Noname manuscript No.
(will be inserted by the editor)

Robustness of pattern scaled climate change scenarios for adaptation decision support

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Received: date / Accepted: date

Abstract Pattern scaling offers the promise of exploring spatial details of the climate system response to anthropogenic climate forcings without their full simulation by state-of-the-art Global Climate Models. The circumstances in which pattern scaling methods are capable of delivering on this promise are explored by quantifying its performance in an idealized setting. Given a large ensemble that is assumed to sample the full range of variability and provide quantitative decision-relevant information, the soundness of applying the pattern scaling methodology to generate decision relevant climate scenarios is explored. Pattern scaling is not expected to reproduce its target exactly, of course, and its generic limitations have been well documented since it was first proposed. In this work, using as a particular example the quantification of the risk of heat waves in Southern Europe, it is shown that the magnitude of the error in the pattern scaled estimates can be significant enough to disqualify the use of this approach in quantitative decision-support. This suggests that future application of pattern scaling in climate science should provide decision makers not just a restatement of the assumptions made, but also evidence that the methodology is adequate for purpose in practice for the case under consideration.

Keywords pattern scaling · adaptation decision support · climate change

1 Introduction

Understanding the potential impacts of climate change and variability on natural and human systems is an important input for adaptation planning and policy

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making. Global Climate models (GCMs) output interpreted through pattern scaling, change factors, and statistical and dynamical downscaling methodologies are frequently employed to quantify these impacts. 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 be simulated by simpler and less computationally demanding 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 to the global mean temperature change for the corresponding forcing scenario and period (the scaler). The spatial pattern of change is also assumed to remain constant at any time horizon or forcing scenario [22,23].

The pattern scaling approach is currently used to generate projections of climate change [4,27] and to quantify their impacts on, for instance, ecosystems [40,42] and water resources [44,38] , and the contribution of land use changes to climate change [16]. Within the framework of the Representative Concentration Pathways (RCPs), the scenarios for climate change research that constitute the basis of the IPCC Fifth Assessment Report, pattern scaling is considered as a tool to generate climate projections not directly simulated by GCMs [26]. The assumption is that the climate projections obtained using pattern scaling can provide reliable information to evaluate the impacts, adaptation and vulnerabilities under climate change. In particular, for climate change impacts studies, it is argued that while pattern scaling provides the large scale patterns of change, its use in combination with some downscaling/weather generator method generates the information needed at "decision relevant" scales [26].

This paper addresses directly some of the questions possed by Moss et al [26, 25]. In their work the authors 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".

While the main characteristics of the projections obtained using this approach and its limitations have been discussed in the literature [22,23,11,28], the extent to which these limitations affect the estimations of changes in climatic risks for decision support has not been addressed previously. This work aims to study this particular point in a perfect model scenario. The paper starts with a brief description of the pattern scaling approach developed in references [22,23], followed by a discussion of three major assumptions underlying the methodology: 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 not affected strongly by errors in the base climate; and third, that the external forcings do not modify the internal variability of the climate system. It is argued that these assumptions are not expected to hold in general at regional or local scales, and consequently evidence of their validity is required for each particular study that applies the pattern scaling approach to evaluate impacts of climate change.

Assuming that there are scales at which the method can be used, an evaluation of the internal consistency of the approach is performed. Applying a commonly used version of the pattern scaling approach [1,24,30,38,39,41,42] to a large ensemble of climate model runs, an evaluation of whether or not the decision relevant information generated by pattern scaling is internally consistent with the one provided by full model simulations is carried out. The pattern scaled projections are compared with the original ensemble model runs they are derived from, to investigate if the errors obtained are significant enough to affect estimates of climate change risks. Using as an illustrative example the risk of occurrence of heat waves in Southern Europe, it is shown that the original model information is distorted, changing the estimates of warming relevant for humans and ecosystems adaptation, errors being large enough to mislead adaptation decisions. The pattern scaling approach analyzed here is shown to be unfit for purpose in this case. Modifications to the method that could improve the estimates of risk are discussed in the supplementary information.

