OVERVIEW OF NEAR-TERM DECADAL CLIMATE PREDICTION AND ITS APPLICATIONS

TECHNICAL NOTE

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Summary

This document provides a synthesis of the current knowledge on decadal prediction. The document is divided in three parts. The first section provides an overview of the external forcings and the slow climate oscillations that provide predictability at the decadal timescale. The second section describes the different steps of a typical decadal prediction experiment: initialization, simulation, post-processing and forecast quality assessment. That section also provides a short summary on to the level of skill currently available from decadal prediction systems. Finally, the third section provides an overview of different applications that have attempted to make use of decadal predictions, in particular in agriculture-relevant sectors. The document concludes by offering a perspective on the development of decadal prediction in the upcoming years.

Contents

1. Introduction

The evolution of the climate systems in the near future depends on changes in atmospheric composition and other external forcings as well as in the slow naturally generated internal climate variability. Until very recently, the only sources of future climate information that were available to interested users were seasonal predictions and climate projections. The former provide a future outlook of the earth's climate system for a period ranging from 1 to 18 months into the future while the latter covers a continuous temporal range from the past century to the end of this century (or beyond) but with no relationship with the contemporaneous internal climate variability. At the seasonal timescale, the climate evolution mainly depends on the internally generated variabilities of the climate system and less on the changes in the externally forced components that occur over the period of forecast. On the other hand, climate projections are solely driven by changes in external forcings without constraints on the internal variability.

As an alternative to these types of climate information, recently developed decadal climate prediction systems attempt to fill the gap that exists between these two timescales (i.e. from a year up to a decade), where the evolution of the climate is impacted by both internally generated variability and externally forced components. Decadal prediction is then, in simple terms, the extension of seasonal forecasts wherein climate models are initialized by introducing observation-based data and run for a decade or so under the influence of contemporaneous changing external forcings (for instance, with rising greenhouse-gas concentration), as in climate projection. Predicting the variations in climate at this timescale is considered one of the most challenging problems faced by the climate forecasting community due to the relatively weak constraints that can be applied on the internal variability and the relatively weak anthropogenic external forcings at this timescale.

The first attempt at producing decadal climate predictions was made in the framework of the EU-funded ENSEMBLES project (2004-2009). Since then, the field of decadal prediction has grown significantly, in part due to the large socio-economic interest generated by these predictions. Clear examples of the growing interest in this field of research are the inclusion of decadal predictions in the recent phases of the Coupled Model Intercomparison Project (CMIP5 and CMIP6[1]), the production and publication of real-time decadal predictions and a growing body of literature on potential applications of these forecasts, some of which are reviewed in the last section of this document.

With this review, we aim to provide an overview of the current state of decadal prediction, by providing a description of the different sources of predictability at the relevant timescale

[1] The decadal prediction component of CMIP6 is referred to as the Decadal Climate Prediction Project, or DCPP.

(section 2), an overview of the different steps required in a typical forecasting experiment, from initialization to skill evaluation (section 3) as well as a survey of different applications that have been attempted in this field (section 4). Finally, we conclude by describing upcoming activities in decadal prediction and offering a perspective for this field of research.

2. Sources of decadal predictability

Decadal prediction lies at the boundary between seasonal forecasting and climate change projections. While seasonal forecasting is considered an initial value problem (the evolution of the atmosphere-ocean system is largely determined by the initial condition) and climate projections a boundary value problem (the system evolution depends on the external forcing and formulation of boundary condition; e.g. Meehl et al., 2009; IPCC, 2007), decadal prediction is considered a joint initial-boundary value problem (Figure 1), with both internal processes and external forcings playing a role in decadal climate variations.

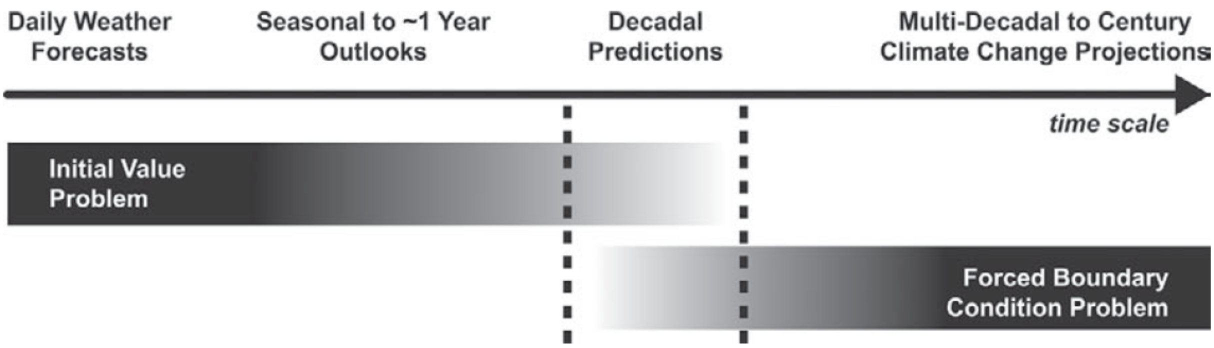

Figure 1*. Schematic illustrating progression from initial value problems, with daily weather forecasts at one end, and multidecadal to century projections as a forced boundary problem at the other, with seasonal and decadal prediction in between (figure adapted from Meehl et al., 2009).*

At the decadal timescale, the observed climate variability can be understood as the superimposition of an anthropogenically-driven trend on natural fluctuations. This simple view assumes that there is no interaction between the trend and the natural fluctuations, which might not be necessarily the case. While the trend is driven by changes in anthropogenic emissions, the natural fluctuations are generated internally by the interactions of the different components of the climate system (atmosphere, ocean and sea ice) or externally by other factors such as volcanic eruptions and solar activity. (Latif and Keenlyside, 2011). Provided that these different factors operate on a sufficiently long timescale (multinannual or longer) and can be estimated with a sufficient level of accuracy, they can potentially be a source of skill in a decadal prediction context.

2.1. External forcings

An external forcing refers to a forcing influence that is not part of the climate system itself but that nonetheless causes changes in the climate system. Anthropogenic forcings, which are usually understood to include both concentration of greenhouse gases as well as concentration of aerosols, are such agents. In fact, while anthropogenic forcings play an essential role in the typical climate projections, they are also an important source of predictability in a decadal prediction context, both at the global and the regional level (Guemas et al., 2013).

Changes in solar irradiance is another external forcing that has been associated with changes in the climate system. It is well known that the sun goes through a ~11-year cycle, as measured by the number of sunspots, and this solar cycle has been shown to modulate global temperatures (Lean and Rind, 2008). Furthermore, minima in solar activity have been associated with 1-2 year lagged negative North Atlantic Oscillation (NAO) conditions in surface temperature and surface pressure and cold (warm) winters over northern Europe and the United States (southern Europe and Canada) (Ineson et al., 2011; Thieblemon et al., 2015; Scaife et al., 2013). The delay between the solar cycle and the NAO response is due to the propagation time of the signal from the stratosphere to the surface.

