What is the current state of scientific knowledge with regard to seasonal and decadal forecasting?

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Abstract

Environmental factors, such as the frequency, intensity and duration of extreme weather events, are important drivers of migration and displacement of people. There is therefore a growing need for regional climate predictions for the coming seasons to decades. This paper reviews the current state of the art of seasonal to decadal climate prediction, focusing on the potential sources of skill, forecasting techniques, current capability and future prospects.

Keywords: seasonal, decadal, climate, prediction, predictability

1. Introduction

Individual weather events are generally not predictable more than a couple of weeks in advance. This is because the atmosphere is chaotic, so that errors in the initial conditions grow over a few days into large-scale disturbances. However, the atmosphere can also be influenced by external factors. This is clearly illustrated by the annual cycle. For example, we expect more mid-latitude storms during winter than summer, although the precise time and location of each winter storm cannot be predicted more than a coupled of weeks in advance.

Predicting the annual cycle is, of course, trivial if the climate is not changing. However, the climate has already changed in response to human activities, and this will continue for the foreseeable future (IPCC 2007). Furthermore, there are other natural factors that can cause particular seasons, or even years or decades, to be abnormal. The combination of natural variability with a changing climate will be felt most acutely through changes in the frequency and intensity of extreme events, including droughts, floods, storms, fires and heat waves. There is therefore an increasing need to know how likely climate events with large societal impact, such as displacement or migration of people, will be in the coming seasons to decades. This paper reviews the science of seasonal to decadal forecasting.

2. Potential sources of seasonal to decadal forecast skill

To illustrate potential sources of predictability we show the associated amplitude of variability in surface air temperature, mean sea level pressure and precipitation during the boreal winter (December to February) and summer (June to August) in figures 1–7. The sources are both external (e.g., variations in solar output) and internal to the climate system (e.g., ENSO). These maps are purely empirical, and provide a first order estimate of the potential signal from different sources. Confidence in the patterns is greatly increased if climate models show the same relationships, and if the underlying physical processes are understood.

The largest source of seasonal forecast skill is the El Niño southern oscillation (ENSO, e.g. Philander 1990). ENSO is a coupled mode of variability in the tropical Pacific that grows through positive feedbacks between sea surface temperature (SST) and winds: a weakening of the easterly trade winds produces a positive SST anomaly in the eastern tropical Pacific which in turn alters the atmospheric zonal (Walker) circulation to further reduce the easterly winds. The time between El Niño events is typically about 2–7 yr, but the mechanisms controlling the reversal to the opposite La Niña phase are not understood completely (Kirtman 1997). ENSO influences seasonal climate almost everywhere (figure 1, Trenberth and

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Figure 1. Observed ENSO teleconnections. (a) Time series of SST in the Nino3 region (150°–90°W, 5°S–5°N). (b)–(g) Composite differences between positive and negative phases of ENSO, for boreal winter (DJF, (b)–(d)) and summer (JJA, (e)–(g)). All time series are linearly detrended, and normalized by removing the mean and dividing by the standard deviation. Composite differences are divided by 2 to show the amplitude of the variability. The contour interval is 0.25 (standard deviations), with values greater than 0.2 in magnitude significant at the 95% level based on a one-sided t test. SSTs (a) are taken from HadISST (Rayner et al. 2003), surface temperatures (b), (e) are taken from HadCRUT3 (Brohan et al. 2006), sea level pressures (c), (f) from HadSLP2 (Allan and Ansell 2006), and precipitation from GPCC (Rudolf et al. 2005). Positive ENSO years (pink squares in (a)) are 1902, 1911, 1913, 1918, 1925, 1930, 1939, 1940, 1957, 1965, 1972, 1982, 1986, 1991, 1997 and 2009. Negative ENSO years (cyan squares in (a)) are 1916, 1917, 1942, 1949, 1955, 1967, 1970, 1973, 1975, 1978, 1988, 1999 and 2007.

Caron 2000, Alexander et al. 2002), either by directly altering the tropical Walker circulation (Walker and Bliss 1932), or through Rossby wave trains that propagate to mid and high latitudes (Hoskins and Karoly 1981). The strongest impacts occur in Indonesia, North and South America, east and south Africa, India and Australia. There is also a notable influence on the North Atlantic oscillation (NAO), especially in late winter (Brönnimann 2007). ENSO also modulates the vertical wind shear and stability in the tropical Atlantic atmosphere, leading to fewer (more) hurricanes during El Niño (La Niña) years (Goldenberg and Shapiro 1996, Tang and Neelin 2004).