Needless to say, in cases where climate model simulations do not have skillful information at the impact 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.

2 Methods and data

2.1 Pattern Scaling approach and underlying assumptions

In reference [22] the pattern scaling approach is defined as follows. Suppose that $T(\mathbf{x}, t)$ is the actual pattern of change in the variable T at position $\mathbf{x}$ and time t, as simulated by a full GCM. Then, an *approximate* pattern of change $T^*(\mathbf{x}, t)$ for this variable can be obtained in terms of a spatial pattern $P(\mathbf{x})$ and the global mean change $\hat{T}$ according to

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

where $P(\mathbf{x})$ is the spatial pattern that minimizes the distance between T and T^* defined by $\int dt[T(\mathbf{x}, t) - T^*(\mathbf{x}, t)]^2$. This approximation encapsulates the assumption that the spatial pattern of change $P(\mathbf{x})$ is constant in time, so 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 generalization of the above equation to include monthly or seasonal dependence is straightforward, the temperature change field $T(\mathbf{x}, t)$ becomes $T(\mathbf{x}, i, t)$ with i labeling a month or season in year t, and consequently there is a pattern $P(\mathbf{x}, i)$ for every possible value of i .

The spatial pattern $P(\mathbf{x})$ derived from a full GCM, is then used to generate time and space dependent changes for other forcing scenarios given only time series of $\hat{T}$ from simple models, reducing the number of forcing scenarios for which the full GCM must be deployed. Simple, fast climate models such as energy balance models, can be run under various forcing scenarios to provide the global mean temperature changes $\hat{T}$. The main characteristics of the projections obtained using this approach and its limitations have been discussed previously [22, 23, 11, 28]. For instance, Mitchell et al [22] show that for the forcing scenarios they consider, the root mean square 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). While true, this property of the methodology is not desirable in applications evaluating impacts, since it implies that the approach does not reproduce the variability of the full GCM ensemble.

The extent to which these limitations impose any constraint on the use of pattern scaling to estimate changes in climatic risks for decision support is discussed in section 3. Meanwhile, in the remaining of this section the plausibility of three basic assumptions that should be satisfied for the pattern scaled field T^* to be a good approximation to the fully simulated field T is discussed.

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

This assumption requires 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. In other words pattern scaling is only viable if local temperatures scale linearly with global mean surface temperature. Since the global mean surface temperature changes (scaler) are in general simulated by simple energy balance models, their changes are determined by changes in global radiative forcing (net forcing downwards at the top of the atmosphere). Therefore, the pattern scaling approach implicitly presupposes that the only way in which changes in forcing affects local temperature changes is through the way it affects global temperature change, and conversely, that apart from a fixed spatial pattern, the main driver of local surface temperatures changes is global radiative forcing mediated by the global mean temperature changes. At regional/local spatial scales however, processes other than radiative transfer are important in determining local climate. For instance Lawrence et al [20] show that even though land cover changes in the community climate system model (CCSM) do not result in very significant global changes, larger regional and seasonal changes are observed mostly driven by the surface hydrology, with radiative forcing playing a less important role.

The linearity assumption for local climate responses is also questionable when considering modeling studies showing that gradual changes in some control parameter can cause abrupt non-linear transitions in related systems. In reference [31] it is shown that a gradual reduction in sea ice concentrations in the Barents-Kara sea induces highly non-linear changes in the high latitude atmospheric circulation (from anomalous cyclonic to anti-cyclonic and then back to cyclonic circulation as the sea ice concentration decreases) that have a large impact on the European winters. This findings suggest that even if changes in global mean temperature are smooth, that does not need to be the case for regional variables.