Finally, changes in the solar cycle have also been associated with modulation of Atlantic landfalling hurricanes (Hodges and Elsner, 2010; Hodges et al., 2014), although in the latter case, the mechanism at play is not entirely clear. Given the regularity and the periodicity of the solar cycle, it is is arguably an important source of near-term prediction skill, in particular for the northern hemisphere. In fact, it has been identified as an important ingredient in increasing the forecast quality of winter NAO predictions (Dunstone et al., 2016).

Large volcanic eruptions also show a significant influence on the climate system, as they deposit large quantities of sulfate aerosols in the stratosphere, where such particles can remain for a few years. This aerosol loading warms the stratosphere by absorbing outgoing longwave radiation and cools the troposphere by reflecting incoming solar radiation. The resulting radiative forcing can decrease the global mean surface temperature by several tenths of a degree and induce regional cooling that can exceed one degree (Swingedouw et al., 2017). For example, the recent eruptions of Mt Agung (1963), El Chichón (1982) and Pinatubo (1991) are all associated with an average global cooling of a few tenths of a degree during the subsequent years. However, the regional impact of a volcanic eruption is less clear, with studies suggesting widely different impacts, including on the NAO and El Niño-Southern Oscillation (ENSO) (Adams et al., 2003; Emile-Geay et al., 2008; Hirono, 1988; Maher et al., 2015; Ohba et al., 2013). It has been suggested that large volcanic eruptions lead to El Niño-like conditions in subsequent years, as the last three major volcanic eruptions mentioned above were followed by El Niño conditions. However, as for the NAO, studies on this issue have led to divergent conclusions (Christiansen, 2008; Driscoll et al., 2012; Ortega et al., 2015; Zanchettin et al., 2013). Recent studies suggest that one reason behind these conflicting results might be a sensitivity to the initial state of the climate system, with different background conditions leading to different physical mechanisms and a different climate evolution (Ménégoz et al., 2017; Zanchetin et al., 2013; Pausata et al., 2016; Khodri et al., 2017).

It should be pointed out however that it is not possible to predict volcanic eruptions. So while the skill of climate predictions is generally increased when volcanoes are considered, this is somewhat misleading as the response of the climate system to the volcano eruption can only be estimated once an eruption has occurred.

2.2. Multi-annual to decadal climate oscillation

Slow, natural climate oscillations are an important source of skill in decadal prediction. Internally generated climate oscillations operating at the decadal timescale are found to be primarily driven by oceanic components and can induce large variations in weather and climate over large parts of the globe (Hurrell and Deser, 2010). Using available observations and climate model simulations, three oceanic regions have been identified as exhibiting dominant interannual to decadal variability: the North Atlantic, the Pacific and the Southern Ocean (Deser and Phillips, 2017).

2.2.1. North Atlantic region

The North Atlantic is a region with substantial multiannual and decadal variability. The Atlantic Multi-decadal variability (AMV), also referred to as the Atlantic Multi-decadal Oscillation (AMO), is found to be the most dominant mode of multiannual to decadal climate variability in the North Atlantic basin, with some links to the South Atlantic variability. A few definitions of the AMV have been provided, but it is most often defined as the oscillation in North Atlantic sea surface temperature (SST) anomalies that appears once the upward trend in temperature is removed. The duration of the anomalies vary in time, but are typically observed to last for a few decades. It is generally accepted that the system is in the warm phase of the AMV and that this warm phase started in the mid-1990s, but there are hints that it might now be entering into the cold phase of the AMV (Klotzbach et al., 2015). The recent warm phase followed a cold phase that covered the period from the late 1960s to the mid-1990s.

It should be pointed out that the AMV signal is not uniform across the North Atlantic, as it shows stronger anomalies over the subpolar gyre (SPG) region, as well as the tropical Atlantic and the eastern boundary of the North Atlantic basin (Ruprich-Robert et al., 2017). Figure 2a shows the horseshoe-like spatial pattern of the warm phase of the AMV. Figure 2b shows the time series of the AMV index computed over the period 1890-2015 using the method proposed by Trenberth and Shea (2006), where the index is computed by subtracting the global mean SST anomaly to the SST anomalies averaged over the North Atlantic domain (0°-60°N, 80°-0°W).

The AMV is generally thought to arise from internal climate variations linked to a large-scale ocean current called the Atlantic meridional overturning circulation (AMOC) (Knight et al., 2005; Delworth and Mann, 2000; Frankcombe et al., 2010; Zhang et al., 2007). The variations in the AMOC modulate a northward movement of near-surface warm water and a compensating southward movement of cold, deeper waters, thus driving changes in ocean temperature. The atmosphere, through changes in the strength and positions of the NAO, can strengthen or weaken the AMOC, leading to multidecadal temperature oscillations in the Atlantic ocean. Signals similar to the AMV appear in long climate-model simulations, thus lending support to the AMOC as the origin of the AMV. However, some recent work has also involved both natural and anthropogenic aerosols (more specifically, to the indirect effect) as a prime driver of the AMV (Booth et al., 2012). It seems likely that the AMV results from both natural oscillation and external forcings, but separating their respective role remains a significant challenge at this time. Understanding the mechanism underlying the AMV has significant implication on our ability to predict future climate and is currently the topic of much research in the climate community.

The AMV has been identified to have wide-ranging impacts, including on summer temperatures across North America and Europe (Collins and Sinha, 2003; Sutton and Hodson, 2005; Ting et al., 2011), rainfall over the Sahel region (Folland et al., 1986; Zhang and Delworth, 2006; Ting et al., 2011) and United States (Knight et al., 2006), the Indian monsoon (Zhang and Delworth, 2006) and the frequency and intensity of Atlantic hurricanes (Goldenberg et al., 2001; Knight et al., 2006).

2.2.2. Pacific region

While the Atlantic decadal variability is dominated by the AMV, the dominant mode of variability in the North Pacific region at multiannual to decadal timescales is the Pacific Decadal Oscillation (PDO, Mantua et al., 1997). Defined as the leading principal component of the monthly SST anomaly over the North Pacific domain 20°-70°N, the PDO is a recurring pattern of ocean-atmosphere climate variability centered over the mid-latitude Pacific basin. Figure 2d presents the PDO index from observations over the period 1890-2015 and Figure 2c shows the observed pattern of the PDO during the cold phase. The cold phase exhibits a cooler than normal SST along the west coast of North America and throughout the tropical Pacific, and warmer temperatures over the central and western North Pacific. The PDO impacts both surface air temperature and precipitation over Australia (Deser et al., 2004) and the North American continent (Mantua and Hare, 2002; Wise, 2010), and in particular drought conditions over the United States (McCabe et al., 2004). The PDO also impacts the Asian Monsoon, with the positive phase of the PDO associated with decreased rainfall and increased summer temperature over the Indian subcontinent (Krishnan & Sugi, 2003).

