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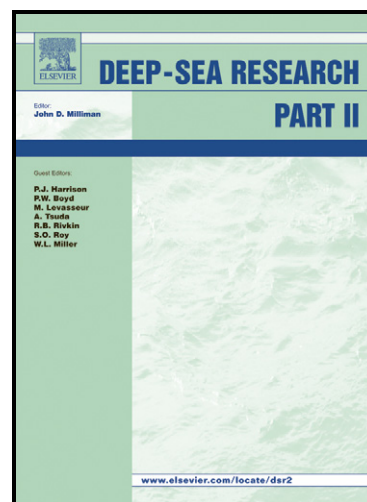
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A Perspective on Decadal Climate Variability and Predictability

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Abstract

The global surface air temperature record of the last 150 years is characterized by a long-term warming trend, with strong multidecadal variability superimposed. Similar multidecadal variability is also seen in other (societal important) parameters such as Sahel rainfall or Atlantic hurricane activity. The existence of the multidecadal variability makes climate change detection a challenge, since Global Warming evolves on a similar timescale. The ongoing discussion about a potential anthropogenic signal in the Atlantic hurricane activity is an example. A lot of work was devoted during the last years to understand the dynamics of the multidecadal variability, and external as well as internal mechanisms were proposed. This review paper focuses on two aspects. First, it describes the mechanisms for internal variability using a stochastic framework. Specific attention is given to variability of the Atlantic Meridional Overturning Circulation (AMOC), which is likely the origin of a considerable part of decadal variability and predictability in the Atlantic Sector. Second, the paper discusses the decadal predictability and the factors limiting its realisation. These include a poor understanding of the mechanisms involved and large biases in state-of-the-art climate models. Enhanced model resolution, improved subgrid scale parameterisations, and the inclusion of additional climate subsystems, such as a resolved stratosphere, may help overcome these limitations.

1. Introduction

Climate variability can be either generated internally by interactions within or between the individual climate subcomponents (e.g., atmosphere, ocean, and sea ice) or externally by e. g., volcanic eruptions, variations in the solar insolation at the top of the atmosphere, or changed atmospheric greenhouse gas concentrations in response to anthropogenic emissions. Examples of internal variations are the North Atlantic Oscillation (NAO), the El Niño/Southern Oscillation (ENSO), the Pacific Decadal Variability (PDV), or the Atlantic Multidecadal Variability (AMV). The internal variations project on global or hemispheric surface air temperature (SAT), thereby masking anthropogenic climate change. The past record of Northern Hemisphere averaged SAT, for instance, displays a host of fluctuations on different timescales that are superimposed on the long-term warming trend (Figure 1, upper). In particular, rather strong multidecadal variability is clearly discernable. Climate models suggest a considerable part of the Northern Hemisphere multidecadal variability may be driven by AMV (e. g., Zhang et al. 2007; Semenov et al. 2010) and internal in origin (Ting et al. 2009). The mid-century warming (MCW) during 1920 to 1940, for instance, cannot be simulated to full extent in the multi-model ensemble mean, when the models are forced by all known external forcing (IPCC 2007). Some of the variability presumably originates in the North Atlantic, as suggested not only by climate models but also by a comparison of the Northern Hemisphere temperature record with the AMV-index (Figure 1, lower), which is defined as the area weighted averaged and linearly de-trended sea surface temperature (SST) over the North Atlantic (0-60°N). The latter exhibits similar multidecadal changes that are most likely driven by AMOC variations, as has been inferred from forced ocean model integrations (e. g., Alvarez-Garcia et al. 2008). However, what the relative roles of internal and external processes in driving AMV and Northern Hemisphere SAT are remains controversial. Contributions of anomalous solar forcing, changes in volcanic and anthropogenic aerosols were also suggested to explain the multidecadal variations of the

observed temperatures including MCW (e. g., Stott et al. 2000; Broccoli et al. 2003; Mann and Emanuel 2006; Biasutti and Giannini 2006; Ottera et al. 2010).

We present in Figure 2 more indices derived from observations to visualize the multidecadal variability in selected variables and regions. The North Atlantic Sector is one region of strong multidecadal variability, as noted above, and multidecadal variability can be readily seen, for instance, in European surface air temperature (SAT), Sahel rainfall, and Atlantic hurricane activity. All three indices are coherent with the fluctuations in North Atlantic SST on decadal timescales. Similar behaviour is seen in the North Pacific; however, the correspondence between SAT in the Southwest United States, the region most strongly affected by PDV, and North Pacific SST is obvious but less significant. It should be noted, however, that the instrumental record is rather short, so that high statistical significance cannot be assigned to the links on decadal timescales suggested by Figure 2.

