Prediction beyond the seasonal time scale

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1. Introduction

Dynamical seasonal prediction systems have been developed by institutes such as ECMWF and NCEP and can produce skillful predictions months ahead, in particular in the tropics. The notion that the climate system contains inherent memory on longer time scales as well has lead to exploration of the potential for decadal predictions. In particular, the oceanic heat content and the relatively slow ocean circulation provide memory that may impact the climate system on decadal time scales. Idealized studies have shown that aspects of the climate may be predicted decades ahead. Griffies and Bryan (1997) have pioneered this work by generating ensemble simulations, initialized from a long control run of a coupled atmosphere-ocean-sea ice climate model. Others have followed, and in particular the meridional overturning circulation in the Atlantic ocean associated with deep water formation has gained a lot of attention as one of the sources for decadal predictability (e.g. Collins and Sinha, 2003). Statistical estimates of potential predictability point to the midlatitudes and high latitudes as areas where predictability at decadal time scales may be obtained, with a particular focus on the oceans (Boer 2004).

Motivated by the idealized model studies and because of technical advancements in ocean syntheses data sets, decadal predictions, initialized from estimates of the observed ocean state are made now (Smith et al 2007, Keenlyside 2008, Pohlmann 2009, being prime examples, originating from the EU Ensembles project). The skill of these predictions is limited, but one should be aware that these are first attempts. A multi-model estimate of skill does show skillful predictions in the North Atlantic and in the Pacific, in accordance with earlier statistical estimates of potential predictability (van Oldenborgh et al 2010, subm. to Clim Dyn).

An interesting feature of climate fluctuations at the decadal time scale is that internal variability is sizeable compared to the impact of rising greenhouse gas concentrations. Decadal predictions can reduce the uncertainty of climate predictions due the presence of internal variability. This is relevant to climate predictions at regional scales, because uncertainties due to internal variability dominate at regional scales compared to the uncertainty due to forcing by increasing greenhouse gasses.

There is also increased societal interest in decadal predictions. Typically, large scale investments in various sectors are made for years to decades. There is a practical need for climate information as part of developing climate adaptation strategies. If decadal predictions are skilful they can be of great use in the decision-making process. Currently, users mostly rely on information from (downscaled) projections of climate change, focusing on mean changes. Any additional information on the

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evolution of interannual to decadal variability in the climate system can be of large value to various stakeholders. Lessons can be learned from seasonal prediction activities, where large stakeholder groups use information from climate predictions. When merging the expertise and experiences from the seasonal prediction and climate change science and adaptation communities, both the science can advance and more effective use of climate information can be made.

2. Patterns of decadal variability

A prerequisite of decadal predictability is the presence of decadal variability. The climate system can be regarded as a set of subsystems with different statistical properties interacting with each other. One of the simplest models of climate has been proposed by Hasselmann (1976). Noting that the atmosphere is a fluid with a chaotic character and fast response time that forces the ocean with a large heat capacity and long diffusive time scales associated with it, he proposed a simple model, which can be described as:

$$\frac{dX}{dt} = \alpha X(t) + \zeta(t)$$

Here X represents a climatic variable, ζ is a white noise term representing atmospheric chaotic variability, and α is a damping parameter. The solution to this system for X results in a red noise process (such a model is also called an autoregressive (AR)1 process, usually formulated as $X_t = \alpha X(t-1) + \zeta(t)$).

When analyzing the spectral properties (in the time domain) of many climatic variables, such as global mean surface temperature, a red noise spectrum is found. The atmospheric properties, such as the winds, display a white noise spectrum. So, this simple model can act as a 0-hypothesis of climate variability. Any deviations from the red noise behaviour, in particular peaks in the spectrum, indicate oscillatory behaviour. The presence of such patterns of variability opens the potential of predicting the phase and amplitude of the variability with dynamical atmosphere-ocean-sea ice-land models when properly initialized.

Patterns of decadal variability have been found in the observational records. Most notably the Pacific Decadal Oscillation (Mantua et al 1997) and the Atlantic Multidecadal Oscillation (Schlesinger and Ramankutty, 1994) have received a lot of attention in the literature. These patterns are often identified in the sea surface temperature. Strictly speaking, these patterns can not be qualified as 'oscillations' as the observational records are too short to distinguish the patterns from red noise. However, paleo records indicate that, indeed, oscillatory behaviour is found in surface ocean characteristics (e.g. Delworth and Mann, 2000). In general, the amplitude of these fluctuations is much smaller than the interannual variability generated by El Niño Southern Oscillation.