2. Model simulated changes are not affected strongly by errors in the base climate.

The variables in equation (1) represent changes in space dependent climate variables $T^*(\mathbf{x}, t)$, and changes in global mean temperature $\hat{T}(t)$. Since the spatial pattern $P(\mathbf{x})$ is derived from model simulated changes, it can only represent a plausible spatial pattern of change if the model simulated changes correspond to plausible physical changes independently of the errors in the model base climate. In other words, the pattern scaling approach requires that climate models' simulated changes over the next century or so are skilful and can be used to derive the spatial patterns needed to generate further future projections, even though climate models have biases when compared with the present climate [21, 2].

When non-linear physical processes are invoked, models with significant biases can not be expected to reliably simulate plausible future changes in climate. Examples of this are the snow-albedo feedback at high latitudes [12] and sea-ice feedback [5, 15]. In the case of snow-albedo feedback, if the simulated temperature has a large positive bias, then there is no snow in the model 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. Since a decrease in soil moisture content is related to the occurrence of heat waves [35], it is plausible that patterns of large warming in some regions are a spurious result due to the model bias. The snow-albedo feedback can also have non-local effects. If the snow cover decreases over the land surface due to positive biases, the land surface warms faster than the ocean due to reduced albedo, and this can induce changes in the local atmospheric circulation pattern (surface convergence over the land and divergence over the ocean) [7]. This example suggests that model errors in a particular location could not only affect the projections on that location but could also have effects on surrounding regions through, for instance, changes in atmospheric circulation patterns.

3. External forcings do not modify of the internal variability of the climate system.

In the pattern scaling approach, the effect of external forcings is only taken into account through the global mean temperature response usually derived from a simple climate model that does not include any internal variability. Therefore by construction, the pattern scaled projections do not allow for the possibility of external forcings changing the mean response of the natural internal variability of the climate system, ignoring potential feedbacks between these two components.

It is well known however that for non-linear systems in general, changes in forcings affect the internal variability of the system in a non-linear way [19], and it is expected that similar results hold for the climate system [9]. It has been shown for instance, that in some cases there is a significant contribution of ENSO-related variations to the observed long term warming trends over the oceans [3] . This result suggest that changes in ENSO features due to anthropogenic climate change could affect the long term warming trends, effectively modifying the mean state of the climate system.

These assumptions raise doubts as to whether the pattern scaling technique is adequate for purpose at regional or local scales in general; changes at these scales are not expected to be linear. This doubt extends to the generalizations of pattern scaling that consist on sampling combinations of different sources of uncertainties in the spatial pattern and the scaler [17,14,8]. The key questionable step here is the linearity assumption. In the Supplementary Information a methodology to test this assumption within the perfect model setup is described. The results show that wether or not the linearity assumption holds depends on the Giorgi region [10] and time averaged considered, and on the methodology employed to estimate the errors in the spatial patterns.

2.2 Model Data

The remainder of the paper analyzes whether (or not) the pattern scaling approach preserves model information relevant for adaptation decision making, using an ensemble of climate model simulations that, by construction, is assumed to represent the "true" climate. This ensemble was generated by the climateprediction.net (cpdn) experiment [6,33] using the HADCM3L model [18], 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 cpdn experiment explores the effects of both, initial conditions and model parameter perturbations, the latter by perturbing the physics in the atmosphere, ocean and sulphur cycle components. Each simulation involves a 1920-2080 transient run driven by a set of natural forcing scenarios and the SRES A1B emissions scenario [29]. Details about the parameter perturbations, flux correction and forcings used in the experiment can be found in [6,33].

The ensemble used in this paper consists of a 32 member initial conditions (I.C.) model runs with standard values of the physical parameters. The cpdn experiment stores monthly time series of a variety of climate variables for the Giorgi regions [10,36]. In this paper, the pattern scaling approach is applied to monthly temperature time series for the Giorgi regions. Even though these regions are larger than the typical local or regional scales relevant for many impact studies, they are nevertheless useful for the purpose of evaluating the ability of the pattern scaling approach to preserve model information relevant to estimate climate risks.