Uncertainty in climate change projections for the 21st century arises from three distinct sources: internal variability, model and scenario uncertainty. Using data from a suite of climate models Hawkins and Sutton (2009) separate and quantify these sources (Figure 3). For lead times of the next few decades the dominant contributions are internal variability and model uncertainty, and we shall concentrate on these two aspects in this paper. The importance of internal variability generally increases at shorter time and space scales. ENSO, for instance, is one of the major factors affecting inter-annual variability, even on a global scale, and the super El Niño of 1997/1998 “helped” to make the year 1998 one of the warmest on record to date. The analyses of Hawkins and Sutton (2009) suggest that for decadal timescales and regional spatial scales (~2000km), model uncertainty is of greater importance than internal variability. Model biases are still rather large, as discussed below (see Figure 8), and model

improvements will most likely lead to higher prediction skill on all timescales. Both contributions to prediction uncertainty, internal variability and model bias, are potentially reducible through progress in climate research.

In this review paper, we focus on the mechanisms of internal decadal-scale variability and discuss the model biases in state-of-the-art climate models. A large body of literature exists on the dynamics of decadal variability which give rise to decadal predictability, and we try to summarize this knowledge in a concise way. Some of the described mechanisms may operate in both the Pacific and Atlantic, and only those papers are reviewed that described them first to our knowledge. Bjerknes (1964) concluded from his early analysis of the observations in the mid-latitude Atlantic region that the atmosphere drives the ocean at inter-annual timescales, while, at the decadal to multidecadal timescales, it is the ocean dynamics that produce long-term variability in the oceans which may feed back onto the atmosphere. Many subsequent observational and modelling studies agree basically with this view (e.g., Delworth et al. 1993; Latif 1998 and references therein), so the predictability potential in the Atlantic Sector is probably large at decadal to multidecadal timescales (e. g., Boer 2000, Boer 2004, Latif et al. 2006a). Although the mechanisms behind the variability in the Atlantic Sector are still controversial, there is some consensus that the longer-term multidecadal variability is driven, at least partly, by variations in the Atlantic thermohaline circulation (THC), the so called Atlantic Meridional Overturning Circulation (AMOC). Most studies agree on that the multidecadal variability in the North Atlantic is rather persistent (e. g., Delworth and Mann 2000; Knight et al. 2005). However, there is some controversy on this point. In fact, a recent study based on a 440-year high-resolution reconstruction of SST in the western tropical Atlantic suggests that the AMV may not be persistent (Saenger et al. 2009).

The source of decadal predictability in the North Pacific is probably different to that in the Atlantic. In the North Pacific, a strong overturning circulation does not exist, and variations in the wind-driven circulation are the most likely candidate for the generation of decadal to multidecadal variability (e.g., Latif 1998, Miller and Schneider 2002, Schneider and Cornuelle 2005, Latif 2006). Rossby wave propagation appears to be important in this context. Interdecadal variability is also observed in the equatorial Pacific and numerous mechanisms have been proposed to explain it. These include tropical-extropical interactions (e. g., Gu and Philander 1997; Kleeman et al. 1999; Vimont et al. 2001), coupled variations within the tropics (Meehl and Hu 2006), nonlinearity of ENSO (Rodgers et al. 2004), and low-frequency residual of ENSO (Power and Colman, 2006). Part of Pacific decadal variability may also originate from external forcing, e. g. the eleven-year solar cycle (Meehl et al. 2009).

However, what we know about the origin of decadal-scale variability often stems from models, which exhibit large biases. Thus a big effort should be made to improve models. This will not only improve simulation of internal variability but also enhance the models' ability to predict it, if suitably initialized. Finally, a number of interesting community and contributed white papers presented at the OceanObs '09 Conference addressing decadal variability and predictability will be published in two books (e. g., Hurrell et al. 2010) and are available under <http://www.oceanobs09.net/blog/>.

The paper is organized as follows. Section 2 provides a conceptual description of the mechanisms that can lead to internal decadal variability. We consider only variability that involves interactions between the ocean-sea ice system and the atmosphere. This type of variability must be treated within a stochastic framework. We do not address here the origin of chaotic variability originating in either only the atmosphere or the ocean-sea ice system through their internal nonlinear dynamics, although the

latter by itself can also produce decadal-scale variability. In Section 3, we discuss some aspects of potential decadal predictability. Factors limiting the full exploitation of this predictability are described in section 4, along with areas where model improvement is needed. The paper is concluded with a discussion in Section 5.

2. Mechanisms for decadal variability

The climate system displays variability over a broad range of timescales, from monthly to millennial and to even longer timescales. It is impossible to describe the full range of climate variability deterministically with one model, since the governing mathematical equations are rather complicated and analytical solutions not known. A numerical solution of the complete set of equations is possible but not feasible for very long timescales of many millennia, because the necessary computer resources are not available, and will not be available over the next years. What is therefore needed is a hierarchical approach: the application of complex models for short timescales and reduced models for long timescales. However, the hierarchical approach is intellectual challenging and by no means satisfying, as the omission of important physics, such as of small-scale processes, is not justified in many cases given the highly nonlinear dynamics of the climate system.

