteen decades between 1920 and 2079.

In what follows, we evaluate the pattern scaling approach when applied to the Giorgi regions monthly temperature time series. Giorgi regions are larger than the scales that are usually relevant for many impact studies. However we assume that if the pattern scaling approach fails to reproduce model relevant information at these large scales, the failure will persist, or presumably become more significant at smaller scales.

3 Results

3.1 Consistency of pattern scaled temporal variability.

In this section our aim is to understand how the pattern scaling approach changes the temporal variability of the model runs projections, and the impact of those errors in adaptation decisions. We assume that the I.C. ensemble,i.e., set A, provides an estimation of internal temporal variability in this model system, and evaluate whether that is changed in the pattern scaled ensemble.

We calculate the spatial pattern $P(x, y)$ from the I.C. ensemble mean. We then compute the "pattern scaled model runs" (PSR) using equation (1) and taking as $\hat{T}(t)$ the simulated global mean temperature for each individual model run (MR) in the set A. We consider two temporal scales: decadal and monthly means.

We observe that when applying the pattern scaling technique to decadal means our results are broadly consistent with [5]. For instance we find that the root mean square error (r.m.s) between spatial patterns of each MR and its corresponding PSR for different decades are relatively small (less than 0.3^0) and stationary, reflecting the stationarity of the range of variability of the set A (over the 21st century the I.C. ensemble does not increase its spread as a function of time). Moreover, these r.m.s. fall within the range of r.m.s between any pair of MRs. Arguably this result is not surprising. By construction , pattern scaling smoothes any regional/local variability in time and replaces it by the much smaller temporal variability of the global means. Long term decadal means have the similar effect : they smooth short term variability. Therefore, it must be expected that projections obtained using pattern scaling applied to decadal means should be close to decadal averages of model projections when spatially averaged over the Globe. However, an evaluation of the PSR ensemble based on r.m.s between the spatial patterns of the pattern scaled trajectory and the GCM trajectory for any given time is misleading, particularly if we are interested in the range of projections for a given decade and region. In figure 1 we illustrate this point for Northern Europe and three different decades. The figure shows the differences between the PSR and MR cumulative distribution functions (CDFs). For instance, the top panels show that, in the 2020s, the probability of exceeding 2^0 according to the MR ensemble $(1 - CDF_{MR})$ is more than three times larger than the same probability evaluated with the PSR ensemble $(1 - CDF_{PSR})$. Similar results are obtained for other regions. Clearly, the range of projections simulated by the MR ensemble is underestimated by the PSR ensemble.

Implications for impacts analysis: occurrence of heat waves

The reduced variability of the PSR ensemble with respect to the MR ensemble observed for decadal means is exacerbated when pattern scaling is done for monthly time series. Following the procedures in [6] we now extract a pattern P in eq.1 for each individual month using the set A mean, and then obtain PSRs by scaling this pattern using the global annual mean temperature change of each model run. How relevant are the differences between the ranges of variability of the two ensembles will depend on the particular impact being studied.

As an example to illustrate this issue, we consider the occurrence of heat waves in Southern Europe. We assume that a heat wave can be quantified , to a first approximation, in terms of changes in mean summer temperature only. Motivated by the fact that during the 2003 European heat wave the mean summer temperature of Southern Europe (defined as the region between 10W and 40E, and 30 and 50N) was 2.3^o higher than the 1961-1990 mean [28], we define an occurrence of a heat wave in the future every time the projected summer mean temperature change in Southern Europe is larger than 2.3^o. We then analyze how adaptation decisions to reduce the vulnerability to heat waves depends on whether one considers the MR or the PSR ensembles to quantify their occurrence. Figure 2 summarizes our findings. The frequency distribution of the 2003 Southern European mean summer temperatures for the PSR and MR ensembles shows that the former looses the more extreme lower and higher temperatures projected by the models (fig 2.a). Time series for different quantiles of the PSR and MR ensembles are plotted in fig 2.b., showing how the risk of overshooting the threshold (horizontal black line) as quantified by the MR or the PSR ensembles is highly ensemble dependent, particularly at the beginning and the end of the time series. Figure 2.c shows the change in time of the fraction of PSR and MR projections that overcome the 2.3 threshold.