Like the AMV, the origin of the PDO is still not entirely clear, but the current consensus is that the PDO is not a single phenomenon, but is instead the result of a combination of different physical processes, including both remote tropical forcing and local North Pacific atmosphere-ocean interactions, which operate on different timescales to drive similar PDO-like SST anomaly patterns (Newman et al., 2016). A few studies (Mochizuki et al., 2010, 2012) have shown some level of skill at predicting the PDO, skill which has been linked to the model's ability in capturing observed subsurface temperature changes in the North Pacific ocean. But, generally, the skill of current forecast systems at predicting the PDO, and the SST over the Pacific in general, is relatively limited (Kim et al., 2012). It was also shown that the limited skill is due, in part, to the system's failure in representing two major warming events that occurred in 1963 and 1968 (Guemas et al., 2012) and to the difficulty faced by the models to simulate the interannual teleconnections linked to ENSO (Nidheesh et al., 2017).

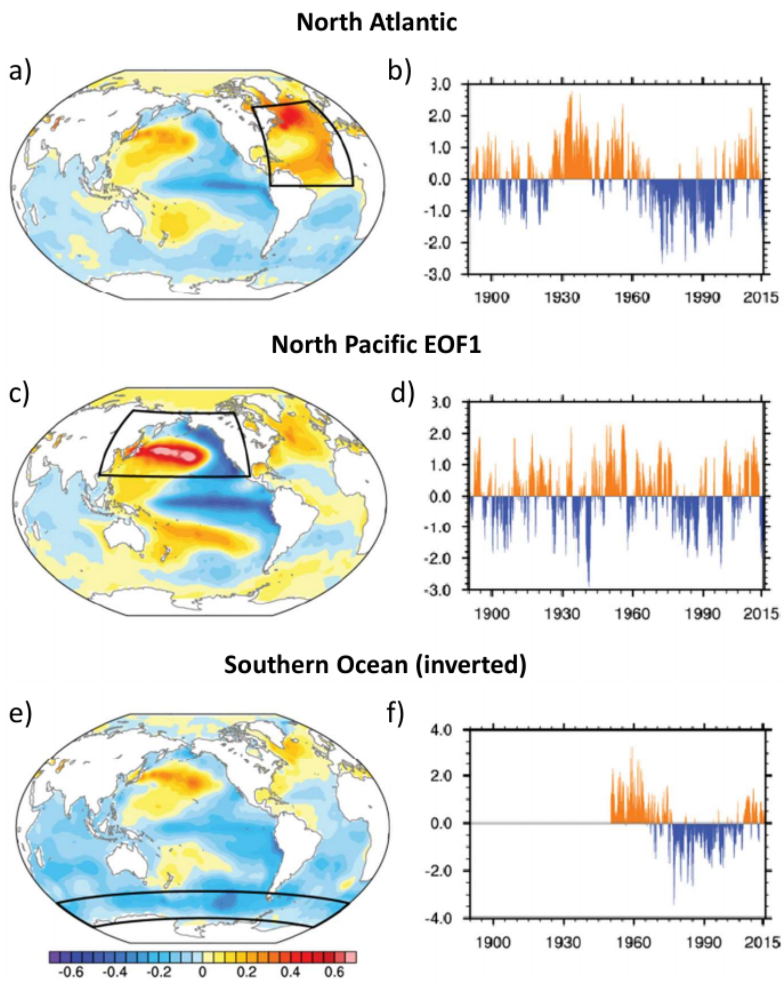

Figure 2. Observed spatial and temporal characteristics of sea surface temperature anomaly (SSTA) variability in selected oceanic basins. (left) Global SSTA (˚C) regression maps based on the (a) North Atlantic SSTA (c) leading principal component of North Pacific SSTA and (e) inverted Southern Ocean SSTA. All indices were standardized prior to computing the regression maps. Index regions are outlined by black boxes. (Right column) Standardized 3-month running mean time series (1890-2015) of the (b) North Atlantic SSTA, (d) leading principal component of North Pacific SSTA, and (f) inverted Southern Ocean SSTA. The figure is constructed using the NOAA Extended Reconstruction Sea Surface Temperature, version 3b (ERSSTv3b) dataset. (figure adapted from Deser and Phillips, 2017).

2.2.3. Southern Hemisphere

The Southern Ocean has been found to exhibit a multi-decadal SST climate variability, with a period ranging from 40 to 50 years. Figure 2f shows the inverted Southern Ocean index and suggest that the system is currently in a negative phase, which started in the early 2000s. The pattern of this mode of variability shows a uniform sign of SST anomalies over the Southern Ocean, with maximum values over the Amundsen-Bellingshausen-Weddell sea. The Southern Ocean SST has significant climate impacts on the surface air temperature and precipitation over the Antarctic continent (Zhang et al., 2017). Due to its relatively low climate impacts on populated areas and the lack of reliable observation, this mode of variability has received the least attention up to now.

2.2.4. Quasi-Biennial Oscillation

The memory of the atmosphere is much shorter than that of the ocean and the inherent timescale of atmospheric processes is generally considered to be too short to provide predictability on decadal timescales. However, the tropical stratosphere represents an exception to this general rule, with zonal wind anomalies persisting for many months. These very large and quasi-regular interannual fluctuations in stratospheric winds, which are dubbed the quasi-biennial oscillation (QBO), are predictable out to years ahead (Scaife et al., 2014). During the easterly QBO phase, more negative NAO events tend to occur, with higher than normal pressure over the Arctic and lower than normal pressure over the midlatitudes, particularly over the Atlantic storm track region. Therefore, successful multiannual forecasts of the QBO could provide one of the few purely atmospheric sources of climate predictability on multiannual timescales.

However, while there has been some success in predicting the QBO in climate models, this link with the lower atmosphere is not generally well captured in general circulation models (GCMs). As such, the skilful prediction of the QBO itself does not guarantee predictability of the extratropical teleconnection that is important for surface winter climate prediction. Because of that, attempts at using the QBO to improve decadal predictions have, so far, been relatively unsuccessful, but improvement in the troposphere-stratosphere coupling could lead to improvements in decadal predictions.

3. Decadal climate prediction

Decadal predictions are typically produced using a technique similar to that used for seasonal forecasts, i.e. by initializing a climate model. These climate models are a mathematical representation of the Earth’s climate and are built using the basic laws of classical physics and thermodynamics. Systems used in the context of decadal prediction typically include an atmosphere, ocean, sea ice and land surface components. The addition of other components (e.g. vegetation and carbon models) could potentially contribute to improving the skill of the forecasts and there is research currently underway to incorporate some of these components in the decadal prediction framework and study their impact. However, current decadal prediction systems are typically limited to these four components.

