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ENSEMBLES Deliverable D1.16

Assessment of relationships between errors in seasonal to decadal hindcasts and longer term climate projections found in perturbed physics ensembles using the DePreSys system

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1. Introduction

In this study, we investigate whether seasonal and/or decadal forecast errors could be used to constrain long term climate change projections, as suggested by Palmer et al. (2008) (hereafter P08). If the same chain of physical processes is responsible for both seasonal variations and long term climate change, as hypothesised by P08, then climate change projections for the end of the century could be recalibrated based on the reliability of seasonal forecasts. However, Scaife et al (2009) argue that there are some processes controlling future climate projections that did not strongly influence past seasonal variability. If these processes are reliably modelled, recalibrating climate projections using seasonal forecast reliability could wrongly discount useful climate projections.

During the past few years, other metrics of model performance have been used in attempts to constrain climate change projections at either a global or regional level. A number of studies have attempted to weight members of multi-model or perturbed physics ensembles according to how well they reproduce observed multiyear averages of aspects of recent climate (e.g. Giorgi and Mearns (2002), Murphy et al (2004), Schmittner et al. (2005); Tebaldi et al. (2005), Watterson (2008)). Observed changes in surface temperature during the past century have also been used as a constraint in a number of studies (e.g. Allen et al. (2000), Stott et al. (2006), Greene et al. (2006)), and Murphy et al. (2009) combine both these types of information). All these studies make a basic assumption that errors in simulations of present day climate or past changes are related to errors in climate change projections, and some of them make explicit use of such relationships in calibrating their future projections (see also Piani et al., 2005).

Some promising examples of strong relationships between past errors and future changes have been documented (e.g. Hall and Qu (2006), Knutti et al (2006)), however the relationships may become weaker then multivariate metrics of historical performance are used (e.g. Pierce et al., 2009). At first sight this might be taken to imply that the idea of weighting or calibrating future projections according to past performance is flawed, however we do not believe this is the case. Rather, such a result is likely to arise because models tend to display compensating errors between the many aspects of historical performance which are potentially relevant to projections of any future variable. If so, then this actually emphasises the importance of accounting for a broad range of observational constraints, in order to avoid the risk of mis-calibrating a projection by relying too strongly on one specific aspect of past performance. This provides the motivation for the present study, on the basis that the use of information from seasonal-to-decadal hindcast errors suggested by P08 could be used to augment, rather than replace, the use of constraints based on mean climate or past climate change. For this purpose we use a comprehensive set of initialised decadal hindcasts together with climate change projections from the same model to investigate whether there is any relationship on regional scales between short term forecast errors and climate change projections.

2. Experiments

The experiments used in this study are based on the Decadal Prediction System (DePreSys, Smith et al. 2007), updated to sample model uncertainties, and denoted by DePreSys_PPE in other ENSEMBLES reports. Model uncertainties are sampled using an ensemble of 9 variants of the HadCM3 coupled climate model selected from a larger perturbed physics ensemble used for centennial climate projections by Collins et al (2006). The nine variants are distinguished though the application of multiple perturbations to uncertain model parameters, selected to sample a wide range of climate sensitivities and ENSO amplitudes. Note also that these experiments also differ from Smith et al. (2007) through the use of (a) flux adjustments to limit sea surface temperature and salinity biases, (b) a fully interactive sulphur cycle scheme and (c) updated datasets for radiative forcing agents. The following seasonal, decadal, and climate change experiments are considered in this study, and are part of the ENSEMBLES stream II dataset:

- Seasonal hindcast experiments are started 4 times per year over the period 1960-2005. Averages of the forecasts with lead times of 2 to 4 months are analysed in this study.

- Decadal hindcast experiments are performed every year over the same period (1960-2005) and averages over 9 years are analysed.

- Centennial climate projections are performed until the year 2100 following the A1B scenario of the IPCC AR4. The climate response is calculated as the average over the period 2070-2100 with respect to the period 1970-2000.

3. Results

The forecast errors and climate change responses of the experiments are compared with surface air temperature (HadCRUT3v, Brohan et al. 2006) and precipitation (GPCC, Schneider et al. 2008) observations spatially averaged over Giorgi regions (Giorgi and Francisco 2000) shown in Table 1.