3 Results

The aim of this section is to analyze the differences between the pattern scaled and model runs' projections, and then evaluate the significance of those errors when using pattern scaled projections to evaluate changes in climatic risks. To this end, the I.C. cpdn ensemble described in the previous section is taken to define the full range of variability; and by construction it is considered to provide quantitative decision relevant information.

The method analyzed here follows the implementation of the pattern scaling approach described and/or employed in references [1,24,30,38,39,41,42]. In this approach, the pattern of change is calculated for a given time slice in the future, s, as the ratio between the local and the global temporal averages of temperature changes as follows

$$P_s(\mathbf{x}, im) = \frac{< T(\mathbf{x}, im) >_s - < T(\mathbf{x}, im) >_{\text{baseline}}}{< \hat{T} >_s - < \hat{T} >_{\text{baseline}}}, \tag{2}$$

where the $< T(\mathbf{x}, im) >_s$ and $< T(\mathbf{x}, im) >_{\text{baseline}}$ are the average of temperature change field $T(\mathbf{x}, im)$ for month or season im over the time slice s or the baseline period respectively, and similarly for the global mean temperature $\hat{T}$. This pattern represents the local (at position $\mathbf{x}$) warming for month or season im per unit of global annual warming. Therefore, assuming a linear dependence of the local change on $\hat{T}$, when the pattern P_s is multiplied by a global annual temperature change $\tilde{T}$ simulated by an energy balance model (or any other GCM), it shields the corresponding spatial temperature change. This spatial change is added to the observed time series of anomalies from climatology over the baseline period , $T_{\text{baseline}}(\mathbf{x}, im, y)$, to yield realizations of climate change superimposed to year-to-year variability as follows

$$T^*(\mathbf{x}, im, s, y) = P_s(\mathbf{x}, im)\ \tilde{T}(y) + T_{\text{baseline}}(\mathbf{x}, im, y) \tag{3}$$

where s denotes the time slice, and y runs over the years within that time slice.

Since it has been shown that scaling from the ensemble mean improves results when compared to scaling from an individual simulation (see for instance [34]), the spatial pattern P_s is derived using $T(\mathbf{x}, im)$ and $\hat{T}$ for the I.C. ensemble mean. The baseline period is $1961-1990$, and s corresponds to seven time slices consisting of thirty years periods centered at the seven decades simulated by the I.C. ensemble between 2000 and 2079.

A set of changes are generated by multiplying the pattern P_s by the change in global mean temperature simulated by each model m in the I.C. ensemble, i.e., $P_s(\mathbf{x}, im)\ \tilde{T}_m(y)$. As mentioned above, the inter annual variability is obtained when adding these changes to the anomalies from the observed climatology. In the perfect model scenario set up, instead of the observed time series for the baseline period, a randomly selected model (say model M) from the I.C. ensemble is used for $T_{\text{baseline}}(\mathbf{x}, im, y)$. This allows to evaluate whether or not the pattern scaled ensemble in period s encloses the model simulated time series for model M. The ensemble generated by adding $P_s(\mathbf{x}, im)\ \tilde{T}_m(y)$ to model M anomalies from its climatology is called PSR. Note that, by construction, for each of the seven time slices labeled by s there is an ensemble of pattern scaled thirty years long time series.

Implications for climate risks analysis: occurrence of heat waves.

How significant are the differences between the I.C. ensemble model runs (MR) and the pattern scaled projections (PSR) when using this information for decision support? The answer depends on the particular impact being studied, the region under consideration and the time frame.

Consider for instance, the occurrence of heat waves in Southern Europe (defined as the region between 10W and 40E, and 30 and 50N). It is assumed that a *heat wave* in this region can be quantified in terms of the change in mean summer (June-July-August) temperature only, and that a heat wave occurs every time the projected change is larger than $2.3°C$ [37]. The choice of threshold is just illustrative, based on the 2003 European heat wave, when the mean summer temperature of Southern Europe was $2.3°C$ higher than the 1961-1990 mean [37].