Due to the large amount of computing power required to run a decadal prediction experiment, compared to both seasonal forecasts and climate change projection (more on this below), the resolution of decadal prediction system is relatively low by today's climate model standard. For example, the models used for CMIP5 to perform near-term decadal prediction by MetOffice (HadCM3) had a spatial resolution for atmosphere at 2.5° and for ocean at 1.25° while EC-Earth had ~1.25° resolution for both atmosphere and ocean. However, there has been a notable increase in model resolution since CMIP5. For the upcoming CMIP6 exercise, the GFDL GCM will have a resolution of 1° for the atmosphere and 0.5° for the ocean whereas EC-Earth will be run with a 1° spatial resolution in the ocean and ~75 km in the atmosphere. Furthermore, BSC, within the context of the H2020 EUropean Climate Prediction (EUCP) project, is also planning to run EC-Earth at 0.25° in the ocean and ~40 km in the atmosphere.

3.1. Initialization

There are multiple steps in the production chain of decadal predictions, starting with the production of initial conditions and their integration in the climate model. The primary goal of the initialization is to align the model's natural variability with that of the Earth climate system. As mentioned above, climate models used for decadal prediction are typically constructed by combining four main components: an ocean model, a sea ice model, an atmosphere model and a land model. Each of these components must then be initialized, although some studies have shown that systems initializing only the ocean component, the slowest evolving component, also have a significant level of skill (Keenlyside et al., 2008; Pohlmann et al., 2009).

The most commonly used source of initial conditions are reanalyses data. Reanalyses are a combined form of observational data and climate models, thus representing a best estimate of the climate system at a specific time. However, identifying the best way to integrate information from reanalyses into climate forecast systems is far from trivial and different strategies have been investigated.

In the first strategy, the so-called full-field initialization, the ocean component is brought close to observations, i.e. the ocean model uses values close to the observed values of temperature and salinity. This can be done either directly, by replacing the model restart by a restart built from an interpolation of the reanalyses, or using a continuous simulation with the same climate model in which the reanalysis data are assimilated in a simple way (e.g. via nudging). However, because the climate models are only an imperfect representation of the true climate system, they contain systematic errors and biases, which cause the model climatology to be different than that of the real world. As such, when they are initialized using this technique, the simulations quickly drift towards the model's climate and some post-processing must then be applied to remove the drift from the simulation and extract the climate signal. This forecast drift is one of the long-standing issues in the field of climate forecasting.

The so-called anomaly initialization approach is an alternative strategy that aims to minimize the temporal drift of the systems towards their preferred climatology. With this technique, the observed anomalies for a given date are superimposed onto an estimate of the model climatology. While the drift is minimized in this case, it is not removed entirely, but more importantly, this technique can produce a mismatch between the observational anomalies and the model climatology in some regions (e.g. ENSO region, high-latitude convection areas and the Gulf Stream).

Analyses comparing the forecast quality of the two methods have offered mix results so far (Smith et al., 2013a; Magnusson et al., 2013; Hazeleger et al., 2013; Volpi, 2014). Most groups are currently leaning towards using full field initialization, but some groups are also exploring some sort of modified version of anomaly initialization (Volpi et al., 2017; Polkova et al., 2018).

As mentioned above, it is also possible to use initial conditions derived from long coupled assimilation runs performed with the same system as the one used for producing the decadal predictions. In this case, a climate simulation is run over the recent past (e.g 1960 onward), during which its different components are nudged toward the observed state of the climate. This type of simulation allows for the production of initial conditions that are more compatible with the decadal prediction system and is arguably the the most promising technique at the moment. However, the technical requirements for the production of such initial conditions is currently outside the capabilities of most groups performing decadal predictions.

3.2. A decadal prediction experiment

Decadal climate prediction experiments are hindcasts designed to assess historical forecast quality. Coordinated experiments, such as the Decadal Climate Prediction Project (DCPP) of the upcoming CMIP6, are a relatively costly endeavour in terms of computing resources.

One of the reasons for the computational cost is the long period over which hindcasts need to be produced. Decadal prediction experiments usually cover the period 1960-present day. Prior to 1960, the ocean observational system is not deemed of sufficient quality to provide adequate initial conditions to the forecasting system, although attempts to start further back in time than 1960 have been investigated in the context of the SPECS project (Mueller et al., 2014). Another dimension of the computational cost are the forecast time and the frequency of the start dates. In CMIP5, decadal hindcasts were requested to run for 10 years (in some cases up to 30) and initialized every five years (starting in 1960). However, results suggest that a five-year sampling frequency of the start dates is not sufficient to provide robust estimates of the forecast quality (Boer et al., 2016). For CMIP6, the minimum length of the hindcast was decreased to five years, but the start date frequency was increased to one per year. It should be mentioned that in the context of decadal prediction, the same start date is used for all the simulations of a given year (usually a date between November 1st and January 1st).

Because the signal-to-noise ratio in decadal prediction is small, multiple ensemble members are required for each start date. The set provided by the ensemble members aim to capture the full forecast uncertainty linked to an incomplete knowledge of the initial conditions. There is no agreed upon ensemble size, as this number is dependent on the signal one is interested in. However, the CMIP6 protocol requires a minimum of 10 members for each start date and suggests that more are desirable.

Given these constraints, one can easily estimates the computational cost associated with a decadal prediction experiment: 57 start dates (1961-2018) x 5 (10) years x 10 members = 2,850 (5,700) simulated year. For the same number of members, such experiment is more than twice as expensive as a typical historical+future scenario CMIP6 experiment, which covers the period 1850-2100.

Of course, multiple members of the same model do not address uncertainties linked to imperfect representation of the climate system by the GCMs (Doblas-Reyes et al., 2009). For this, a multi-model ensemble, such as the one created in the context of CMIP, is desirable. The Met Office has also investigated changing model parameters within their GCM (Smith et al., 2007), but to our knowledge, they are the only ones to have done it thus far.

It should be pointed out that all hindcasts take into account observed changes in external forcings such as greenhouse gases, solar activity, stratospheric aerosols associated with volcanic eruptions and anthropogenic aerosols until present day and from the Representative Concentration Pathway (RCP) afterwards (the RCP4.5 scenario in the case of CMIP5 simulations; Meinshausen et al. 2011). However, an actual forecast could not take into account the observed changes in external forcings, but could only use a best possible estimate prior to the initialized date. Any significant unexpected changes in these forcings (e.g. large volcanic eruptions and subsequent volcanic aerosol loadings) during the forecast period could degrade the forecast quality. To that effect, the forecast quality obtained by using forcings based on observations or on scenarios in the hindcasts is an overestimation of the expected quality of an actual forecast.