Large volcanic eruptions, although relatively rare (typically less than one per decade) also have a significant impact on climate (figure 2, Robock 2000). Aerosol injected into the stratosphere during an eruption cools global mean temperature for a couple of years. The hydrological cycle and atmospheric circulation are also affected. Globally, precipitation is reduced due to a cooler and therefore dryer atmosphere but winters in northern Europe and central Asia tend to be milder and wetter due to additional changes in the NAO. Volcanic eruptions are not predictable in advance, but once they have occurred they are a potentially important source of forecast skill (Marshall et al. 2009). Furthermore, volcanoes impact ocean heat content and circulation for many years, even decades (Stenchikov et al. 2009). In particular, the Atlantic meridional overturning circulation (AMOC) tends to be strengthened by volcanic eruptions (Stenchikov et al. 2009). Volcanoes could therefore be a crucial source of decadal prediction skill (Otterå et al. 2010), although further research is needed to establish robust atmospheric signals on these timescales.

Although much progress has been made recently, solar influences on climate remain uncertain (Gray et al. 2010). The most predictable component of solar activity is the Schwabe solar cycle (figure 3) in which both the number of sunspots and the solar radiative output vary with an average period of approximately 11 yr. Observations suggest a warming of about 0.1 °C in global temperature between the minimum and maximum phases (Lean and Rind 2009), with small changes in tropical atmospheric circulation. Furthermore, stratospheric temperatures are influenced by the solar cycle through absorption of UV radiation by ozone. Associated changes in stratospheric winds can influence the high-latitude troposphere, including the NAO and hence European winter climate (Matthes et al. 2006). If measured since 1900, the influence of the solar cycle appears to be fairly weak, and climate models typically simulate even smaller responses, suggesting only modest predictability. However, much stronger signals in boreal winter are seen over the more recent period (figure 3, Woollings et al. 2010) or by aggregating into different phases of the quasi-biennial oscillation (QBO, Gray et al. 2010). Furthermore, recent satellite observations suggest that changes in UV radiation may be much larger than...
Figure 2. As figure 1 but for volcanic eruptions. (a) Time series of detrended global annual mean surface temperatures (from HadCRUT3). (b)–(g) Composite difference between the two years following major volcanic eruptions (pink squares in (a)) and the mean of all of the other years. The major volcanic eruptions are Santa Maria (October 1902), Ksudach (March 1907), Katmai (June 1912), Agung (March 1963), El Chichon (March 1982) and Pinatubo (June 1991).

Figure 3. As figure 1 but for solar radiation. Time series of total solar irradiance (a) are those recommended for CMIP5 (Lean 2009). Positive years are 1956–58, 1979–81, 1989–91, 2000–02. Negative years are 1953–54, 1963–64, 1975–76, 1985–86, 1995–96, 2008.

previously thought (Harder et al. 2009). Solar influence on climate continues to be an active research area that might lead to significant seasonal to decadal prediction skill. Indian Ocean Dipole variability appears as a fluctuation in the east–west gradient of sea surface temperature across the Indian Ocean that is associated with changes in winds...
Figure 4. As figure 1 but for the quasi-biennial oscillation (QBO). Time series of QBO (a) are from Naujokat (1986). Positive years are 1966, 1975, 1977, 1982, 1984, 1985, 1990, 1992, 1994, 1998, 2001 and 2008. Negative years are 1953, 1958, 1962, 1965, 1967, 1969, 1974, 1976, 1981, 1983, 1986, 1991, 1993, 1995 and 2000.

Figure 5. As figure 1 but for Atlantic multi-decadal variability (AMV). The AMV index (a) is an index of north Atlantic SST (Enfield et al 2001) obtained from www.esrl.noaa.gov/psd/data/timeseries/AMO/. All time series were smoothed and normalized with a 9 yr running mean. Positive years are 1934–42, 1948, 1952–57, 1999–2005. Negative years are 1906–22, 1971–78. Assuming 4 degrees of freedom, the contour values $\pm 0.25$ and $\pm 0.5$ are statistically significant at the 87% and 95% levels, respectively.

and rainfall (Saji et al 1999, Webster et al 1999). It has only recently attracted serious research attention but appears to affect African and Indian climate on interannual timescales (e.g. Conway et al 2007) and may even help to extend the range of ENSO predictability due to its interaction with the Pacific (Izumo et al 2010).
Figure 6. As figure 5 but for Pacific decadal variability (PDV). The PDV index (a) is derived from a principal component analysis of SST in the Pacific north of 20°N (Mantua et al 1997, Zhang et al 1997) obtained from http://jisao.washington.edu/pdo/PDO.latest. Positive years are 1937–41, 1981–91. Negative years are 1948–61, 1964–75.