The climate system is comprised of components with very different internal timescales. Weather phenomena, for instance, have typical lifetimes of hours or days, while the deep ocean needs many centuries to adjust to changes in surface boundary conditions. Hasselmann (1976) introduced an approach to modelling the effect of the fast variables on the slow in analogy to Brownian motion. He suggested treating the former not as deterministic variables, but as *stochastic* variables, so that the slow

variables evolve following dynamical equations with stochastic forcing. The chaotic components of the system often have well-defined statistical properties and these can be built into approximate stochastic representations of the high-frequency variability. The resulting models for the slow variables are referred to collectively as *stochastic climate models*, although the precise timescale considered slow may vary greatly from model to model. We describe in the following different types of stochastic models that were suggested for the generation of the internally driven decadal variability (Figure 4). The precise mechanisms underlying decadal variability will eventually determine the level of predictability we may expect.

2.1 The zero-order stochastic climate model

We consider in the following discussion the atmosphere as the fast and the ocean-sea ice system as the slow component. In the simplest case, the atmosphere is treated as a *white noise* process, i.e. the spectrum of the atmospheric forcing, such as the air-sea heat flux, is white, which means that its amplitude is frequency independent. Internal atmospheric decadal variability is implicitly included in the white noise representation. We additionally assume in this simplest case that linear dynamics govern the slow system and a local model in which the atmospheric forcing at one location drives only changes in the ocean-sea ice system at this very point; neither the atmosphere nor the ocean-sea ice system exhibit spatial coherence. The ocean-sea ice system defined in this way integrates the weather noise, and the resulting spectrum of a typical variable say sea surface temperature is *red*, which means that the power increases with timescale corresponding to the inverse of the square root of frequency. To avoid a singularity at zero frequency a damping was introduced by Hasselmann (1976).

Frankignoul and Hasselmann (1977) have shown that observed SST variability is consistent with such a local model in parts of the mid-latitudes, away from coasts and fronts, whereas the simple stochastic model fails in regions where mesoscale eddies or advection are important. Hall and Manabe (1997) explained differences in SST and sea surface salinity (SSS) spectra by the simple model and report that a complex climate model does reproduce this behaviour. We note again that this model is linear and no coupling of different timescales is implied. Thus the ocean-sea ice system simply amplifies the variance present in the atmosphere at long time scales.

Barsugli and Battisti (1998) by extending the Hasselmann (1976) model constructed a simple stochastically forced, one-dimensional, linear, coupled energy balance model and obtained important insight into the nature of coupled interactions in the mid-latitudes. They concluded that the experimental design of an atmospheric model coupled to a mixed layer ocean model would provide a reasonable null hypothesis against which to test for the presence of distinctive decadal variability (see also section 2.4). The follow-up work by Bretherton and Battisti (2001) examined the predictability of such a system.

2.2 Stochastic models with mean advection and spatial coherence

Several refinements were proposed since Hasselmann first introduced stochastic climate models. Lemke et al. (1980) applied a dynamical model based on white noise atmospheric forcing, local stabilizing relaxation and lateral diffusion and advection to explain sea ice variability. Longitudinally dependent forcing, feedback, lateral diffusion and advection parameters were derived by fitting the model to the observed cross-spectral matrix of the sea ice anomaly fields. Lemke et al. (1980) inferred that diffusion

and advection of sea ice anomalies were important in sea ice dynamics. In particular, the model advection patterns agreed reasonably well with the observed ocean surface circulation in the Arctic Ocean and around Antarctica. Frankignoul and Reynolds (1983) described the use of a local stochastic model, including the effects of advection by the observed mean current, to predict the statistical characteristics of observed SST anomalies in the North Pacific on timescales of several months. They find that mean advection has only a small effect in general, although in regions of large currents, the advection effects were important at lower frequencies. Finally, Herterich and Hasselmann (1987) have fitted a more general nonlocal stochastic model, incorporating advection and diffusion, to observed SST anomalies over the same region. Their analysis, however, supported previous models in which the origin of mid-latitude SST anomalies on timescales of months to a few years can be basically attributed to local stochastic forcing by the atmosphere.