3.3. Post-processing

Post processing the forecast output is a necessary step in decadal prediction due to the development of biases in the simulations. As mentioned above, these biases tend to develop rapidly and are due to the fact that the models quickly drift towards their own preferred state. Thus, it is necessary to deal with these biases in order to extract useful information from the simulations. Biases are reduced when either forecast anomalies are computed to be compared with observed anomalies or when the simulations are bias adjusted for the predictions to have statistical characteristics similar to those of an observational reference.

The most commonly used approach to extract anomalies is the so-called ‘per-pair’ method (Garcia-Serrano and Doblas-Reyes, 2012). With this approach, an average predicted climatology is calculated for each forecast time. This forecast time-dependent model climatology is then subtracted from each hindcast to obtain drift-adjusted anomalies over the entire period. These anomalies can then be compared directly to observed anomalies or added on to the observational reference climatology to produce bias-corrected forecasts. Figure 3a provides an example of the uncorrected model output and an observational reference, while Figure 3b shows the bias-corrected forecasts. We note that a general recommendation for drift / unconditional bias correction for decadal climate predictions was published by the International Clivar Project Office (ICPO, 2011).

This bias adjustment assumes that the model drift is independent of the start date and does not account for potential time dependence in the biases. In the previous example (Figure 3b), the removal of the mean bias produced a state that was biased low early in the period and biased high towards the end of the period, suggesting that the bias adjustment was too small early on and too large later on. In that case, a correction that accounts for time-dependent biases is required. Kharin et al. (2012) suggested adjusting these time-dependent biases in the forecast mean by detrending the forecast and adding the linear trend estimated from the observational reference. Figure 3c shows the impact of trend adjustment technique on the unconditional bias-corrected forecast.

In addition to the above-mentioned biases that are primarily linked to the difference in the equilibrium (mean) state between forecast and observational reference, there also exist conditional biases in the forecast output which are interpreted as the systematic errors in the strength of the predictable signal. Goddard et al. (2013) cautions that these conditional biases in decadal predictions can be so large that model forecasts are outperformed by climatological forecasts. As such, several recent studies (Goddard et al., 2013; Eade et al., 2014; Pasternack et al., 2018) have assessed the added value of advanced conditional bias-adjustment techniques. For instance, Samson et al. (2016) developed a unified framework for the evaluation of statistical bias-adjustment methods for seasonal-to-decadal probability forecasts. As a part of their study, they analyzed CMIP5 hindcasts and recommended implementing conditional bias adjustment of the ensemble mean to obtain reliable forecasts in regions where the model has only limited skill. Figure 3d presents the forecast corrected with all the biases present in this section.

To conclude, the magnitude of the required bias adjustment can be quite large compared to the predicted signal and thus a large effort is devoted to reducing systematic errors a priori in the climate model.

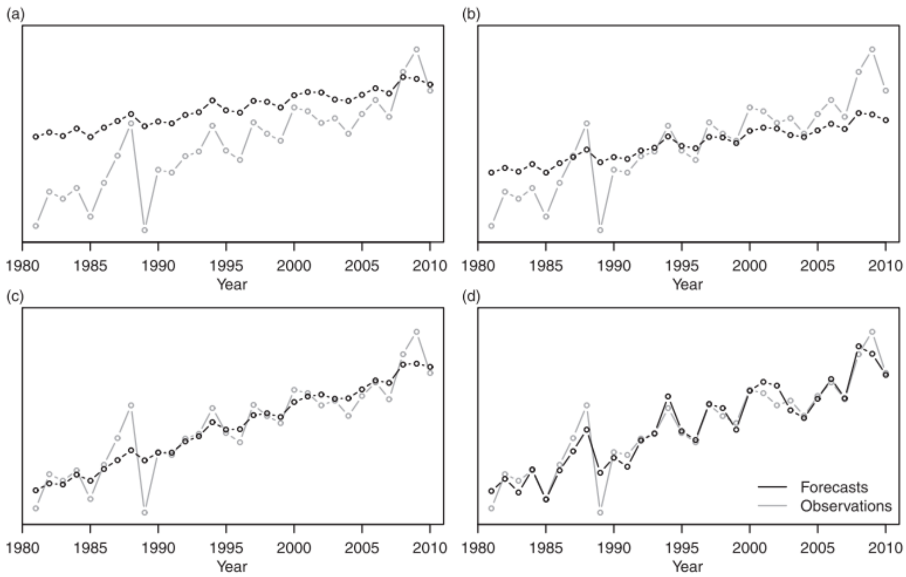

Figure 3. Examples of the impact of the applied bias correction of the forecast ensemble mean. Time series of ensemble mean forecast (black) and observation (grey) (a) before bias adjustment, (b) after mean bias adjustment, (c) after mean and trend bias adjustment, and (d) after mean, trend and conditional bias adjustment. (figure extracted from Sansom et al., 2016).

3.4. Forecast quality assessment

Evaluating the quality of the predictions is considered a fundamental step in climate prediction because it assesses whether the prediction system can be trusted to forecast certain events and/or whether it offers an improvement with respect to a standard, which could be a climatological or a persistence forecast. This so-called verification process is typically based on validating extensive sets of hindcasts or retrospective predictions against observational references. A first attempt to define a verification framework for decadal predictions was provided in Goddard et al. (2013), who suggested a methodology for forecast quality assessment at the interannual-to-decadal timescale.

There are many challenges to obtaining reliable forecast quality estimates of decadal predictions. Some of the most important are: (1) the relatively short length of the hindcast period and/or of the observational reference over which the forecast quality is evaluated, (2) the limited ensemble size of the hindcasts, which is constrained by limited computational resources as highlighted above, and (3) the errors associated with the imperfect observational reference (Bellprat et al., 2017; Menary et al., 2018). All these different factors introduce uncertainty in the forecast quality assessment and they should be properly communicated to the users when the climate information is used in a climate service context.

Forecast quality metrics can either be deterministic or probabilistic. While deterministic measures provide information on the ensemble mean or a deterministic categorical forecast, probabilistic metrics attempt to evaluate the full hindcast distribution in order to provide a more comprehensive picture of system performance. Two commonly used deterministic metrics are the Anomaly Correlation Coefficient (ACC) and the Root Mean Square Error (RMSE; Smith et al., 2010; van Oldenborgh et al., 2012; Doblas-Reyes et al., 2013). The former measures the linear association between the predicted anomalies and those of the observational reference whereas the latter evaluates differences between predicted anomalies and those of the observational reference (Knight et al., 2014). Both ACC and the RMSE have their own merits and shortcomings. For example, the ACC is found to be insensitive to a constant bias in the predictions or constant difference in the amplitude of predicted and observed data. On the other hand, the RMSE tends to be very sensitive to such errors.