Figure 7. As figure 5 but for trends. For comparison with AMV and PDV, which show a transition from neutral to peak conditions over about 15 yr (figures 5 and 6), we show 15 yr normalized differences.

The QBO is a wave-driven reversal of tropical stratospheric winds between easterly and westerly with a mean period of about 28 months (Veryard and Ebdon 1961, Reed et al 1961, see Baldwin et al 2001 for a review). The QBO influences the stratospheric polar vortex and hence the winter NAO and Atlantic–European climate—especially in winter (figure 4(c)). Because the QBO is predictable a couple of years ahead, this provides moderate predictability of European winter climate (Marshall and Scaife 2009).

Sudden stratospheric warmings occur in boreal winter on average once every two years. A dramatic warming of the high altitude polar atmosphere occurs over just a few days with
temperature increases of 50 K or more (Scherhag 1952). This warming is accompanied by a complete reversal of the usual eastward flow in the high altitude winds (Matsumo 1971). It has now become well established that these events can lead to forecast skill for cold spells in Europe and the Eastern USA out to a month ahead (Thompson et al 2002, Marshall and Scaife 2010).

The Madden Julian oscillation (MJO) occurs primarily in the tropical West Pacific and Indian Oceans (Madden and Julian 2005). It occurs as an eastward progression of heavy rainfall and atmospheric convection with a typical timescale of 40–60 days (Madden and Julian 1971). Recent evidence points to a remote influence of the MJO on the extratropics in the Pacific basin (Kim et al 2006) and also in the Atlantic (Cassou 2008). The MJO can therefore provide forecast skill on monthly timescales, however it is poorly represented in current forecast models and useful forecast skill for the MJO is currently limited to about two weeks (e.g.) (Arribas et al 2011).

Atlantic multi-decadal variability (AMV) is likely to be a major source of decadal predictability (figure 5). Observations and climate models indicate that north Atlantic SSTs fluctuate with a period of about 30–80 yr, linked to variations of the Atlantic Meridional Overturning Circulation (AMOC; Delworth et al 2007, Knight et al 2005). Climate models suggest that the AMOC and AMV can vary naturally (Vellinga and Wu 2004, Jungclaus et al 2005) or through external influences including volcanoes (Stenchikov et al 2009, Otterå et al 2010) and greenhouse gases (IPCC 2007). Idealized model experiments suggest that natural fluctuations of the AMOC and AMV are potentially predictable at least a few years ahead (Griffies and Bryan 1997, Pohlmann et al 2004, Collins et al 2006, Dunstone and Smith 2010). If skillful AMV predictions can be achieved, observations (e.g. figure 5) and modelling studies (Sutton and Hodson 2005, Zhang and Delworth 2006, Knight et al 2006, Dunstone et al 2011) suggest that important climate impacts, including rainfall over the African Sahel, India and Brazil, Atlantic hurricanes and summer climate over Europe and America, might also be predictable.

Pacific decadal variability (figure 6) is also associated with potentially important climate impacts, including rainfall over America, Asia, Africa and Australia (Power et al 1999, Deser et al 2004). The combination of PDV, AMV and climate change appears to explain nearly all of the multi-decadal US drought frequency (McCabe et al 2004), including key events like the American dustbowl of the 1930s (Schubert et al 2004). However, mechanisms underlying PDV are less clearly understood than for AMV. Furthermore, predictability studies show much less potential skill for PDV than AMV (Collins 2002, Boer 2004, Pohlmann et al 2004, Branstator and Teng 2010).

Climate has already changed, and will continue to do so, under human influences (IPCC 2007). A first order estimate of the likely effects is provided by the trend since 1900 (figure 7). This is over-simplified because not all of this trend is attributable to human activities, the response to greenhouse gases is non-linear so that future human-induced changes could be different, and other anthropogenic forcings such as aerosols and ozone could produce responses very different to the trend. Nevertheless, in many regions the trend is comparable to the variability associated with AMV and PDV, suggesting that anthropogenic climate change is a potentially important source of decadal prediction skill. Future recovery of stratospheric ozone may also provide some predictability, particularly of southern hemisphere winds (Son et al 2008).