Atmospheric variability on timescales of a month or longer is dominated by a small number of large-scale spatial patterns, whose time evolution has a significant stochastic component (Davis 1976). One prominent example is the NAO, and we shall discuss the role of the NAO in driving variations in the AMOC below. One may expect the atmospheric patterns to play an important role in ocean-sea ice-atmosphere interaction, and advection can play a role in this coupling. A one-dimensional stochastic model of the interaction between spatially coherent atmospheric forcing patterns and an “advective” ocean was developed by Saravanan and McWilliams (1998). Their model equations are simple enough and allow analytical treatment. The model solution can be separated into two different regimes: a *slow-shallow* regime where local damping effects dominate advection and a *fast-deep* regime where nonlocal advection effects dominate thermal damping. An interesting feature of the fast-deep regime is that the ocean-atmosphere system shows preferred timescales, although there is no underlying oscillatory

mechanism, neither in the ocean nor in the atmosphere. The existence of the preferred timescale in the ocean does not depend on the existence of an atmospheric response to SST anomalies. It is determined by the advective velocity scale associated with the upper ocean and the length scale associated with low-frequency atmospheric variability. This mechanism is often referred to as “spatial resonance” or “optimal forcing”. For the extra-tropical North Atlantic basin, this timescale would be of the order of a decade. Interestingly, Deser and Blackmon (1993), Sutton and Allen (1997), and Alvarez-Garcia et al. (2008) find such a decadal timescale in surface observations of the North Atlantic. However, the studies differ in the derived propagation characteristics. The stochastic-advective mechanism may also underlie the Antarctic Circumpolar Wave (ACW, e. g. White and Peterson 1996), as shown in the model study of Weisse et al. (1999) who drove an ocean-sea ice general circulation model by spatially coherent but temporally white forcing. The same model experiment is also described below, when we discuss the stochastically driven variability of the THC.

2.3 Stochastic wind stress forcing of a dynamical ocean

We have considered so far no varying ocean dynamics and only thermohaline forcing, i.e. heat and freshwater forcing. Frankignoul et al. (1997) used a simple linear model to estimate the dynamical response of the extra-tropical ocean to spatially coherent stochastic wind stress forcing with a white frequency spectrum. The barotropic fields are governed by a time-dependent Sverdrup balance, the baroclinic ones by the long Rossby wave equation. At each frequency, the baroclinic response consists of a forced response plus a Rossby wave generated at the eastern boundary. For forcing without zonal variation, the response propagates westward at twice the Rossby wave phase speed. The model predicts the shape and level of the frequency spectra of the oceanic pressure field and their variation with longitude and latitude. The baroclinic response is spread over a continuum of frequencies, with a

dominant timescale determined by the time it takes a long Rossby wave to propagate across the basin and thus increases with the basin width. The baroclinic predictions for a white wind stress curl spectrum are broadly consistent with the frequency spectrum of sea level changes and temperature fluctuations in the thermocline observed near Bermuda.

Schneider et al. (2002) found some evidence for the accumulation of stochastic atmospheric forcing along Rossby wave trajectories in the North Pacific. Stochastic wind stress forcing may thus explain a substantial part of the decadal variability of the oceanic gyres, especially in the North Pacific. The importance of stochastically driven baroclinic Rossby waves was also described in Latif (2006) who studied the multidecadal variability in the North Pacific in a coupled ocean-atmosphere general circulation model. As such the bulk of the potential predictability found in the North Pacific (see Figure 8 below) is probably related to the propagation of long baroclinic Rossby waves (e.g., Schneider and Cornuelle 2005). The degree of air-sea coupling, however, needs to be considered in this context (e.g., Latif and Barnett 1994, Latif 2006), as well as the role of remote forcing by the tropics (e.g., Trenberth and Hurrell 1994; Gu and Philander 1997; Jacobs et al. 1994). It should be mentioned in this context that similar mechanisms could also operate in the North Atlantic.

2.4 Hyper modes

We describe now a case in which the atmosphere is no longer represented by a simple stochastic model but deterministically by an atmospheric general circulation model (AGCM). The ocean is represented by a vertical column model (CM) in which the individual levels communicate only by vertical diffusion. Such a coupled model (AGCM-CM) was studied, for instance, by Dommenget and Latif (2008) and displays a

number of features of observed decadal variability. Since varying horizontal ocean dynamics are not considered, air-sea interactions are still strongly simplified in the model. Yet some important aspects of the space-time structure of SST variability can be explained. The concept of a *Global Hyper Climate Mode* is defined, in which surface heat flux variability associated with regional atmospheric variability patterns is integrated by the large heat capacity of the extra-tropical oceans, leading to a continuous increase of SST variance towards longer timescales. Atmospheric teleconnections and coupled feedbacks associated with anomalous heat flux or wind mixing such as the wind-evaporation-sea surface temperature (WES) feedback spread the extra-tropical signal to the tropical regions. Once SST anomalies have developed in the tropics, global atmospheric teleconnections spread the signal around the world creating global hyper mode. Calculations with a further reduced stochastic model suggest that a hyper climate mode can vary on timescales longer than 1,000 years.