The use of the pattern scaling approach to estimate changes in the risk of heat waves presupposes that the top and bottom panels in Figure 2.b for instance are equivalent. Observe that they vary tremendously: while the PSR ensemble would suggest that no significant changes in the risk of heat waves will be observed until the 2030s, the MR ensemble projects a 10% increase by the 2020s. Moreover, the PSR ensemble projects a sudden increase in risk around the 2040s, while the MR ensemble projects a smoother increase of the risk over the 21st century. If a decision maker was to base her adaptation planning on this information, the pathways to be undertaken according to these two ensembles would be significantly different. In the case of the PSR ensemble, there is still time to wait and see if new observational evidence or modeling approaches can reduce the uncertainties in the projections. For the MR ensemble however, the risk increases significantly already during the next decade, and the time left to put in place measures to reduce the vulnerability of the exposed population to heat waves, or to wait for improved climate information is much shorter. Clearly, for a given level of risk tolerance, the pattern scaled ensemble generates false confidence potentially leading to mal adaptation.

This example illustrates that the pattern scaling approach fails to reproduce decision relevant information contained in the full GCM simulations. We remark that we are not suggesting that the MR ensemble projections are robust to quantify the risk of heat waves in Southern Europe in the 21st century, we are simply arguing that if they were, they would be very much misrepresented by the PSR ensemble.

3.2 Consistency of warming rates for pattern scaled projections under different forcings

In this section we focus on another aspect of pattern scaling. As already mentioned, this approach is considered as a quicker and cheaper way to generate multiple climate change scenarios to evaluate impacts of climate change, but without the need to run expensive GCMs. The generation of multiple scenarios thus requires that patterns derived from a set of models run under a given forcing scenario are used to emulate climate change projections for other different forcing scenarios. It has been shown that the accuracy of pattern scaling deteriorates when extrapolating to higher forcing scenarios, with errors being greater when scaling from low to high scenarios than when scaling from high to low [6, 29]. Here we are interested in understanding the implications of these errors in the pattern scaled projections for adaptation decisions. Due to the fact that the PPE or set B has been run under just one forcing scenario (SRESA1B), we can not use it to address exactly the problem posed above,i.e., errors incurred when pattern for one emissions scenario is used to generate projections for other emission scenario. We can however ask whether spatial patterns derived from sets of fast (slow) warming models can reproduce the magnitude and speed of temperature changes simulated by slow (fast) warming models when scaled by the global mean temperatures of the later. Information about rate of changes is relevant, for instance, to evaluate the ability of many ecosystems to adapt to changes in climatic conditions, as this ability is strongly dependent not only on the magnitude of the warming, but also on the rate at which changes occur [3].

Implications for impacts analysis: warming and warming rates

We consider for our illustration two sets of models within the set B, those whose 2030s decadal mean temperature change falls within the range $(2 \pm 0.5)^0C$ (1084 model runs) and those whose 2030s decadal mean temperature change falls within the range $(3 \pm 0.5)^0C$ (240 model runs), using as a baseline the period $1961 - 1990$. We refer to first group as the 2^0C ensemble and the second one the 3^0C ensemble. We then generate two sets of pattern scaled trajectories. The first one is obtained deriving the spatial pattern $P(x, y)$ in equation (1) from the 2^0C ensemble mean and scaling it by the global mean temperatures (GMTs) simulated by the model runs in the 3^0C ensemble. The second one is obtained deriving the spatial pattern $P(x, y)$ in equation (1) from the 3^0C ensemble mean and scaling it by the global mean temperature of the model runs in the 2^0C ensemble. Even though the differences between the two spatial patterns are not large (within a tenth of a degree for all regions), there are errors in the PSR as compared with the corresponding MR due to the different warming rates of the two sets of models.

As illustrated in figure 3 for Northern Europe, when scaling the pattern of models that warm slowly (2^0C ensemble) by the GMTs of models that warm faster (3^0C ensemble), the resulting PSRs mostly overestimate the warming (figure 3.a)). For instance, in all decades nearly 50% of the PSRs overestimate the warming by more than 0.5^0C when compared to the corresponding MRs. Alternatively, when scaling the pattern of models that warm faster (3^0C

ensemble) by the GMT of models that warm slowly (2^0C ensemble), the resulting PSRs mostly underestimate the warming (figure 3.b)). In this case, by 2020s about 15% of the PSRs underestimate the warming by 0.5^0C, and the proportion increases to one third of the PSRs by the 2040s and 40% later on in the 21st century.