Often, it is of interest to evaluate forecasts with respect to a baseline. This baseline can either be a simpler and/or cheaper alternative (e.g. climatology) or a previous version of the forecast system. Such assessment provides the user with information on the added value of the decadal prediction system against an alternative approach. One such popular metric for deterministic forecasts in decadal prediction is the Root Mean Square Skill Score (RMSSS; Doblas-Reyes et al., 2013). The RMSSS is estimated as one minus the ratio of the RMSE of the ensemble-mean prediction over the RMSE of the reference system.

$$\text{RMSSS} = 1 - \frac{RMSE\ (forecasted)}{RMSE\ (reference)} \qquad [1]$$

Using only deterministic metrics fails to take advantage of all the information contained in the full set of hindcasts. For this, one must rely on a probabilistic assessment (Jolliffe and Stephenson, 2012). Some of the most used probabilistic measures are the Brier score (BS), the ranked probability score (RPS) and the Continuous Ranked probability score (CRPS). These different skill measures can also be formulated as skill scores (BSS, RPSS, CRPSS) by comparing the score obtained from the forecasts to the corresponding score obtained from a reference forecast (see Equation 1).

However, probabilistic measures such as the BSS, RPSS and CRPSS require a large ensemble size to produce robust results. For example, work from Müller et al. (2005) and Weigel et al. (2007) have shown that the skill as measured by probabilistic metrics such as the RPSS are strongly influenced by the ensemble size, with lower estimates of skill being associated with smaller ensemble size. Their conclusion was supported by a recent study from Corti et al. (2012), who also recommended using a large ensemble size to obtain robust estimates. This is a challenge in a decadal prediction context since only a few ensemble members tend to be produced (5-10 members is usually the standard).

Apart from the above-mentioned quality measures, which are primarily associated with measuring the forecast accuracy, another crucial aspect, from a user perspective, is the reliability of the forecast system. An ensemble prediction system is said to be ‘reliable’ when the forecast probabilities match the observed relative frequencies of occurrences. For example, events forecasted to occur 70% of the time should occur, on average, 70% of the time such forecast is issued. In effect, evaluating the reliability is a critical step, as it allows the users to assess whether they can trust the probabilities that come out of the prediction system. The reliability diagram and the rank histograms are the tools most commonly used to assess the reliability of decadal climate predictions.

A good example of such reliability analysis can found in Corti et al. (2012). The authors show that both near-surface temperature over total global land area, Europe and Africa as well as SST over the North Atlantic, Indian Ocean and, to a lesser extent, North Pacific exhibit good reliability for lead times up to 6-9 years.

3.5. Current forecast quality

The forecast quality of near-surface air temperature has been assessed by a number of studies (Kim et al., 2012; van Oldenborgh et al., 2012; Corti et al., 2012; Doblas-Reyes et al., 2013; Choi et al., 2016). These studies generally find significant skill for forecast years 2-5 and 6-9 and generally agree that a significant portion of that skill is linked to the long-term warming trend associated with the increase in anthropogenic greenhouse gases and aerosols, although the influence of natural variability and external forcings on the forecast skill varies with regions. For example, Guemas et al. (2013) identified the Indian Ocean as the region with the lowest ratio of internally-generated over externally forced variability and attributed most of the skill over that region to changes in external forcings.

On the other hand, the North Atlantic region is found to be the region that benefits the most from initialization: forecasts show positive skill for different climate variables such as SST (van Oldenborgh et al., 2012), surface air temperature (Kim et al., 2012; Doblas-Reyes et al., 2013) and upper 300 metre ocean temperature (Branstator and Teng, 2012) over that region, for forecast times up to 9 years. Several studies have also assessed the multi-year skill of the primary mode of decadal climate variability in this region, the so-called AMV. For instance, studies by García-Serrano et al. (2012; 2015), Kim et al. (2012), van Oldenborgh et al. (2012), Mochizuki et al. (2012) and Wei et al. (2017) have all demonstrated significant improvement in the forecast skill of the AMV in initialized compared to non-initialized simulations. Accurately predicting this mode of decadal variability is crucial for European crop yield forecasting given the influence of the AMV on the large-scale atmospheric circulation patterns over the Euro-Atlantic region (Zampieri et al., 2016).

Over Europe, Mieruch et al. (2014) found positive skill over almost all Europe for summer temperature at forecast years 1-5 and, over Eastern Europe, Italy and Iberian Peninsula for years 6-10, and found lower skill for the winter season than for the summer season. Similar results were obtained by Guemas et al. (2015), who also found some skill for summer precipitation for forecast years 2-5 over Northern Europe. Guemas et al. (2015) attributed most of the skill to the model response to the external radiative, but also identified some of the skill as originating from the ability of the forecasting systems at predicting the AMV.

More generally, the skill for precipitation is, not surprisingly, much lower than the skill for near-surface air temperature, with possibly the exception of the Sahel region. Studies from Mohino et al. (2016) and Sheen et al. (2017) have shown the Sahel rainfall to be predictable on multi-annual timescales and they claim that the skill relies on the ability of the model at predicting the warming trend, the AMV and, to a lesser extent, the SST over the Pacific ocean. Aside from the Sahel region, Salvi et al. (2017) have explored the possibility of enhancing the skill of decadal precipitation predictions using two statistical downscaling approaches (linear regression and kernel regression) over the continental United States. They concluded that a linear regression method showed better skill in terms of mean values while a kernel regression method showed better skill for both long term variability and extremes.

A few studies have also evaluated the skill of decadal prediction systems at predicting Atlantic tropical cyclones and extratropical cyclones. Using the MetOffice Decadal Prediction System (DePreSys), Smith et al (2010) were the first ones to show predictability of Atlantic hurricane frequency beyond the seasonal timescale. This result has since been confirmed by a number of studies (Dunstone et al., 2011; Caron et al., 2014, Vecchi et al., 2013, Caron et al., 2018), while additional studies have shown that other metrics of Atlantic hurricane activity could also be forecasted at the multi-annual timescale (Caron et al., 2015; Camp and Caron, 2017).

Comparatively, considerably less work has been done on extra-tropical cyclones. Two studies have investigated the ability to predict winter storms at the multi-annual timescale and found some significant skill for forecast times of 2-5 years (Kruschke et al., 2014) and even 6-9 years (Kruschke et al., 2015), with the skill for intense cyclones being generally higher than when all systems are considered. However, they found that most of this skill was associated with the external forcing from changing greenhouse gas and aerosol concentrations and that initial conditions provided little additional skill, except for certain areas like the North western Atlantic and the Eastern Mediterranean region (Kruschke et al., 2015).