The SST anomaly patterns simulated at multidecadal timescales in the AGCM-CM are in some regions remarkably similar to those derived from observations and from long control integrations with sophisticated coupled ocean-atmosphere general circulation models. The hyper mode mechanism could, for instance, underlie the Pacific Decadal Variability, whose structure is reasonably well reproduced (Figure 5). Ocean dynamics and large-scale ocean-atmosphere coupling may modify the hyper modes, especially in the tropics, and influence the regional expression of the associated variability. Equatorial ocean dynamics such as those operating in ENSO, for instance, would enhance the variability in the eastern and central Equatorial Pacific. Such feedbacks would make the model certainly more realistic, but are not at the heart of the mechanism which produces the hyper mode. If the hyper mode scenario applies to the real world, the decadal predictability potential would be only modest and not exceed that expected from an autoregressive process of the first order. However, considerable potential decadal

predictability exists in the North and South Pacific (discussed below), indicating that variability in these regions is not solely due to the hyper mode mechanism.

2.5 Stochastically driven AMOC variability

Competing mechanisms were proposed for the Atlantic Meridional Overturning Circulation variability. One idea is that low-frequency AMOC variability, consistent with the stochastic model scenario, is driven by the low-frequency portion of the spectrum of atmospheric forcing. Mikolajewicz and Maier-Reimer (1990) describe results from a multi-millennial integration with the Hamburg Large-Scale Geostrophic (LSG) Ocean General Circulation Model that was driven by spatially correlated white-noise freshwater flux anomalies. In addition to the expected red-noise character of the oceanic response, the model simulated enhanced variability in a frequency band around 320 years in the Atlantic basin. This is due to the excitation of a damped oceanic eigenmode by the stochastic freshwater flux forcing. The physics behind the variability involve a dipole-like salinity anomaly advected by and interacting with the mean THC.

Weisse et al. (1994) describe decadal variability with a timescale of the order of 10 to 40 years in the North Atlantic in the same experiment. It involves the generation of salinity anomalies in the Labrador Sea and the following discharge into the North Atlantic. The generation of the salinity anomalies is mainly due to an almost undisturbed local integration of the white noise freshwater fluxes. The timescale and damping term of the integration process are determined by the flushing time of the well-mixed upper layer. The decadal mode affects the AMOC and represents a discharge process that depends nonlinearly on the modulated circulation structure rather than a regular linear oscillator. It

should be mentioned, however, that the (uncoupled) stochastically forced LSG model integrations described above were performed with mixed boundary conditions, which may considerably distort the physics of the coupled ocean-atmosphere system.

Delworth and Greatbatch (2000), investigating the multidecadal variability in the coupled model simulation of Delworth et al. (1993), describe an internal ocean mode in their analysis of a series of coupled and uncoupled ocean model integrations. The multidecadal variability simulated in the model discussed in Delworth et al. (1993) is based on interactions of the gyre and thermohaline circulations, in which the anomalous salt advection into the sinking region plays a crucial role in determining deep convection. Delworth and Greatbatch (2000) show that the multidecadal AMOC fluctuations are driven by a spatial pattern of surface heat flux variations that bear a strong resemblance to the NAO. No conclusive evidence is found that the AMOC variability is part of a dynamically coupled atmosphere-ocean mode in this particular model. Griffies and Tziperman (1995) interpreted the variability in terms of a stochastically forced four-box model of the AMOC. The box model was placed in a linearly stable thermally dominant mean state under mixed boundary conditions (Stommel 1961). A linear stability analysis of this state reveals one damped oscillatory THC mode in addition to purely decaying modes. Direct comparison of the variability in the box model and coupled ocean-atmosphere general circulation model reveals common qualitative aspects, supporting the hypothesis that the coupled model's AMOC variability can be understood by the stochastic excitation of a linear damped oscillatory THC mode.

Analyses of ocean observations and model simulations by Latif et al. (2006b) support this picture. They suggest that there have been indeed considerable multidecadal changes in the AMOC during the last century. AMOC variations were indirectly reconstructed in that study from the history of observed SST.

Since AMOC variations are associated in climate models with variations in the poleward heat transport, a fingerprint of relative AMOC-strength can be defined as the SST-difference between the North and South Atlantic. Latif et al. 2004 previously showed that this approach worked well for decadal AMOC-variations in a climate model. The observed changes in the dipole-SST index are argued to be driven by the low-frequency variations of the NAO through changes in Labrador Sea convection (Figure 6a) and follow the NAO index with a time delay of about a decade, consistent with the ocean general circulation model studies by Eden and Jung (2001) and Eden and Willebrand (2001). North Atlantic SST is strongly influenced by AMOC changes, and the two quantities exhibit a clear lead-lag relationship in some models, as visualized in Figure 6b showing results from the Kiel Climate Model (KCM, Park and Latif 2008, Park et al. 2009).