To put these temperature differences into context, some authors have estimated that changes in the growing season temperature within the range $[-0.5^0C, 0.5^0C]$ can cause changes in yields of $[5\%, -5\%]$ for maize. Temperature changes within the range $[-1^0C, 1^0C]$ can cause yields' changes of $[10\%, -10\%]$ for barley and $[4\%, -4\%]$ for wheat [30, 31]. Of course there are large uncertainties in these estimates, and they refer to growing season temperatures and not annual averages. They serve however as an illustration of how significant the errors in pattern scaling can be in relation to the current estimates of impacts of global warming in crop yields.

We also analyze the decadal warming rate, i.e., the change in temperature between any two consecutive decades. We find that in general, the PSR ensemble has a reduced range of warming rates as compared to the MR ensemble, consistently with the fact that the PSR ensemble has a reduced variability. In figure 4 we show the scatter plots for MRs warming rates vs PSRs warming rates for different decades for Northern Europe. We observe that differences between warming rates for PSRs and corresponding MRs can be as large as 1^0C in magnitude [3] and in some cases the sign of the changes are different. This has implications for, for instance, the use of pattern scaling to generate climate projections to evaluate ecosystems' adaptation to climate change. In general, ecosystems are sensitive not only to the amount of change but also to the rate at which the change occurs. It's likely that the slower the change the greater the potential for adaptation by dispersal or through natural selection for physical or behavioral characteristics that are better suited for a changed climate. Some authors have estimated that ecosystems can withstand warming rates of about $0.05 - 0.1^0C$/decade [3]. Basing adaptation decision on pattern scaled projections that can under or over estimate the rate of warming by several times these magnitudes has the risk of resulting in maladaptation.

We conclude that the errors in the magnitude of the decadal warming and decadal warming rates as estimated with the pattern scaled projections, are of the same order or larger than the amount of warming that could severely

[3] Notice this is several times the observed current warming rate of $0.13^0C/decade$ [27]

affect crop production, or the rate of changes that could diminish the ability of ecosystems to adapt to new climatic conditions. Pattern scaling errors are large enough to mislead adaptation decisions and pattern scaled projections would not be fit for purpose for, for instance, crop production adaptation planning.

4 Conclusions

Pattern scaling was developed as a tool to generate climate projections not directly simulated by GCMs [5, 6, 29], and is currently used under the assumption that the generated climate projections enlarge the ensemble of directly simulated projections providing information to evaluate the impacts, adaptation and vulnerabilities under climate change. In this paper we have investigated whether or not this methodology can actually generate robust and reliable decision making information. It seems unlikely that this is the case in many situations of interest. We therefore suggest consistency tests be employed whenever patter scaling is considered as a tool in decision support.

Firstly we discuss the assumptions underlying pattern scaling, and whether these hold at the regional/local scales relevant for adaptation decisions. The three main assumptions are : local climate responses to changes in external forcing are linear in global mean temperature changes; model simulated changes are robust; and 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. The first assumption fails when considering regional/local spatial scales where processes other than radiative transfer are important in determining the local climate. The assumption that model simulated changes are robust fails when the regional/local climate is determined by processes where model biases might affect significantly simulated changes. In the case of the third assumption it has been shown to fail for simpler non linear systems [24]. For the climate system, it could perhaps be argued that induced changes to internal variability can be neglected when focusing on long term global mean temperature changes to inform mitigation policies. But it is not clear that this approximation can be justified at the smaller spatial and temporal scales relevant for impacts and vulnerability studies. Even at larger scales, it assumes not significant feedbacks from changes in the small scales.