Here, only the Atlantic Multidecadal Oscillation (AMO) will be shortly discussed, since it is of relevance to the climate over Europe. This pattern of variability displays a large scale north south gradient in the Atlantic Ocean. It shows decadal fluctuations with (warmer North Atlantic) from the 1920s until about the 1960s, negative values (cooler North Atlantic) up to about the mid 1990s and a return to positive values after that. Since the world warmed due to enhanced greenhouse concentrations as well, a good measure of the AMO corrects for the world-wide warming, although it is still a matter of debate whether the AMO projects on the global mean temperature. These temperature variations are associated with societally relevant climate phenomena, such as the occurrence of hurricanes and Sahel droughts. Nearly all coupled atmosphere-ocean-land-sea ice climate models generate AMO-like variability, although the time scales, patterns and mechanisms that generate the variability varies between the models. However, nearly all models relate the AMO to variations in the Atlantic deep meridional overturning circulation (AMOC). Increases in strength transport larger amounts of heat into the North Atlantic by the upper branch of the overturning circulation, while reduction in overturning transport leads to cooler North Atlantic. The challenge is to predict these variations in the ocean circulation. With the recent increase in the coverage of ocean observations, in particular due to the ARGO floats, there may be enough oceanographic observations to constrain the ocean state.

3. Potential predictability

The potential for decadal predictions can be derived using complex climate models. Two estimates will be discussed here. The first is a statistical estimate, based on long control runs, or if available, from observational data. The second is an estimate using idealized prediction experiments. We will use the EC-Earth model (Hazeleger et al 2010) to illustrate the different measures of predictability.

3.1. Diagnostic potential predictability

A statistical measure of predictability used in many studies is the diagnostic potential predictability. It measures the ratio of variance within a particular time scale with respect to the total variance. Often, long control runs have been used for studying this measure (e.g. Boer, 2000). It is defined as:

$$DPP = \frac{\sigma_v^2 - \frac{1}{m}\sigma^2}{\sigma^2}$$

With σ_v^2 the variance of *m*-year means and σ^2 the total variance. Figure 1 shows the DPP for the EC-Earth model for 10-year mean sea surface temperatures obtained from a multicentury control run. The reader should ignore regions with sea ice. Two regions stand out: the subpolar gyre in the North Atlantic and the Southern Ocean. Remarkably the Pacific shows hardly potential predictability, but it becomes more apparent at somewhat shorter time scales. Potential decadal predictability in the subpolar gyre is robust amongst models and indicates that oceanic processes are relevant for predictability in this region, possibly associated with the AMOC.

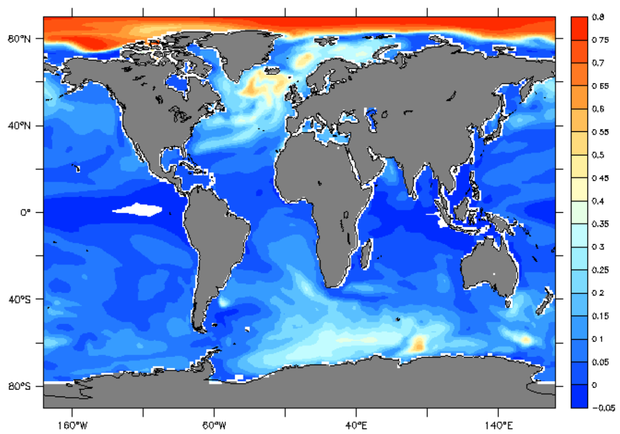


Figure 1: Diagnostic potential predictability for decadal mean sea surface temperatures in EC-Earth (sea ice covered areas should be discarded) obtained from a multi-century control run.