4. Climate services and decadal prediction

The International Conference on Climate Science and Climate Services that took place in Exeter on October 2016 highlighted gaps in the use of climate predictions in a climate service context. Overall, experts concluded that climate predictions have an enormous potential for helping a wide range of end-users. However, while seasonal predictions are an operational product, decadal predictions are mostly a research activity at this stage (Hewitt et al., 2017) and there are relatively few studies assessing the added value of decadal predictions for decision-making. As explained below, this situation is quickly changing, the operationalisation of decadal prediction taking place as this is written.

Several studies have focused on investigating the impact of decadal climate variability on sectors such as water management or agriculture. For instance, water yields in the Missouri River Basin (MRB) are highly influenced by the phase of the PDO and the conditions in the tropical Atlantic region (Mehta et al., 2011b), which then impact crops yield, such as dryland corn, spring wheat and winter wheat, over the USA (Mehta et al., 2012). Extending this study, Jithitikulchai et al. (2018) reported that these decadal climate phenomena impact the growing degree-days, precipitation, and drought conditions across the United States. In particular, effects are found in the major production areas of corn, soybeans, and wheat, such as the Corn Belt and most of the Southeastern United States.

A general approach to the needs of a wide range of sectors is provided in Vera et al. (2010), together with the identification of the main gaps between the provision of decadal climate information and societal needs. More specific information on the needs of the water and agriculture production sectors is provided in Mehta et al. (2011a; 2013), where they display the results of the work done in collaboration with stakeholders on the Missouri River basin. To our knowledge, this is the only study of its kind.

One of the most common requirements of stakeholders is the provision of reliable predictions of extreme climate indicators at different timescales, since they have large impacts on both society and the environment[2]. In the agriculture sector, and in particular crop production, temperature and precipitation extremes are the most impactful (Fontana et al., 2015; Lesk et al., 2016 and references herein) and are prime candidates to be included in a decision support tool for farmers.

However, while significant progress has been made in analysing extreme events in seasonal predictions (Zeng et al., 2011; Hamilton et al., 2012) and climate projections (Kharin et al., 2007; Clark et al., 2010; Russo and Sterl, 2011; Dosio, 2017), much less attention has been given to the evaluation of extremes in decadal predictions. Eade et al. (2012) assessed the skill of decadal predictions at predicting extreme warm and cold events and wet rainfall events using hindcasts generated with DePreSys (Smith et al., 2007, 2010). They

[2] http://www.wcrp-climate.org/images/documents/grand_challenges/GC_Extremes_v2.pdf

demonstrated that the skill increases for multi-year periods (forecast years 2-6 and 5-9) in comparison with individual years. This occurs mostly over Europe in the case of extreme rainfall, and globally for extremes associated with temperature. In addition, they found that the skill is higher for extremes than for the mean over particular areas and that initialization of the predictions with observed conditions does not offer much improvement beyond the first year in comparison with non initialised predictions. An interesting outcome of that work is the illustration of the limitations to the skill assessment posed by the limited observational availability.

Results found by Hanlon et al. (2013a) using the same prediction system confirm that there is significant skill in the predictions of the summer average and hottest 5-day average daily maximum (Tmax) and daily minimum (Tmin) temperatures over Europe. They also found that there is no evidence of improved skill when initialising from observations, which is in agreement with Eade et al. (2012). This work is extended in Hanlon et al. (2014), where the authors applied a similar methodology to evaluate the predictive skill of DePresys for extremes indices based on exceedance of temperature thresholds, as this type of indicators is more relevant for energy use, human health and maize yields in Europe. They found significant skill for hot extreme indices over the Mediterranean and Central Europe, but not for the British Isles, and, similarly to the other aforementioned studies, no significant improvement due to the initialisation of the prediction system.

While the previous studies failed to show any improvement in forecast quality linked to the initialization, Matei et al. (2012) and Hanlon et al. (2013b) have shown such improvements for, respectively, European summer temperatures and temperature extremes. The latter study followed the same approach as Hanlon et al. (2013a) but used four CMIP5 models (CanCM4, HadCM3, MIROC5 and MPI-ESM-LR) as opposed to a single forecast system. They concluded that decadal predictions are skilful for summer average minimum and maximum temperature and for 5 and 10 year averaged indices of daily and 5-day extremes over a large area of Europe, with the British Isles region showing the least skill. They also showed that the MPI-ESM-LR model was the most skillful for all the regions defined in their study (Europe, Western Europe, the British Isles, the Mediterranean, and Central Europe), with additional skill coming from the initialization of this model.

In addition to extreme events, heat stress and drought can adversely impact the growth and development of crops (Jagadish et al., 2007; Lobell et al., 2013; Vignjevic et al., 2015). To date, few climate change impact studies using crop models have considered such heat stress effects (Teixeira et al., 2013; Deryng et al., 2014; Leng et al., 2015). At seasonal timescales, some of the indices used to assess the influence on crop yield variability are the Heat Magnitude Day (HMD) for heat stress (Zampieri et al., 2017) and Standard Precipitation Index (SPI) or Standardized Precipitation Evapotranspiration Index (SPEI) for the drought stress (Stagge et al., 2015; Vicente-Serrano., 2010, 2012; Ceglar et al., 2017, Turco et al., 2017). However, to the best of our knowledge, no studies have yet assessed the skill of decadal prediction system at predicting those indices. Hanlon et al. (2014) did evaluate the skill for a similar index, Cooling Degree Days (CDD), but the study focused on the estimation of power consumption.

In terms of extreme precipitation events, there is the need for improving the water management planning and adaptation strategies such as to secure future water availability for different user needs (Figure 4). Koutroulis et al. (2015) examined the ability of CMIP5 decadal prediction experiments to reproduce temperature and precipitation over Crete Island by using multiple climate forecast systems. After applying a bias adjustment method, they found that the ensemble mean correlation was higher for temperature than for precipitation, especially for the CNRM-CM5 model, at short and medium forecast times. They also examined the ability of predicting the number of wet/dry and warm/cold years, and found that EC-Earth and HadCM3 returned the most skill in that regard.