As direct AMOC observations exist only for the last few years, many studies used ocean models in forced mode using an estimate of observed surface boundary forcing to study AMOC variability. Here we describe results from Alvarez-Garcia et al. (2008) for the period 1958-2000. Multichannel Singular Spectrum Analysis (MSSA) was used to extract the dominant space-time modes of the ocean model data in the North Atlantic poleward of the Equator. The leading mode is multidecadal. It displays prolonged negative SST anomaly during 1970-1980 covering the whole North Atlantic (not shown) and is therefore a negative phase of the multidecadal cycle (see also Fig. 1, lower). The cold SST anomalies are preceded by a basin-wide cell of negative anomalies in the meridional streamfunction, and thus by a weaker overturning about 5 years before (Fig. 7). The anomalously weak overturning is a result of an anomalously weak NAO (Fig. 6) and the associated reduced heat loss of the ocean to the atmosphere in the Labrador Sea at this time. The snapshots of the ocean model's streamfunction five years apart from each other, as reconstructed from the multidecadal mode, show clearly how the negative overturning

anomalies develop in the 1960s and subsequently slowly propagate southward. During 1970-1980, the height of the cold phase in surface temperature, the tendency in the streamfunction is reversed and the negative anomalies start to weaken, until they are replaced by positive overturning anomalies in the mid-1980s in the north. The positive anomalies expand southward and initiate the subsequent warm phase in the 1990s which is characterized by an anomalously strong AMOC.

2.6 Coupled variability involving the AMOC

Coupled air-sea modes were also proposed to explain decadal variability. These also have to be considered in a stochastic framework, as we expect them to be damped and not self-sustained.

Timmermann et al. (1998) describe coupled variability with a 35-yr period in a multicentury integration of the ECHAM3/LSG climate model. Variations of the AMOC are again at the heart of the mechanism.

The mean AMOC is relatively strong in that model, which may explain the rather short period. Let us consider a situation in which the North Atlantic is covered by positive SST anomalies. The atmospheric response involves a strengthened NAO, which leads to anomalously weak evaporation and Ekman transport off Newfoundland and in the Greenland Sea, and the generation of negative SSS anomalies.

These weaken the deep convection in the oceanic sinking regions and subsequently the strength of the AMOC, leading to a reduced poleward heat transport and the formation of negative SST anomalies, which completes the phase reversal. It should be mentioned in this context that salinity dominates the evolution of density anomalies in the sinking region.

Eden and Greatbatch (2003) describe results from a simple stochastic atmospheric feedback model coupled to a realistic model of the North Atlantic. A north-south SST dipole, with its zero line centred

along the sub-polar front, drives the atmosphere model, which in turn forces the ocean model by patterns of surface fluxes derived from NAO-based regression analysis as in Eden and Jung (2001). The coupled model simulates a damped decadal oscillation for sufficiently strong coupling. It consists of a fast wind-driven, positive feedback of the ocean and a delayed negative feedback orchestrated by the onset of an anomaly in the THC located in the sub-polar North Atlantic. This anomaly transports more or less heat across the sub-polar front, changing the sign of the SST dipole. The positive feedback turns out to be necessary to distinguish the coupled oscillation from that in a model without any feedback from the ocean to the atmosphere.

Vellinga and Wu (2004) describe a coupled feedback on centennial timescales from a coupled GCM (HadCM3). They report that the ITCZ both strengthens and moves northwards if AMOC is anomalously strong. The increased freshwater flux into the ocean associated with a stronger ITCZ results in a freshwater anomaly in the equatorial Atlantic. The resulting negative salinity anomaly is then gradually advected northwards by the mean ocean circulation into the subpolar gyre on a timescale of a few decades, a mechanism also described by Latif et al. (2000) and Latif (2001). A negative salinity anomaly in the subpolar gyre reduces the density here resulting in decreased deep convection, providing a delayed negative feedback.

Finally, the stochastic concept was taken up within the coupled framework by Kirtman and Shukla (2002) who introduced the interactive ensemble coupled strategy, a tool for understanding how atmospheric stochastic forcing affects climate variability. The procedure is to use multiple realizations of the atmospheric GCM coupled to a single realization of the ocean GCM. The ensemble mean state of the atmospheric GCM fluxes are coupled to the ocean model thereby affecting the evolution of the coupled

system. The traditional approach for generating a coupled ensemble is to apply the ensemble averaging to a collection of individual realizations a posteriori. The interactive ensemble technique is distinct from the traditional procedure because here the ensemble mean of the atmospheric models continuously interacts with the ocean model as the coupled system evolves. Yeh and Kirtman (2004) used the method to quantify the relative roles of local and non-local noise on North Pacific variability.