Figure 1 summarizes the results. The top and middle panels show the model I.C. (MR) and pattern scaled (PSR) ensembles' projections for boreal summer temperature change as a function of time. The MR projections are continuous time series for the period 1900-2079, but are plotted here as overlapping thirty years periods to facilitate the comparison with the PSR ensemble. The baseline anomalies of model M are shown, for reference, in the first thirty year period of the middle panel (green line). It is clear that, by construction, the year-to-year variability of the PSR ensemble follows the variability of model M anomalies, independently of the time slice considered (i.e., independently of s). This explains why the actual model M projections (blue line in the middle panel) are not always contained within the range of the PSR ensemble.

The use of the pattern scaling approach to estimate changes in the risk of heat waves presupposes that the top two panels in Figure 1 provide the same information; that is, they should each show near identical curves if pattern scaling is to be effective in estimating that risk. As shown in the figure, however, the time varying risk of overshooting the threshold (defined as the fraction of model runs that overcome the threshold for a given ensemble), is ensemble dependent.

The bottom panel of the figure shows the risk of a heat wave occurrence, estimated as the fraction of model runs that overcome a given threshold ($2.3°$ for

Southern Europe for instance). For clarity, only decadal and thirty year means are shown in the figure. The results for the PSR ensemble do not coincide in general with the MR ensemble. For decadal averages , the results also vary depending on which time slice is used to calculate the pattern. For instance the risk of overshooting the threshold in the 2020-2029s is estimated to be 54%, 38% or 27% for Southern Europe by the PSR ensemble, depending on the time slice analyzed (2000-2029,2010-2039 or 2020-2049 respectively), while the true risk estimated by the MR ensemble is 39% .

The differences in the estimated risks are a consequence of the methodology used to obtained the pattern scaled ensemble PSR, since the estimated risk for a given decade can be obtained by scaling patterns that are calculated using thirty years periods centered at different decades. In other words, the PSR ensemble provides three different estimates for the risk in the 2020s, depending on whether the spatial pattern P_s is calculated using the thirty years periods 2000-2029,2010-2039 or 2020-2049. The negative consequences for decision support are significant: a decision maker interested in the 2020s risk of occurrence of heat waves in Southern Europe will be basing her decision on a risk that is overestimated by 15% if the pattern scaled projections are generated with the 2000-2029 pattern, or a risk underestimated by 12% if the projections are generated with the 2020-2049 pattern for instance. If using the 2010-2039 pattern however, the difference in risks is negligible, since in the context of the perfect model scenario, any error smaller than about 3% is not meaningful for a 32 members ensemble (the smallest possible frequency is 1/32).

One could argue that the methodology employed to obtain the PSR ensemble can only provide information about thirty years means, i.e., averages of climate indicators over the time slice used to estimate the spatial pattern of change. Though it is arguably unlikely that a thirty year mean of the risk of overshooting a temperature threshold could be a valid indicator for planing to adapt to changing risks of occurrence of heat waves, averaging over thirty years significantly reduces the error; the bottom panel of Figure 1 shows that the differences between the PSR and the MR ensemble is less than |4%| in all cases (compare solid and dashed horizontal lines corresponding to MR and PSR thirty years means respectively), becoming negligible according the criteria stated above.

A key distinction here is the difference between the ability of the MR ensemble projections to realistically quantify the risk of heat waves in Southern Europe during the 21st century and the pattern scaling applied to the MR ensemble (that is, the PSR ensemble) to represent the MR ensemble. In terms of decision-support, pattern scaling fails in this case; this failure stands regardless of whether the climate models (MR ensemble) provides credible output.