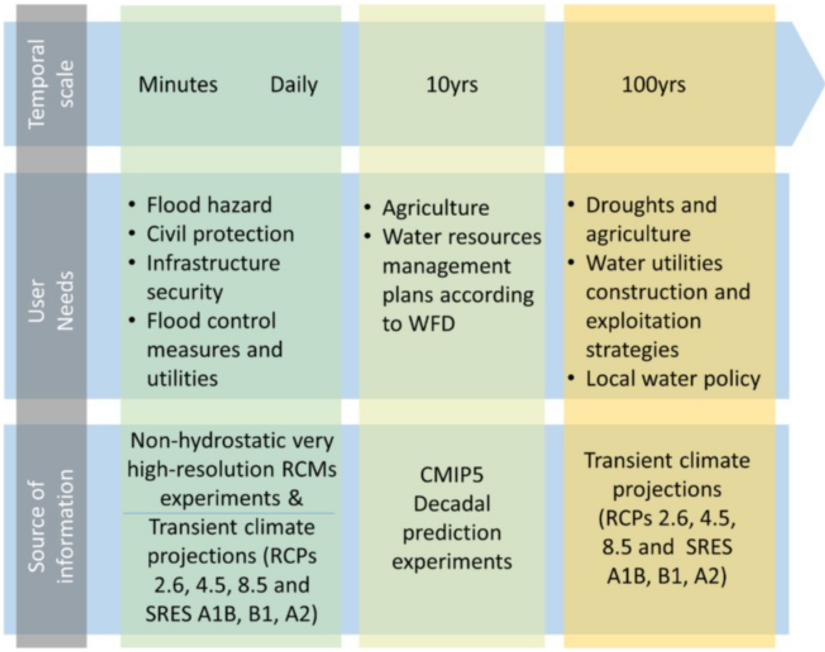

Figure 4. *Illustration of identified user needs, associated sources of information and corresponding temporal scales from Koutroulis et al. (2015).*

Mehrotra et al. (2014) evaluated the skill of rainfall, temperature and geopotential height over Australia in several CMIP5 prediction systems in order to assess whether they could be used to drive impact models for water resources planning and management. They found very limited skill for precipitation at annual and multi-annual timescales, but higher skill for temperature and geopotential, the latter being primarily associated with the long term trend.

Also related to management of water resources, Yuan et al. (2017) used decadal global land-surface ensemble simulations (with a similar design as the decadal hindcast experiments) to predict the Terrestrial Water Storage (TWS). They used a statistical empirical method known as Ensemble Streamflow Prediction (ESP) methodology (with no climate forecast information) to evaluate the skill to predict TWS. They concluded that decadal TWS predictions by ESP have significant ensemble mean correlation values for more than half of the global land areas at 1-4 years forecast time, but that it decreases to 25% and 15% of land areas for 3-6 and 6-9 year forecast times, respectively. They further suggested incorporating ESP prediction conditional on decadal climate indices such as AMV and PDO to enhance the skill at longer forecast times.

Finally, a few studies, particularly as part of the MiKlip project (Mittelfristige Klimaprognosen, a german research project on decadal climate prediction) have focussed on assessing decadal predictability of climate variables useful to the wind energy sector (Reyers et al., 2015, 2017; Haas et al., 2016; Moemken et al., 2016). Although these studies vary widely in terms of variables, lead times, metrics, downscaling and data pre-processing methods, they suggest that climate forecast systems have the potential for predicting regional peak winds and wind energy potentials at multi-annual timescales over Europe, and in particular over North and Western Germany.

5. Conclusions and next steps

This document summarises the current knowledge on multiannual to decadal climate predictability and prediction and illustrates the role of decadal climate predictions in a climate services context. It has illustrated the characteristics and main modes of decadal variability, the sources of predictability, the elements behind a climate forecast system and the challenges posed by the formulation of dynamical decadal forecasts (bias adjustment, dealing with initial shock and drift, forecast quality assessment) and the current status in our ability to predict at those time scales. A thorough assessment of the possibilities to improve the user-oriented climate information through the employment of decadal predictions is offered, with multiple examples of both successes and gaps. The document does not present new results nor conclusions from recent experiments. Instead, it intends to set the scene for a further development of climate prediction and to establish collaborations with communities like climate services or climate change projections.

This section concludes with a description of the international scene in which decadal climate prediction is developed. The goal is to offer a map of the main actors and the most relevant initiatives in which the development of decadal prediction applications will take place.

DCPP (Boer et al. 2016) has been mentioned above as a coordinated multi-model project that will investigate decadal climate prediction, its predictability and the underlying physical processes. DCPP will be producing decadal hindcasts, mainly with global dynamical forecast systems, for the period 1960 to 2015 and forecasts mimicking a real-time production until 2020. The simulations will be run for a minimum of five forecast years starting with a minimum frequency of every second year with at least 10 ensemble members, with the preference to extend the forecast time to ten years and the initialisation frequency to every year, and the option of increasing the ensemble size if resources allow. These climate simulations will start being made available starting later this year. The results of the DCPP are a key contribution to the CMIP6 and a source of information, through peer-reviewed publications, to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) and also, to the World Climate Research Programme (WCRP) Grand Challenge on Near Term Climate Prediction (GC-NTCP).

The Grand Challenge on Near-Term Climate Prediction (GC-NTCP) aims to facilitate the development of decadal prediction towards its operational use. A primary goal of the GC-NTCP is to produce annually updated climate outlooks for the forthcoming years based on real-time forecasts produced by a number of institutions gathering both meteorological services and research institutes as part of an informal exchange (Smith et al., 2013b). Currently, the Met Office displays the forecasts from the individual contributors in graphical format. The forecast are offered for forecast years one and 1-5 on an annual basis for surface-air temperature, precipitation, Atlantic meridional overturning circulation (AMOC) and sea level pressure. BSC is a regular contributor to this real-time decadal climate prediction exercise. The experience gained over the years from providing informal decadal prediction exchange by the Met Office and the positive evidence of useful forecast quality in the decadal climate predictions, inspired the World Meteorological Organisation (WMO) to proceed with making decadal prediction operational. The relevant bodies within WMO have endorsed this activity and the activity to make this kind of climate data available to meteorological services around the world has now started. It is, for the first time, an activity that recognises the key role of institutes other than meteorological services in the production of operational data. This is why the BSC has been able to apply to the WMO to become one of the recognised operational decadal prediction centres contributing to the lead centre that will be hosted by the Met Office. The other pioneering institutions contributing to the multi-model decadal prediction system are the Met Office, Environment Canada and the Deutscher Wetter Dienst (DWD) through its collaboration with the Max Planck Institute for Meteorology.

In addition to the efforts to make decadal prediction operational, research has started to generate seamless climate data sources from the near-term to longer timescales. For instance, the H2020 project EUropean Climate Prediction System (EUCP) will explore the added value of blending together the initialized decadal climate predictions with climate projections over the time period of 1 to 30 years (i.e., up to 2045), taking advantage of both the developed approaches to provide a seamless multi-decadal climate information. EUCP will also contribute directly to the GC-NTCP activities.

A number of projects are now focussed on producing high-resolution simulations that might lead to better and more user relevant decadal predictions. For instance, an ongoing German research project, MiKlip is dedicated to develop both low and high resolution climate models. A derived project from MiKlip, named PRObabilistic DEcadal Forecast for central and western Europe (PRODEF), further aims at increasing the spatial resolution of the decadal hindcasts and prediction by regionalization. PRIMAVERA, a H2020 project funded by European Commission, is as well developing the next generation of ultra high-resolution atmospheric and coupled climate models, which will be used in a decadal prediction context.

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