The seasonal and decadal hindcast errors for the Giorgi regions (Table 1) are shown for temperature and precipitation in figure 1a and 1b, respectively. All data are normalised with the standard deviation of the detrended observational time series to avoid correlations arising by chance in regions with large seasonal and decadal variability. As expected, the ensemble means (black upper case letters) have in general smaller hindcast errors than the individual simulations (coloured lower case letters). Additionally, a relationship exists between the seasonal and decadal hindcast errors, with correlations (R) of 0.44 (0.55) and 0.74 (0.75) for temperature and precipitation respectively, for individual ensemble members (ensemble means).

A: Australia	L: Western Africa
B: Amazon Basin	M: Eastern Africa
C: Southern South America	N: Southern Africa
D: Central America	O: Sahara
E: Western North America	P: Southeast Asia
F: Central North America	Q: East Asia
G: Eastern North America	R: South Asia
H: Alaska	S: Central Asia
I: Greenland	T: Tibet
J: Mediterranean Basin	U: North Asia
K: Northern Europe	

Table 1: Key to regions defined by Giorgi and Francisco (2000).

(a) (b)

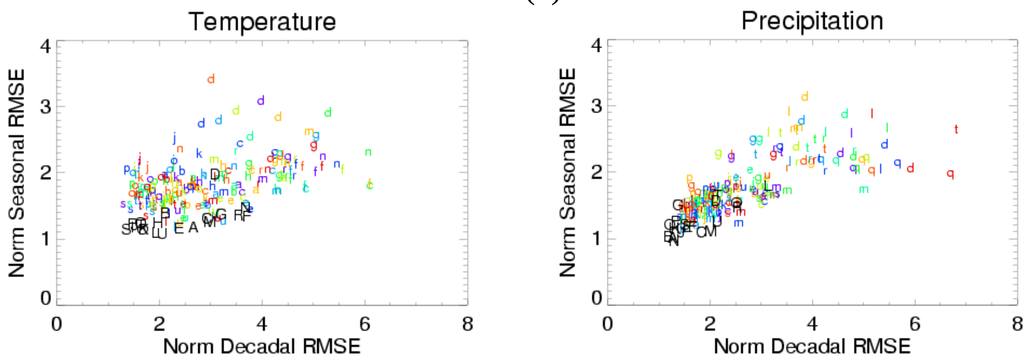

Figure 1: Normalised seasonal and decadal (a) temperature and (b) precipitation hindcast errors for the individual ensemble members (small coloured letters representing the regions in Table 1, with different colours for each ensemble member) and ensemble means (capital black letters) in Giorgi regions.

The relationship between the regional climate change response and seasonal and decadal hindcast errors is shown in figures 2 and 3 for temperature and precipitation respectively. For individual ensemble members this relationship is weak, although slightly stronger for precipitation than temperature (R= -0.09 (0.16) and -0.10 (0.24) between climate change response and seasonal and decadal RMSE respectively, for temperature (precipitation)). However, for the ensemble mean the correlations are slightly higher (R= -0.15 (0.19) and -0.36 (0.36)).

The experiments can also be analysed in an idealised way. For this “perfect model” approach the ensemble mean is considered as the truth and the difference to the individual ensemble members is used to calculate the hindcast “error” (figure 4). Again, a linear relationship is found between the seasonal and decadal forecast errors for temperature and precipitation (R= 0.27 and 0.39, respectively).

(a) (b)

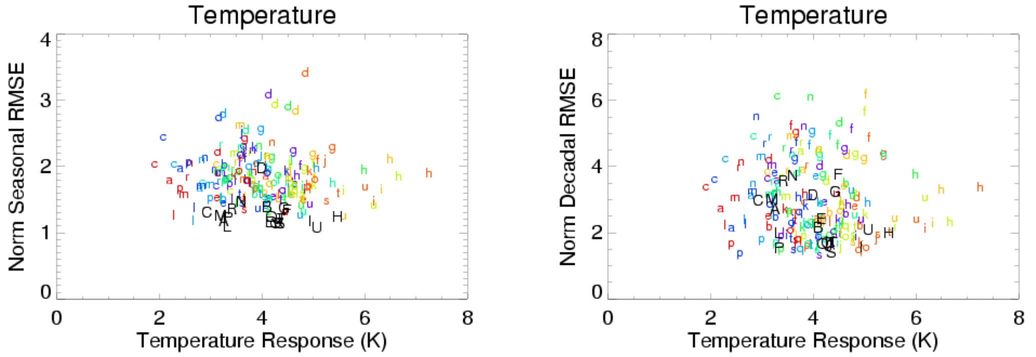

Figure 2: Climate change temperature response and normalised (a) seasonal and (b) decadal hindcast errors for the individual ensemble members (small coloured letters) and ensemble means (capital black letters) in Giorgi regions.