The climate system also has inertia (or memory), which can provide predictability on seasonal and possibly longer timescales. In particular, the heat capacity of the ocean is three orders of magnitude larger than that of air. Upper ocean heat content anomalies can therefore potentially influence the atmosphere for many months or even years. Thus, although generated by random atmospheric processes and therefore not predictable in advance, they can provide predictability once they become established. Other examples where the climate system has a long memory include soil moisture (Koster et al 2010), snow cover (Cohen and Fletcher 2007), sea ice (Balmaseda et al 2010) and vegetation (Zeng et al 1999). Sea level varies regionally on decadal timescales (IPCC 2007), and may be partly predictable if ocean heat and salt content can be predicted.

3. Forecasting techniques

Forecasts can be made using purely statistical techniques, dynamical models, or a combination of both. Statistical and dynamical methods are complementary: improved understanding gained through successful statistical forecasts may lead to better dynamical models, and vice versa. Furthermore, statistical methods provide a baseline level of skill that more complex dynamical models aim to exceed.

Statistical forecasts exploit observed relationships between the variable to be predicted and other variables that have already been observed. There is a wide variety of techniques including simple linear regression, linear inverse models, constructed analogues and non-linear neural networks (e.g. OrtízBevia et al 2010). Most statistical techniques assume the climate system is stationary, and it is uncertain how reliable historical relationships will be as climate changes.

Dynamical models are based on the fundamental physical principles of conservation of mass, Newton’s second law and the laws of thermodynamics. The mathematical equations describing these principles for continuous fluids such as the atmosphere are solved approximately, usually by computing average values in a three-dimensional grid covering the globe. Furthermore, there are small-scale processes, such as turbulence or atmospheric convection, that cannot be explicitly resolved and whose average effects must be parameterized. In principle, finer resolution grids will be more accurate, but they also require disproportionately more computing power. Present generation dynamical models therefore inevitably contain systematic errors in their climate simulations. Nevertheless, they are able to provide very accurate weather predictions, and reasonable skill on longer timescales and the basic physics included is enough that they can spontaneously reproduce many of the observed features of the climate system such as...
jet streams, the Hadley circulation and the El Niño southern oscillation.

In order to predict the evolution of natural internal variability dynamical models must be initialized with the current state of the climate system. This requires observations. Predictions beyond a couple of weeks rely mainly on the relatively slow timescales in the ocean, although observations of sea ice, snow cover and soil moisture are also potentially important. Observations of the ocean state, especially below the surface, are therefore crucial for seasonal to decadal predictions. The upper 2000 m of the ocean is now relatively well observed by a network of 3000 Argo floats (Roemmich and Owens 2000) that measure profiles of temperature and salinity, both of which are needed to determine the density, and hence dynamical balance, of sea water. However, before the year 2000, subsurface ocean observations were very sparse, especially of salinity. This is a particular problem for historical hindcasts (forecasts made retrospectively but only using observations that would have been available at the time), which are needed to assess the likely skill of forecasts.

Even with a relatively good coverage of observations, initializing dynamical models is non-trivial. Constraining a model with observations generally disrupts the model’s dynamical balance, leading to rapid re-adjustments, known as initialization shocks, which can lead to loss of forecast skill. Furthermore, systematic biases cause a model to drift away from the observed state towards its preferred climatology. It is standard practice in seasonal forecasting to compute this drift as a function of lead time and start month in a set of hindcasts and then remove it from the forecast (Stockdale 1997). Characterizing the drift ideally requires many hindcasts sampling different phases of the variability that is being predicted. It is not clear whether this can be achieved accurately enough with the limited hindcast set typically employed for decadal forecasts. Furthermore, it is possible for the model drift to depend on the climate change signal. For example, if the model’s response to greenhouse gases is incorrect, then the bias will change as the greenhouse gas forcing becomes stronger. For these reasons, several decadal prediction studies to date have adopted the alternative approach of initializing climate models with observed anomalies (e.g. Smith et al 2007). While this appears to overcome drifts, it does not necessarily avoid initialization shocks or biases from incorrect greenhouse gas responses, and suffers from the additional problem that observed anomalies might not be assimilated at optimal locations relative to features such as the Gulf Stream if these are offset in models compared to reality. It is unclear which approach is best for seasonal to decadal forecasting, and both are currently being evaluated.