3. Potential decadal predictability

Climate prediction has been to date mostly considered on two different time scales: seasonal and centennial. Seasonal prediction is primarily an initial value problem, i.e. the evolution of the system depends on the initial state (e.g., Palmer et al. 2004). Whereas centennial-scale prediction is normally considered a boundary value problem, i.e. the evolution of climate depends on external changes in radiative forcing, such as anthropogenic changes in atmospheric composition or solar forcing (IPCC 2007). What class of problem is decadal prediction: initial value or boundary value? As suggested by observations and models decadal climate variations, global and regional, may arise from internal modes of the climate system and be potentially predictable (i.e. an initial value problem). On the other hand, projections of future climate indicate a rise in global mean temperature of between 2 and 4°C by 2100, dependant on emission scenario and model. This translates to an average rise in global mean temperature of order 0.3°C per decade. This is large compared, for instance, with the observed increase of about 0.7°C during the last century, and argues that decadal prediction is also a boundary value problem. Thus the prediction of the climate over the next few decades poses a joint initial/boundary value problem.

While the predictability of internal fluctuations on seasonal timescales has been intensively studied for more than twenty years, decadal predictability has been systematically investigated for only a few years. Lack of understanding of predictable dynamics at decadal time scales and shortness of observational records are two main reasons that prevent us from studying decadal predictability in a systematic way. Another reason for this is the much longer timescale, which requires rather long model integrations and which is therefore closely related to the availability of large computer resources.

One distinguishes between potential (diagnostic) and classical (prognostic) predictability studies. Potential predictability studies (e.g., Boer 2000 and 2004; Boer and Lambert 2008) attempt to quantify the fraction of long-term variability that may be distinguished from the internally generated natural variability, which is not predictable on long timescales and considered as “noise”. The long-term variability “signal” that rises above this noise is deemed to arise from processes operating in the physical system that are assumed to be, at least *potentially*, predictable. Decadal potential predictability is simply defined as the ratio of the variance on the decadal timescales to the total variance. As such, it does not discriminate among variability arising from a zero-order stochastic model (red-noise process) or higher-order models. Fitted linear inverse models or constructed analogues provide more discriminative estimates of diagnostic predictability (e. g., Hawkins et al. 2010; Teng and Branstator 2010). Classical predictability studies consist of performing ensemble experiments with a single coupled model perturbing the initial conditions (Griffies and Bryan 1997a, b; Grötzner et al. 1999; Collins 2002; Collins and Sinha 2003; Pohlmann et al. 2004). The predictability of a variable is given by the ratio of the actual signal variance to the ensemble variance. This method provides in most cases an upper limit of predictability since it assumes a perfect model and, very often, near-perfect initial conditions. A third method compares the variability simulated with and without active ocean-sea ice dynamics. Those

regions in which ocean-sea ice dynamics are important in generating decadal-scale variability are believed to be regions of high decadal predictability potential (Park and Latif 2005).

All three types of studies yield similar patterns of decadal predictability (Latif et al. 2006a). In contrast to seasonal to inter-annual predictability potential decadal predictability is found predominately over the mid to high-latitude oceans (e. g., Boer and Lambert 2008). The potential decadal predictability decreases with increasing timescale but appreciable values exist up to multidecadal timescales, especially for the North Atlantic and the Southern Ocean (Figure 8). In the North Pacific, the decadal predictability potential is considerably smaller, but probably still useful. It should be mentioned that these results strictly hold only for the internal variability. Results obtained by including externally driven variability such as that related to an increase in atmospheric greenhouse gas concentrations yield rather different results (Hawkins and Sutton 2009). This can be easily understood by considering, for instance, the North Atlantic. AMOC-related decadal variations are strong in this region and appear to be predictable. In contrast, the expected anthropogenic weakening of the AMOC may not be well detectable for many decades due to the existence of the strong internal variability. So, predictability will critically depend on the lead time. On short lead times of a decade, the internal variability may dominate. On long lead times of a century, the weakening in response to changing external forcing may prevail.

4. Limiting factors on realizing decadal predictability

The recent scientific literature provides convincing evidence that climate variations on time scales up to decadal are potentially predictable (e. g., Latif et al. 2006a). Smith et al. 2007, Keenlyside et al. 2008,

Pohlmann et al. 2009, and Mochizuki et al. 2010 describe prediction studies and provide some real forecasts for the next years. These studies, however, should be considered as pilot studies, as both the climate models and their initialization can be much improved. The models suffer from large biases. Figure 9 depicts the typical size of annual mean SST and, over land, SAT errors in the ensemble of IPCC-AR4 models shown in Randall et al. (2007). Typical errors can amount up to 10°C in certain regions in individual models. Hotspots in this respect are, for instance, the eastern tropical and subtropical oceans exhibiting a large warm and the North Atlantic and North Pacific generally suffering from a large cold bias. The latter are of particular importance here, occurring in regions of relatively high decadal predictability potential (Figure 8). Likewise significant discrepancies to observations exist concerning the variability. Many models, for instance, fail to simulate a realistic El Niño/Southern Oscillation (ENSO, see e. g., Latif and Keenlyside 2008 for a review). Thus it cannot be assumed that current climate models are well suited to study the dynamics of decadal variability and to realize the full decadal predictability potential. Conceptually, future work required to realise decadal predictability can be categorized into the following four focus areas.