(a) (b)

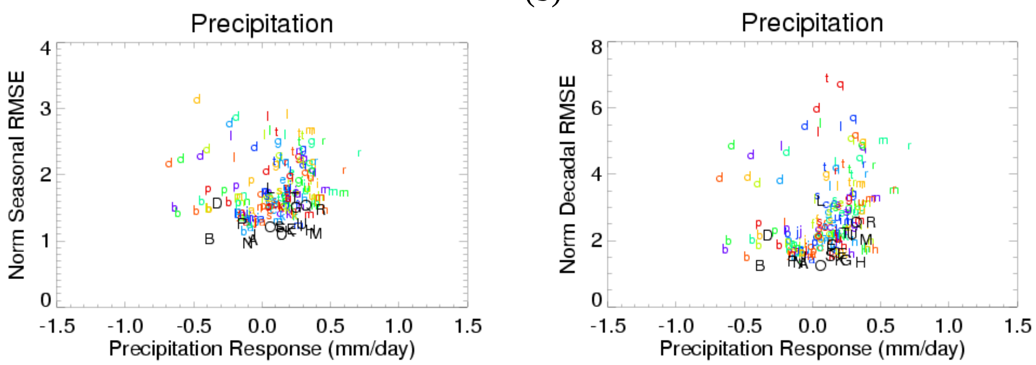

Figure 3: As fig.2 but for precipitation.

(a) (b)

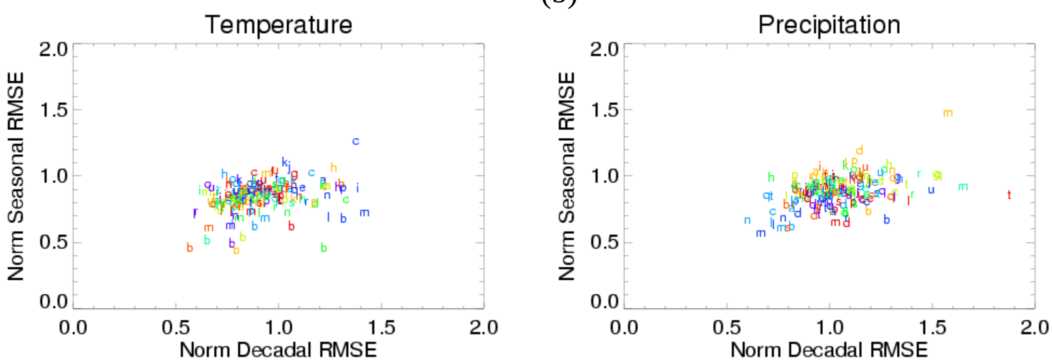

Figure 4: Seasonal and decadal (a) temperature and (b) precipitation hindcast errors for the "perfect model" approach (small coloured letters) in Giorgi regions.

The “perfect model” seasonal and decadal hindcast errors are plotted against regional climate change response for temperature and precipitation in figures 5 and 6. Again, the relationship between the climate change response and the seasonal and decadal hindcast “errors” is weak, but slightly stronger for precipitation than temperature (R= 0.01 (0.20) and -0.10 (0.09) between climate change response and seasonal and decadal RMSE, respectively, for temperature (precipitation)).

(a) (b)