3.2. Prognostic potential predictability

Another measure of potential predictability is the prognostic potential predictability. Here an ensemble approach is used. An ensemble of simulations is initialized from climate states derived from a control run of the same climate model as the one that is used for making the predictions. Typically 10 start dates and 10 ensemble members are used. The measure of predictability is the spread in the ensemble in relation of the total variance:

$$PPP = 1 - \frac{\frac{1}{N(M-1)} \sum_{j=1}^{N} \sum_{i=1}^{M} [X_{ij}(t) - \overline{X_j}(t)]^2}{\sigma^2}$$

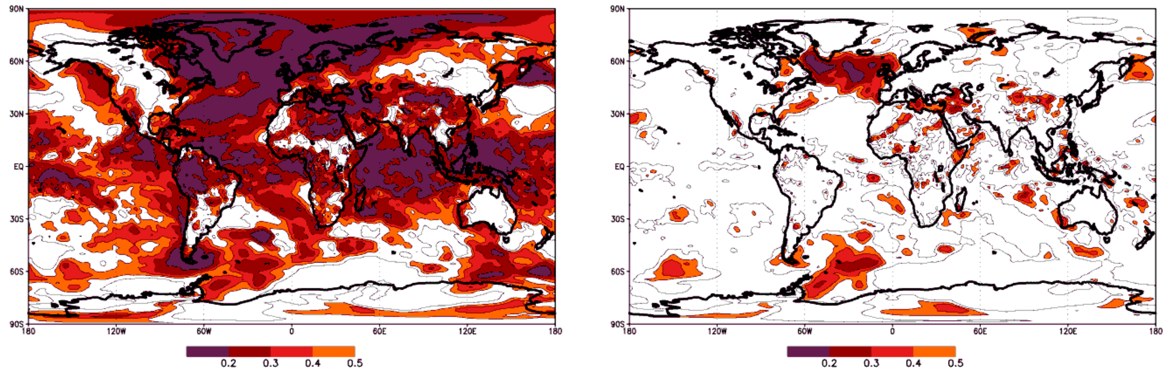


Figure 2: Prognostic Potential Predictability of 2-meter temperatures at 1-10 year lead time in EC-Earth (Torben Koenigk, SMHI, pers. comm.). (a) Without removing long term drift (b) after removing long term drift.

In Figure 2a we show *PPP* for 2-meter temperature in EC-Earth, using lead times from an average over 1 to 10 years. From this measure we see that large areas over the ocean, in particular the Indian and the Atlantic, and large areas over land are potentially predictable. There is a caveat though. The control run used for obtaining this diagnostics was not in balance and exhibits drift. In this case, it means that the long term trend is potentially predictable. In fact, this is relevant information for a stakeholder that uses climate information, although scientifically, no dynamical climate model is needed to make such a prediction.

When removing for the drift statistically, or when a better spunup model is used, familiar patterns of high predictability are found (figure 2b). In particular the North Atlantic subpolar gyre is a hotspot for predictability. Unfortunately, predictability over land-areas appears to be small. Note, however, that this may be due to the specific diagnostic used here and the method to remove the long term drift.

4. Decadal hindcasts

The previous sections show that there is scope for decadal predictions. Attempts have been made to produce decadal hindcasts, starting from 1960 every 5 years (1960, 1965, 1970, ...2000) with a duration of 10 years. Such a prediction involves initialization of the simulations, perturbation and verification, which will be addressed hereafter.

4.1. Initialization

Different than in Numerical Weather Prediction, the ocean needs to be initialized carefully when making decadal predictions. Ocean analyses have been made by different groups with different methodologies (e.g. optimum interpolation, ensemble Kalman filtering, 3-D or 4-D VAR). An overview of these different products and references can be found at the CLIVAR EASYINIT website: http://www.klimacampus.de/easy_init_ocean0.html.

Ocean synthesis data is available from the late 1950s on. However, ocean data is sparse during the pre-ARGO period, especially in the deep ocean. It is unclear whether there are enough observations to constrain the oceanic state. The large observational error hampers the production of hindcasts of decadal prediction. Nevertheless, efforts are under way to systematically assess the impact of observational coverage (e.g. Dunstone and Smith 2010). One should be aware which data to use for the initialization. There are large differences in data assimilation techniques which lead to very different products. In order to maintain physical consistency, it is good practice to use an analysis set which has been produced by the same numerical ocean model as is used in the prediction system.