As shown in the Supplementary Information, the example discussed here is representative of similar results for other regions, choice of threshold and baseline model M. However, if internal variability is sampled not just by the baseline time series of model M, but also an ensemble of random permutations of this time series is considered (see details in the Supplementary Information), the risks estimated by the MR and the PSR ensembles become comparable, reducing the errors to less than 5% for the regions and time averages analyzed.

Recent generalizations of the pattern scaling approach sample combinations of different sources of uncertainties in the spatial pattern and the scaler, such as model structure and scenario uncertainty, and provide probability distributions of changes that attempt to encompass all these uncertainties [14, 17, 8]. These generalizations are not relevant to the results above because the goal was to evaluate whether or not the pattern scaling approach considered here can provide internally consistent decision support information in a "perfect model scenario". This is represented in this work by the initial conditions ensemble of model runs which define the *true* range of variability. Failure in this "perfect model scenario" indicates failure in more complex real world environments even when the recent generalizations work perfectly.

4 Conclusions

The question of whether or not the pattern scaling approach actually provides robust and reliable decision making information was investigated. Generic limitations of this approach have been discussed in the literature; here the aim was to identify whether or not these limitations preclude the use of pattern scaling for quantitative decision support.

Firstly, three major assumptions underlying the methodology were discussed: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 not affected strongly by errors in the base climate; and third, that the external forcings do not modify the internal variability of the climate system. In the Supplementary Information it was shown that, in the perfect model scenario, wether or not the linearity assumption holds depends on the Giorgi region and time averaged considered, and on the methodology employed to estimate the errors in the spatial patterns. Therefore, it was argued that these assumptions are not expected to hold in general at regional or local scales, and consequently evidence of their validity is required for each particular study that applies the pattern scaling approach to evaluate impacts of climate change.

Secondly, under the questionable assumption that there are scales at which the method could be used, the internal consistency of the decision relevant information generated using an initial conditions ensemble of GCM model runs, and a surrogate ensemble of pattern scaled runs derived from it was evaluated. The pattern scaled runs were generated using the initial conditions ensemble mean to derive the spatial pattern, and each individual model run global mean temperature to scale it. Year to year variability was taken into account by adding a time series of anomalies for a predetermined baseline period [1, 24, 30, 38, 39, 41, 42]. These two ensembles are defined to be internally consistent if the information that they provide for decision support is equivalent, as when for instance, the estimated climatic risks are indistinguishable (within a margin of error determined by the ensemble size). Using as an example the risk of occurrence of heat waves in Southern Europe, and under the assumption that the ensemble of GCM model runs has decision relevant information, it was shown that this information is lost or distorted if models (with their internal variability) are replaced by the pattern scaled projections. For the example considered, it was found that if a decision maker was to base her adaptation planning on the information provided by the pattern scaled ensemble or the MR ensemble, the pathways to be undertaken according to the two ensembles would be different due to the different estimates of the changing risk. An approach to reduce the errors based on re sampling from the baseline period was described in the Supplementary information.

In conclusion, deploying the pattern scaling approach analyzed in this paper as a computationally convenient way to generate scenarios for impacts, adaptation an vulnerability is problematic. Our findings make concrete the IPCC 4AR statement that "for some quantities like variability and extremes, such scaling is unlikely to work" [36][1], 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.

Clearly, when climate model simulations do not have skillful information at the impact 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. However, this should not be seen as a limitation for adaptation decision making and planning; comprehensive risk management approaches specifically designed to deal with the deep uncertainties inherent to climate change information can be used to avoid the risk of maladaptation [43, 32, 13].

Acknowledgements This research was supported by the LSE's Grantham Research Institute on Climate Change and the Environment and the ESRC Centre for Climate Change Economics and Policy, funded by the Economic and Social Research Council and Munich Re. EBS acknowledges support from the NERC EQUIP project (NE/H003479/1). LAS gratefully acknowledges the continuing support of Pembroke College, Oxford. We thank all the member of the public who participate in the climateprediction.net project, and the climateprediction.net team for their technical support.