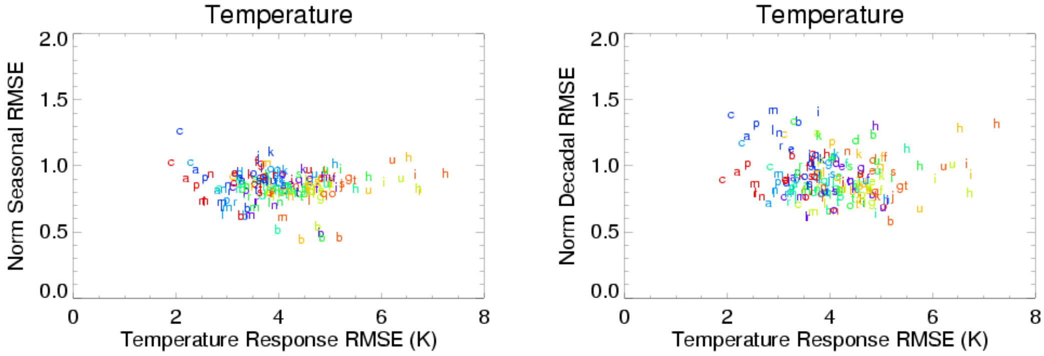

Figure 5: Climate change temperature response and (a) seasonal and (b) decadal hindcast errors for the individual ensemble members (small coloured letters) in Giorgi regions.

(a) (b)

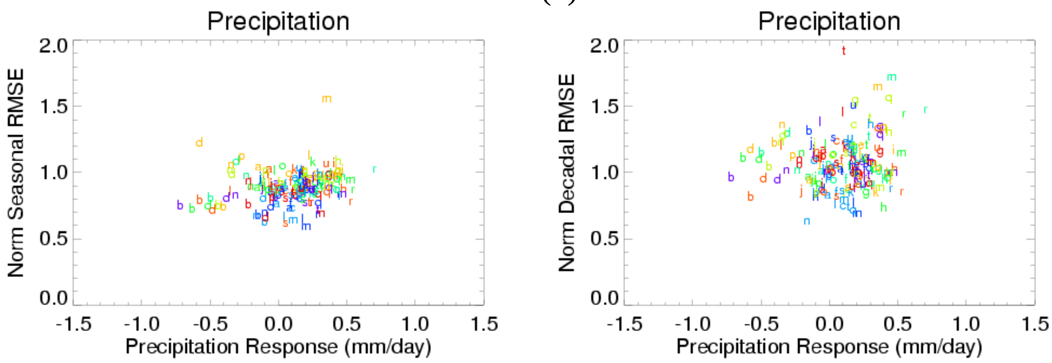

Figure 6: As fig.5 but for precipitation.

Conclusions

We have found a relationship between the seasonal and decadal regional hindcast errors in our experiments. The correlation (R) between seasonal and decadal ensemble mean hindcast errors for 21 “Giorgi” regions is 0.55 and 0.75 for temperature and precipitation respectively. There is a similar relationship when the data are analysed in an idealised way, taking the forecast ensemble mean as the “observations”, although it is unclear why the relationship is weaker (R=0.27 and 0.39 for temperature and precipitation) in this case. This is an encouraging result, as prospects for direct calibration of decadal forecasts based on past decadal hindcasts are limited by the small number of independent cycles of past decadal variability available for assessment. In contrast, it is easier to build up large samples of quasi-independent seasonal hindcast datasets, hence the use of past seasonal verification data to calibrate future decadal predictions is a promising avenue for research.

The relationship between seasonal and decadal forecast errors and climate change response is much weaker (R=-0.15 (0.19) and -0.36 (0.36) between temperature (precipitation) climate change response and seasonal and decadal errors, respectively). Further analysis is required to determine the statistical significance of these correlations. If they are significant, then a modest recalibration of climate projections based on seasonal and/or decadal forecast errors may be possible, as suggested by P08. However, any such recalibration should take into account the fact that relationships between short term forecast errors and centennial climate change are imperfect, presumably because climate change is also influenced by processes that do not control short term variability, as argued by Scaife et al. (2009). We would therefore recommend that seasonal to decadal hindcast errors should be combined with other aspects of historical climate model performance (see Introduction) in order to provide broadly-based metrics which account more fully for the range of potential influences on future projections.

Finally, we note that this is a limited study, considering only projections of long term average temperature and precipitation. Furthermore, we considered only seasonal to decadal hindcasts *of the same variable in the same region* to assess the prospects for calibration of the climate change projections. A more complete study, considering multivariate global aspects of hindcast verification, and a wider range of future projection variables, might yield different conclusions. Also, the results may depend on the model ensemble chosen for investigation. Our results should therefore be interpreted with caution. However they do indicate that a direct calibration of climate change forecasts, based only on short-term hindcast errors, and without hedging the degree of calibration to account for limitations in the strength of the relationships between them, would be very difficult to justify.

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