There are many different techniques for initializing models with observations, ranging from simple optimal interpolation to more sophisticated 4D-var and ensemble Kalman filters. A full description is beyond the scope of this paper, and further details are available in NRC (2010) and Balmaseda et al (2009). Initialization of the ocean is crucial for seasonal to decadal forecasts, but ocean assimilation is less mature than atmosphere assimilation, and is complicated by the historical scarcity of observations. Furthermore, initialization of the land surface and cryosphere are only in early stages of development, partly due to the lack of observations of key quantities such as soil moisture and sea ice thickness.

Uncertainties in forecasts are inevitable. This is because initial conditions will never be known precisely for all variables, climate models are imperfect, and future external forcings are only partly known. Dynamical seasonal to decadal forecasts therefore consist of ensembles of model integrations that attempt to sample the relevant uncertainties. Initial condition uncertainties are typically sampled by perturbing winds and ocean conditions, or with a lagged average approach that combines forecasts starting from different dates. Neither of these approaches necessarily samples the true uncertainties, especially below the ocean surface. Modelling uncertainties are sampled either by perturbing model parameters to create an ensemble of variants of a particular model (Smith et al 2010), or by combining forecasts from different centres to create a multi-model ensemble (Palmer et al 2004, Wang et al 2009, Kirtman and Min 2009). The latter approach has the potential advantage that different model formulations are also sampled, but is ad hoc and requires more coordination and collaboration. Uncertainties in future external forcing are currently not sampled. On seasonal to decadal timescales uncertainties in well-mixed greenhouse gases are unlikely to cause large errors, but aerosol and solar uncertainties and possible future volcanic eruptions are potentially important.

Dynamical models provide average values for grid boxes that are typically tens or even hundreds of kilometres in size, whereas users often require forecasts at specific locations. Dynamical model output can be downscaled either statistically, or with a regional model forced at its boundaries by the global model forecasts. Dynamical model forecasts can also potentially be improved by statistical post-processing. For example, some models are able to predict ENSO, but not all of its remote impacts. In this case, observed relationships may be used to infer forecasts of remote regions from model ENSO predictions.

4. Current levels of skill

Skill cannot be judged accurately from a single forecast. This is because, even with a perfectly reliable forecast system, uncertainties give rise to a range of possible forecasts, only one of which will be realized. If the most likely forecast does not occur, it does not mean that the forecast was wrong. Instead, skill statistics must be measured over a set of historical tests, or hindcasts. However, this is complicated by the changing observing system. For example, forecasts benefitting from Argo data could be more accurate than historical hindcasts made with very sparse observations.

Since the pioneering work of Cane et al (1986), seasonal forecasts have improved significantly, both as a result of better climate models and additional observations (Balmaseda et al 2009, Anderson et al 1998). ENSO is now accurately predicted many months ahead, with dynamical models slightly more accurate than most statistical techniques (Saha et al 2006, Wang et al 2009). ENSO teleconnections are also well predicted in the latest models (figure 8). However, overall
levels of skill for temperature and precipitation outside the tropics, and of monsoon rainfall, is low (see Kirtman and Pirani 2009, NRC 2010). Near surface winds are strongly constrained by the ocean in the tropics (Lindzen and Nigam 1987) and are therefore quite predictable there. However, in the extratropics winds are only poorly constrained by the ocean and so predictability is lower. Seasonal forecasts of Atlantic tropical storm activity are skillful (Vitart et al 2007) and are issued operationally. There is also emerging evidence that moderate extremes of temperature are predictable with almost as much skill as the seasonal mean values (Hamilton et al 2011).

Decadal predictions are much less mature than seasonal forecasts. Skilful statistical predictions of temperature have been demonstrated, both for externally forced signals (Lean and Rind 2009) and for idealized model internal variability (Hawkins et al 2011). Lee et al (2006) found evidence for skilful temperature predictions using dynamical models forced only by external changes. Furthermore, several studies show improved skill through initialization, although whether this represents skilful predictions of internal variability or a correction of errors in the response to external forcing cannot be determined. In addition to global temperature (Smith et al 2007) initialization improves predictions of surface temperature mainly in the north Atlantic and Pacific ocean (Keenlyside et al 2008, Pohlmann et al 2009, Mochizuki et al 2009, Smith et al 2010), but evidence for improved predictions over land is less convincing. However, skilful predictions of Atlantic hurricane frequency out to years ahead have been achieved (Smith et al 2010). Some of this skill is attributable to external forcing from a combination of greenhouse gases, aerosols, volcanoes and solar variations, but their relative importance has not yet been established. Initialization improves the skill mainly through atmospheric teleconnections from improved surface temperature predictions in the north Atlantic and tropical Pacific.