Another issue is the systematic model error. By initializing with the full ocean state derived from observations, the state will deviate from a climatological mean model state. Coupled models are poorly constrained and contain severe biases. This issue is known from seasonal predictions. There, calibration of forecasts is performed by determining the mean drift as a function of lead time of the prediction. Figure 3a shows decadal predictions with the EC-Earth model (Hazeleger et al 2010; Wouters et al in prep). Shown are 10 year forecasts of global mean sea surface temperature with EC-Earth, initialized every 5 years from NEMOVAR (Balmaseda pers comm) data. It is clear that every prediction initially exhibits a cooling. This is due to the cold bias of EC-Earth compared to observed climate. One can remove the common drift, assuming stationarity of the drift, which is shown in Figure 3b.

An alternative approach is to initialize only observed anomalies on top of a climatological mean model state. This approach has been used by, for instance Smith et al (2007). Typically, temperature and salinity anomalies are nudged in a coupled model. There are many choices to make in this process. For instance: How to define a climatology? Which variables to nudge? Until which depth to nudge? What time scale to use for nudging? There is no accepted theoretical framework to address these questions and often heuristic approaches are taken.

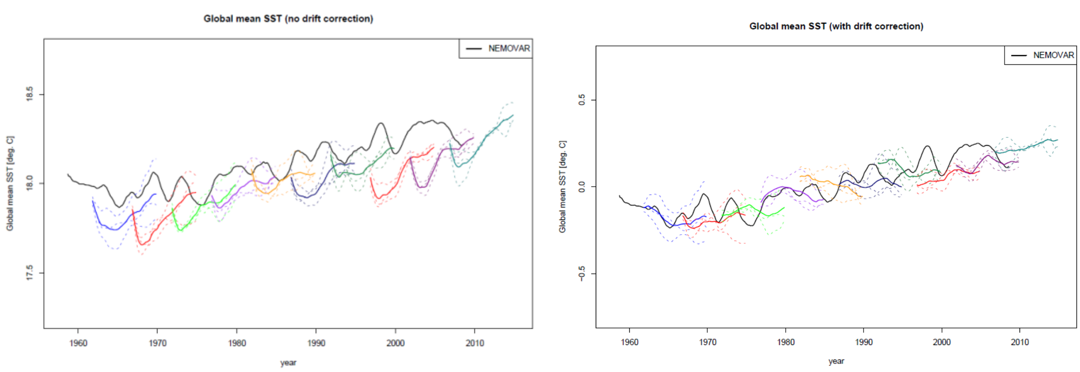


Figure 3: Decadal hindcasts in EC-Earth using full initialization with NEMOVAR ocean analysis data. The NEMOVAR global and annual mean sea surface temperature is shown in black, the hindcasts in color (ensemble mean of 3 members in solid, dashed lines show the spread of the ensembles). (a) Without removing drift (b) when removing the common drift.

There has been some criticism on anomaly initialization. One aspect is that it is that the ocean state is not in equilibrium with its surface forcing, since it is a mixture of a model state and an estimate of the observed state. Another potential problem is that due to biases in the mean state of the model will still lead to drift. Flux correction has been proposed to correct for this drift.

Finally, methods of coupled initialization are under consideration where the fully coupled atmosphere-ocean-land model is used to assimilate observations (e.g. Zhang et al 2007).

4.2. Perturbation and generation of ensembles

The notion of the importance of uncertainties in the observed state, model uncertainty and the chaotic nature of the atmosphere led to the development of probabilistic ensemble prediction systems in Numerical Weather Prediction. Although the main motivation to produce ensemble forecasts at decadal time scales is the same, there are particular aspects to decadal predictions that differ from Numerical Weather Prediction.

At decadal time scales, it is the ocean that primarily drives low-frequency variability. Not much is known about variability in the deep ocean, which makes representing observational uncertainties a subject of ongoing research. An additional aspect which has hardly received attention is to probe uncertainty in the forcing. In particular the forcing related to tropospheric aerosol and possibly land use. In order to address model error different approaches have been taken. It has been shown that multi-model ensembles outperform single model ensembles. However, it is a rather ad hoc approach. A more systematic approach is to perturb uncertain parameters of climate models associated with the parameterizations of subgridscale processes. Finally, a more physical-mathematical approach can be to include stochastic perturbations to a model to represent subgridscale parameterisations (so-called ‘stochastic physics’ approach).