Secondly we evaluated the internal consistency of the approach. That is, assuming that there are scales at which the method can be used, we evaluate whether the decision relevant information obtained using pattern scaling is internally consistent with the one provided by a full GCM simulation. We start by analyzing how the pattern scaling approach changes the temporal variability of the model runs projections, and the impact of those errors in adaptation decisions. We assume that the climateprediction.net I.C. ensemble provides an estimation of internal temporal variability in this model system, and evaluate whether that is changed in the pattern scaled ensemble, and find that the pattern scaled ensemble reduces significantly the variability of the original ensemble. For instance, using as an illustration the occurrence of heat waves in Southern Europe, we find that if a decision maker was to base her adaptation planning on this information, the pathways to be undertaken according to the two ensembles would be significantly different. In the case of the PSR ensemble, there is still time to wait and see if new observational evidence or modeling approaches can reduce the uncertainties in the projections. For the MR ensemble however, the risk increases significantly already during the next decade, and the time left to put in place measures to reduce the vulnerability of the exposed population to heat waves, or to wait for improved climate information is much shorter. We finish by using the Perturbed Physics Ensemble (PPE) as a test bed to analyze whether spatial patterns derived from ensembles of fast (slow) warming models can reproduce the magnitude and speed of temperature changes simulated by slow (fast) warming models when scaled by the global mean temperature of the latest. We find that the errors in the magnitude and decadal rate of temperature change are similar to or larger than estimates of the amount of warming that can severely affect crop yields or the rate of warming that can strongly affect the ability of ecosystems to to adapt to changes in climatic conditions. Therefore, in this case as well, pattern scaling errors are large enough to mislead adaptation decisions.

We conclude that deploying pattern scaling as a quick (and cheap) way to generate scenarios for impacts is problematic. By focusing on particular model outputs, we have seen that assuming that the models have valuable information, that information can not be completely captured if models (with their internal variability) are replaced by pattern scaled projections using a simple climate model and a spatial pattern of change obtained from a full GCM ensemble. In the cases we have analyzed they are not fit for purpose to address problems where the knowledge of temporal and spatial variability is required. Our findings make concrete the IPCC 4AR statement that "for some quantities like variability and extremes, such scaling is unlikely to work" [27] [4], and reinforce the necessity of clearly evaluating the consistency of the method before embarking in particular analysis that can otherwise end up with misleading information.

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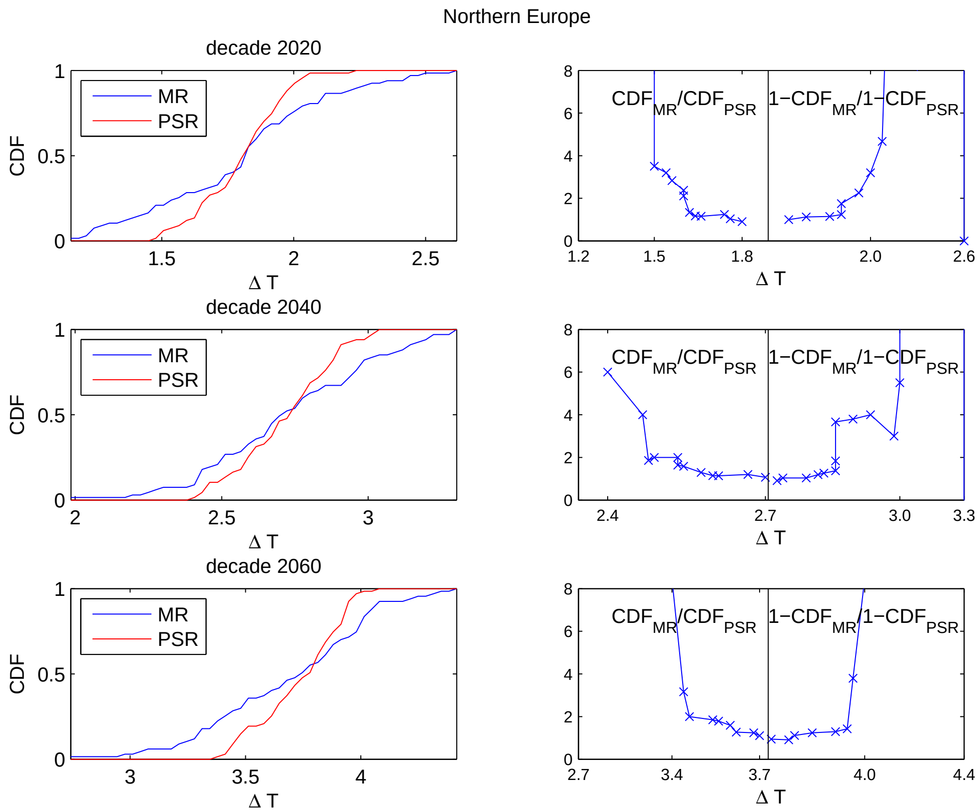
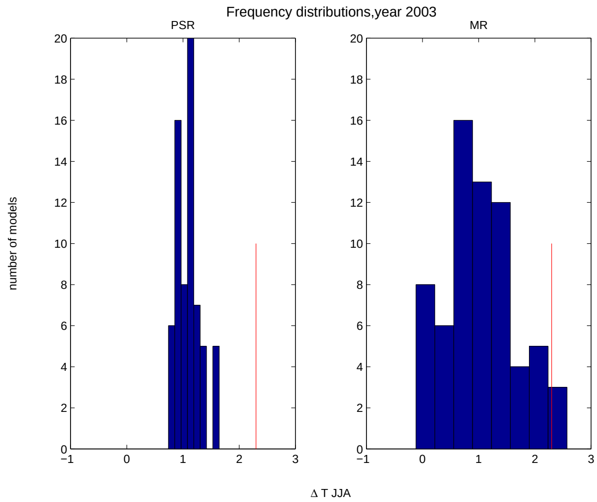