Improved skill in north Atlantic SST is expected to be related to skilful predictions of the Atlantic overturning circulation, but this cannot be verified directly because of a lack of observations. However, recent multi-model ocean analyses (Pohlmann et al 2011) provide a robust signal that the AMOC at 45°N increased from the 1960s to the mid 1990s, and decreased thereafter. This is in agreement with related observations of the NAO, Labrador Sea convection and north Atlantic sub-polar gyre strength. Furthermore, the multi-model AMOC is skilfully predicted up to 5 yr ahead. However, climate models forced only by external factors showed no skill, highlighting the importance of initialization.

5. Future prospects

The level of skill already achieved is, by definition, a lower limit. An upper limit cannot be determined. However, there are potential sources of skill that are currently untapped. These include the land surface, sea ice and stratosphere, and experiments are currently underway to address these. There are also other missing processes, including coupled vegetation, chemistry and land ice, which could improve skill especially on decadal timescales.

Climate model errors are a major source of uncertainty (Hawkins and Sutton 2009). There is therefore considerable scope for improved skill through model development aimed at reducing biases and improving the simulation of teleconnections. This will be achieved both by increased resolution as computers become more powerful, and improved parameterization of unresolved processes. Progress in model
development may accelerate by studying the development of errors in seamless seasonal to decadal predictions. Furthermore, techniques for combining different models to optimize the skill are under investigation.

Initialization of the current state of the climate is essential for seasonal to decadal forecasts. Sustaining the present observing system, especially Argo, is therefore crucial. Indeed, the skill of forecasts that benefit from Argo could be significantly higher than that achieved in historical hindcasts. Recently launched satellites will also provide new observations of important quantities, including sea ice thickness (CRYOSAT), soil moisture, and sea surface salinity (SMOS). There is also considerable scope to improve initialization techniques, especially by developing coupled, multivariate assimilation systems.

It is encouraging that skillful multi-year prediction of Atlantic hurricane frequency has been achieved (Smith et al 2010) and that this appears to be supported by credible predictions of the AMOC (Pohlmann et al 2011, Dunstone et al 2011). However, there is certainly room for further improvement. In particular, the rapid warming of the Atlantic sub-polar gyre and downturn of the AMOC in the mid 1990s is systematically predicted to occur too early (Robson 2010, Pohlmann et al 2011). Nevertheless, observations and modelling studies suggest that changes in the AMOC and hurricanes could also be accompanied by other important quantities including rainfall over the Sahel, parts of North and South America and India. The AMOC is believed to be driven to some extent by the NAO. Improved predictions of the evolution of the AMOC and associated climate will therefore likely require low frequency variations of the NAO to be predicted. It is not clear whether this will be possible. If it is, it will require a stronger forcing of the atmosphere from the ocean than is achieved in most climate models. This is a key area of research for decadal predictions, although there is some evidence that the atmosphere is more strongly coupled to the ocean in higher resolution models (e.g. Minobe et al 2008).

There is clear evidence that seasonal forecasts are more skillful when ENSO is active (NRC 2010). Not only is ENSO itself more predictable once established, but climate in teleconnected regions is more strongly constrained, and therefore more predictable, when ENSO is active. Idealized experiments also suggest that the predictability of AMV depends on the initial state (Griffies and Bryan 1997, Collins et al 2006). Regime dependence of skill could therefore be exploited further to increase confidence in predictions under certain circumstances. These windows of opportunity during which very skilful predictions could be achieved could therefore be used to give forecasts with higher (but conditional) skill. This could arise, for example, if the effects of several different sources of skill align to produce a particularly strong signal.

Uncertainties are inevitable in seasonal to decadal forecasts. Communicating these without raising unrealistic expectations, and exploiting skill that is, in some cases, modest will be a challenge. Nevertheless, these forecasts are already of substantial societal benefit, and will be further improved with future research.

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