In order to generate ensembles in Numerical Weather Prediction, perturbations that grow most rapidly are applied. For the decadal prediction system, the most relevant growing perturbations are likely found in the ocean. Different techniques have been suggested such as bred vectors, stochastic optimals and singular vectors, e.g. for 3-D ocean (Hawkins and Sutton 2009). These techniques have been suggested, but there is no systematic assessment of their value. An additional value of the perturbing techniques is that they can be informative for the design of observing systems.

4.3. Verification

Although still at its infancy, decadal predictions have been published and verified against observations. A probabilistic verification is hardly possible given the short records. Instead, robust and simple verification methods often suffice. Anomaly correlation coefficients of the ensemble mean give high signal/noise ratios and avoid bias corrections. It is best practice to aggregate spatially into regions or patterns of climate variability to improve signal/noise ratios. Long-term trend needs to be dealt with separately, since on decadal time scale the impact of the external forcing (primarily due to CO_2 rise) can be significant and can be regarded as separate from predictability due to initializing the model.

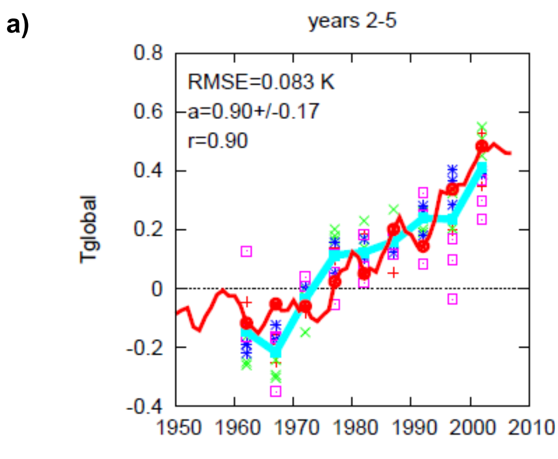
Benchmark statistical models are useful to verify decadal predictions. The simplest statistical benchmark model can be formulated as:

$$X(t+\tau) = A(\tau)X(0)$$

If $A(\tau)$ = 0 then the model represents climatology, if $A(\tau)$ = 1 then the model represents persistence, and for other values of $A(\tau)$ damped persistence. More complicated statistical models can be used as well.

Here we illustrate verification of decadal predictions of the EU Framework 7 ENSEMBLES project. Here, 4 global coupled models have been used with which decadal predictions were made (10 years, 3 members each model, starting every 5 years from 1960 on with ECMWFs IFS/HOPE, UKMOs HADCM3, MétéoFrance' ARPEGE/NEMO, IFM/GEOMARs KCM).

We start with verifying the ensemble multi-model mean global temperature (surface temperature for ocean, 2-meter temperature). With 2-5 years lead time the global mean temperature is very well predictable. The anomaly correlation is 0.9 (Figure 4a, obtained from van Oldenborgh et al. 2010). However, just as with the potential predictability problem, it is more insightful to verify the predictions after removing the long-term trend. After detrending the correlation drops enormously (Figure 4b). However, many patterns of climate variability have a very local expression, sometimes orthogonal to the global mean temperature evolution. So, we also verified the surface temperature at individual gridpoints. In this case, again, the anomaly correlations are very high (even up to 10 years lead time, not shown). However, when the drift (likely due to the external forcing by increased greenhouse gas emissions) is removed, much smaller anomaly correlations are found. Interestingly, there are regions with substantial skill above persistence at multiyear time scales. Among those regions is the subpolar gyre in the North Atlantic Ocean, a region that was identified as a region of potential predictability (Figure 5). This may be associated with variations in deep water formation and possibly the Atlantic Meridional Overturning circulation. As a consequence the Atlantic Multidecadal Oscillation is predictable at multi-year time scales as well.