Figure 1: Relative probabilities of exceeding a temperature change threshold for the MR and PSR ensembles in Northern Europe. The panels on the left hand side show cumulative distribution functions (CDFs) for the MR and PSR ensembles for three different decades. The panels on the right hand side show the relative probability of the change in temperature being smaller than a given value (CDF_{MR}/CDF_{PSR}) (left side) , and the relative probability of the temperature change being larger than a given value ($1 - CDF_{MR}/1 - CDF_{PSR}$)(right side). The vertical line indicates the temperature change for which $CDF_{MR} = 0.5$.



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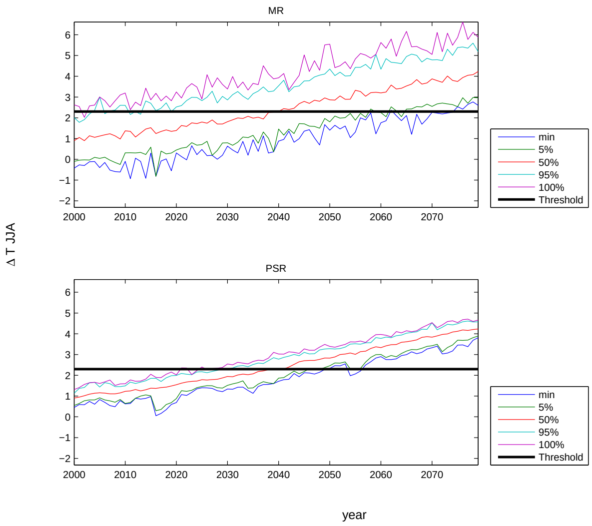

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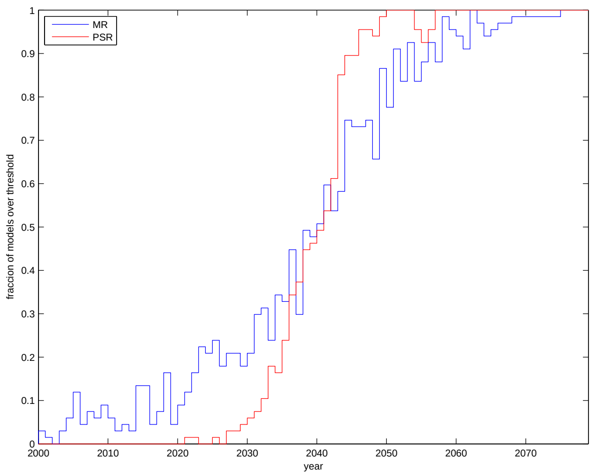
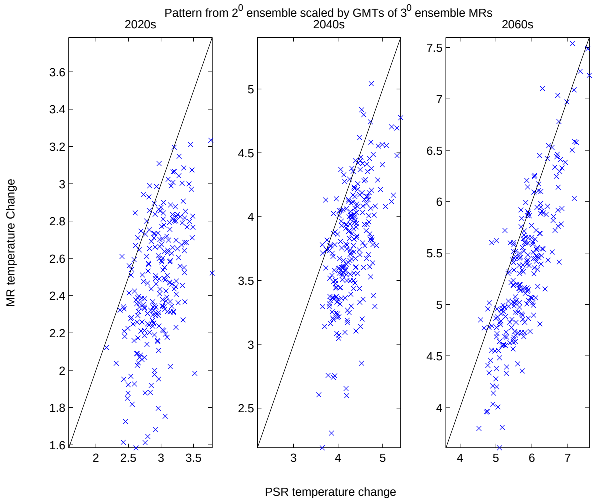


(c)

Figure 2: Southern Europe projections for summer warming and Heat Waves: a) year 2003 frequency distribution of PSR(left) and MR(right) projected mean summer temperature changes, red vertical line indicates 2.3^0 threshold, b) MR(top) and PSR(bottom) ensembles' projections for summer temperature change as a function of time, black horizontal line indicates 2.3^0 threshold, c) change in annual risk of heat wave occurrence as quantified by the MR (blue) and PSR (red) ensembles.