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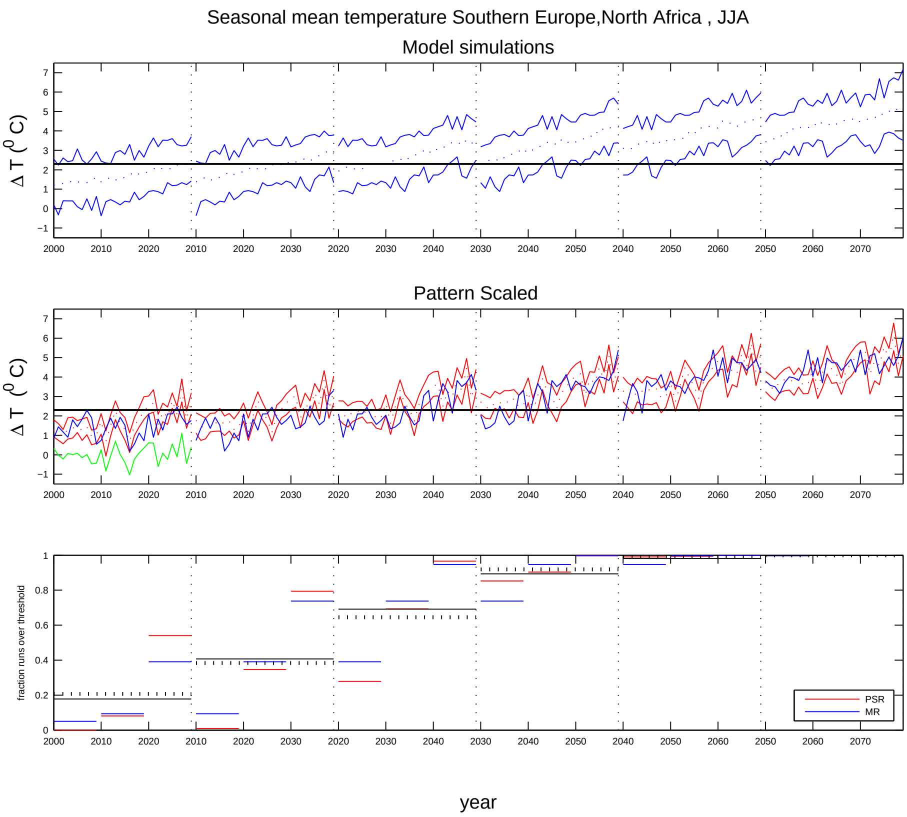

Fig. 1 Southern Europe projections for summer warming and risks of heat waves. **Top and middle panels**: The I.C. (top) and PSR (middle) ensembles' projections for summer temperature change are plotted as a function of time. The thick horizontal line indicates the 2.3° threshold. In these two panels the two solid lines correspond to the ensemble range and the dotted line is the 50% percentile. Notice that for the MR the projections are continuous time series for the period 1900-2079, but are plotted here as overlapping thirty years periods to facilitate the comparison with the PSR ensemble. The blue line in the middle panel correspond to the I.C. model run randomly sampled to be used as surrogate for observed anomalies (model M), and the green line (shown for reference in the first thirty years period) corresponds to the baseline (1961-1990) anomalies of model M used to construct the PR ensemble. Notice that the pattern scaled ensemble does not completely enclose the trajectory of model M (blue line) as expected by construction. **Bottom panel**: the risk of a heat wave occurrence, estimated as the fraction of model runs that overcome the 2.3° threshold, as quantified by the MR (blue) and the PSR (red) ensembles. Solid colored lines indicate fractions of runs over threshold for decadal means, and black solid (MR ensemble) and black dashed (PSR) lines correspond to thirty years means. Notice that the MR projections of changing risk are continuous time series for the period 1900-2079, but are plotted here as overlapping thirty years periods to facilitate the comparison with the PSR ensemble