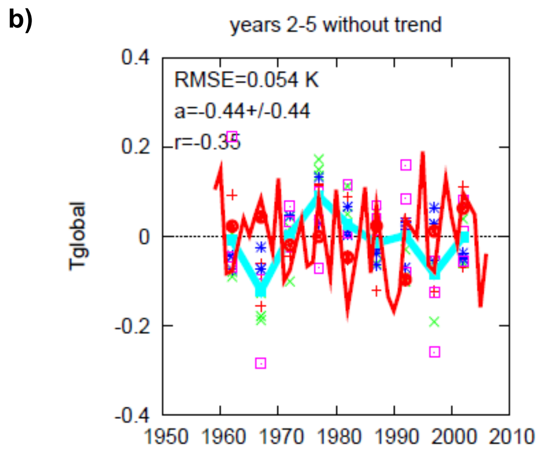


Figure 4: Multi-model decadal hindcasts verification. Red: observed global mean surface temperature, blue the ensemble mean global mean temperature prediction at 2-5 year lead time, symbols the different models (each model has three members). The inset shows the correlation (R, regression coefficient a and the root mean square error RMSE). (a) Without removing the long-term trend (b) when removing the trend.

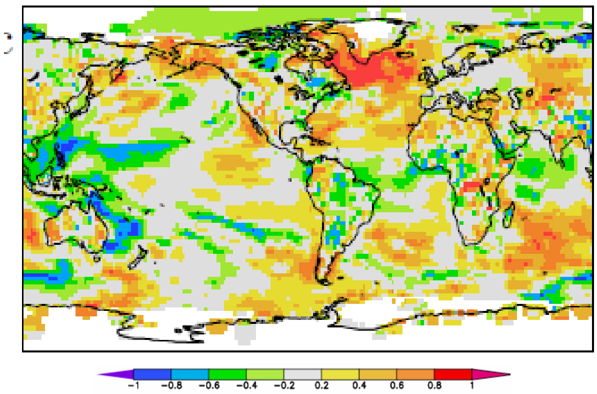


Figure 5: Anomaly correlation between observed and multi-model ensemble mean prediction of surface temperature at 2-5 year lead time.

5. Outlook

Decadal predictions are still at its infancy and the work conducted on these predictions is in the scientific realm. However, there is clearly scope for decadal predictions. Patterns and mechanisms of decadal climate variability have been identified, often related to oceanic processes and ocean-atmosphere coupling. Also, potential predictability diagnostics show that skillful decadal predictions can potentially be made.

There is interest in the user community as well. Many long-term investments on large scale infrastructure often have a time span of decades. On this time scale the uncertainties in climate predictions are dominated by natural variability and model uncertainties, rather than the pathways of greenhouse gas and aerosol emissions. So, any information on the evolution of natural variability is informative in the decision making process of adaptive measures to climate changes.

Taking advantage from expertise in seasonal to interannual predictions, decadal predictions have been made and initial results show skill. Firstly, the multiyear trend in regional temperature is very well predictable. This may not be surprising because of the expected impact of rising greenhouse gasses on the climate system, but can be of substantial practical use. There is clearly predictability in the system. For many stakeholders in the climate adaptation community the source of that predictability is not that relevant.

Scientifically, it is of interest to separate the predictability from the trend (attributed to rising greenhouse gasses) and predictability arising from low-frequency natural variability that is represented in the initial state. Multi-model verification shows that there are regions with skill beyond the trend. It is very promising that these regions coincide with known regions of decadal variability. For instance, the subpolar gyre in the Atlantic stands out, a region where deep water formation takes place associated with the Atlantic Meridional Overturning circulation.

There are still many challenges. One of the main challenges is the systematic error, which is likely dominated by errors in the ocean models. This forces the community to devise different initialisation strategies (e.g. anomaly and full initialisation). There is no systematic assessment of these strategies yet.

The sparseness of ocean observations poses a challenge for determining initial states and for verifying the hindcasts. Reduction of uncertainty in ocean analyses on the one hand and representing the observational error on the other hand needs further research. This includes developing methodologies to effectively perturb the climate models to generate an ensemble.

Not all relevant uncertainties are addressed in current experimental setups. There is a challenge to represent the uncertainty in the initial state and techniques for perturbing the ensemble effectively are still being explored. Also, the uncertainty in the external forcing is not addressed. Especially the climate impact of aerosols has a clear regional expression.

Much can be learned from expertise in seasonal to interannual prediction. As outlined above, decadal predictions are of large scientific interest and there is scope of improvement of skill. Also, the interest of the user community further motivates the scientific community to advance the field of climate predictability.

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