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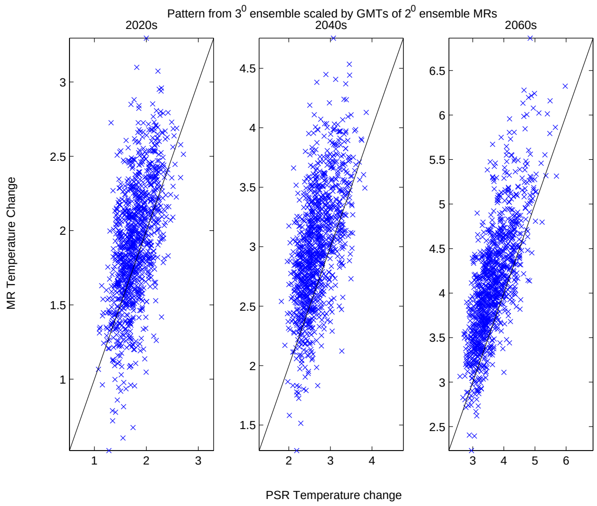
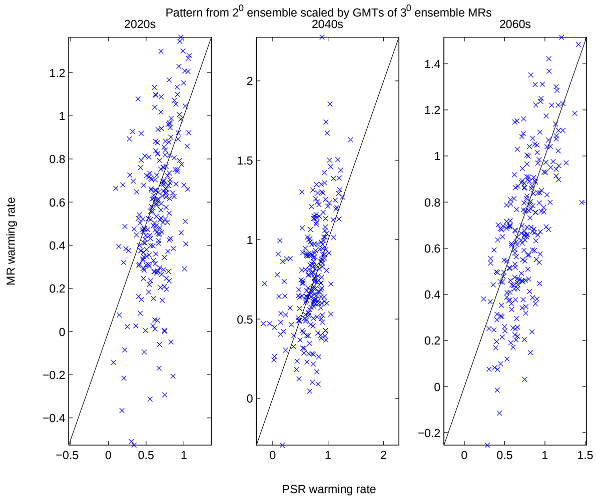


(b)

Figure 3: Dependence of decadal warming on ensemble sensitivity for Northern Europe: a) MR vs PSR temperature changes when pattern extracted from 2^0 ensemble mean is scaled by GMTs of MRs in 3^0 ensemble, pattern scaling overestimate warming in this case. b) MR vs PSR temperature changes when pattern extracted from 3^0 ensemble mean is scaled by GMTs of MRs in 2^0 ensemble, pattern scaling underestimate warming.



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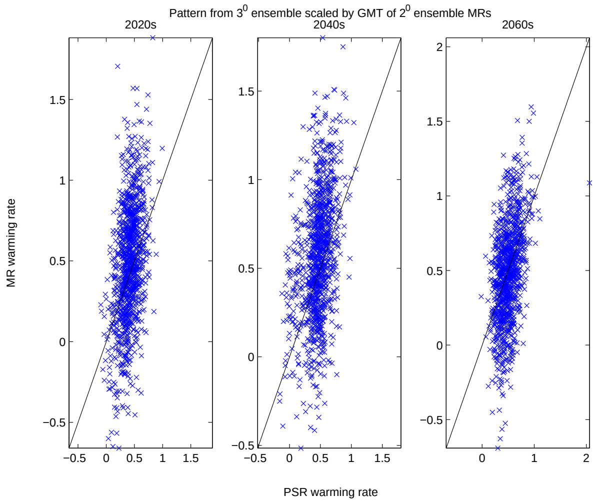

(b)

Figure 4: Dependence of decadal warming rate on ensemble sensitivity for Northern Europe: a) MR vs PSR warming rate when pattern extracted from 2^0 ensemble mean is scaled by GMTs of MRs in 3^0 ensemble . b) MR vs PSR temperature changes when pattern extracted from 3^0 ensemble mean is scaled by GMTs of MRs in 2^0 ensemble.