Mechanisms of decadal variability

The mechanisms leading to decadal-scale climate variability are not well understood and differ largely from model to model. This is apparent from the discussion above on the origin of decadal variability in the mid-latitudes, and further illustrated by simulated variability in the AMOC (Fig. 10; Schmittner et al. 2005): First, there is a huge range in the simulated mean strength, with several models outside observed estimates, and some models exhibiting significant long-term drift. Second, simulated variability differs vastly among models, with some showing primarily inter-annual variability and little or no interdecadal variability, while others exhibit pronounced decadal variations. Third, the response of AMOC to global

warming is also quite uncertain. All this indicates that different mechanisms are active in different models.

A key question is how sensitive the mid-latitude atmosphere is to anomalous SST and sea ice conditions. It has been shown in the past two decades that the extra-tropical atmosphere is sensitive to Tropical Pacific SST in the context of ENSO. However, the atmospheric response to Tropical Atlantic and Indian Ocean SST anomalies is less clear. AGCM experiments indicate winter NAO variations may be partly forced by Tropical Atlantic SST (Okumura et al., 2001), while other studies indicate a significant influence on the East Atlantic Pattern (Pohlmann and Latif, 2005). Decadal changes in the NAO have also been linked to tropical (Hoerling et al., 2001), and specifically Indian Ocean SST (Bader and Latif 2005). Yet, much more work is needed to better understand the extra-tropical response to Tropical Atlantic and Indian Ocean SST anomalies.

Most importantly, however, a much better understanding of the atmospheric response to extra-tropical SST anomalies is in order. Evidence for an atmospheric sensitivity to local SST anomalies even in cold temperature regions is described by Xie 2004. Kushnir et al. 2002 argue that the large-scale extra-tropical atmosphere does respond to changes in underlying SST although the response is small compared to internal (unforced) variability. Two mechanisms were mostly described in the literature. One is an eddy-mediated process, in which a baroclinic response to thermal forcing induces and combines with changes in the position or strength of the storm tracks. This process can lead to an equivalent barotropic response that feeds back positively on the ocean mixed layer temperature. The other is a linear, thermodynamic interaction in which an equivalent-barotropic low-frequency atmospheric anomaly forces a change in SST and then experiences reduced surface thermal damping

due to the SST adjustment. Both processes contribute to an increase in variance and persistence of low-frequency atmospheric anomalies and may thus be important to decadal predictability. Recent studies indicate a prominent role of stratospheric processes in determining the atmospheric response to both tropical and extra-tropical SST anomalies. This rather new development is further discussed below.

Resolution

Many climate models are forced to employ relatively coarse resolution given the limitations in computing power. Several studies show that enhanced horizontal and/or vertical resolution helps to improve model performance. This applies to both the mean state and the variability. A recent example is the study of Minobe et al. (2008) who show the importance of high horizontal resolution in the simulation of the climatology, specifically precipitation, over the Gulf Stream region. The sensitivity of the atmosphere to changes in SST may be also enhanced if higher horizontal resolution is used. This may be relevant to predictability, as coupled modes may have a relatively high predictability potential (an example is ENSO). This issue is the subject of current research, and preliminary work indeed indicates that the atmospheric sensitivity to time-varying SST increases with higher resolution over the Gulf Stream region. Similar processes likely act over Kuroshio/Oyashio Extension.

Another aspect of model bias concerns the impact aspect. We show in Figure 11 an example from hurricane research which highlights the importance of model resolution. Hurricane statistics are known to coherently vary with changes in tropical SST, especially in Tropical Atlantic SST. The latter may be related in climate models to AMOC and thus might be potentially predictable. Despite the large SST biases described below current climate models do reasonably well simulate the decadal-scale SST

variations in the Atlantic. However, tropical storms cannot be well simulated in coarse-resolution models, which are typically used in studies of decadal variability and predictability. A series of model integrations with the ECHAM5 AGCM was conducted by varying the horizontal resolution by Bengtsson et al. (2007). A strong sensitivity of tropical cyclone statistics was found in this set of experiments. Obviously and consistent with observations, the tail of the wind speed distribution extends to much higher wind speeds at high horizontal resolution, and the character of the Global Warming response considerably changes as the resolution increases. The high-resolution models simulate more frequent extreme wind speeds in response to Global Warming, although the total number of storms decreases. The increase in extreme wind speed frequency is not simulated in the coarsest-resolution model (T63).

The QBO (Quasi-Biennial Oscillation), a major mode of inter-annual variability in the stratosphere, provides another example of how an increase in resolution can change model behaviour. Giorgetta et al. (2002) described the first successful QBO simulation in MA-ECHAM5 (middle atmosphere version of ECHAM5) which was run with 90 vertical levels. The standard version of ECHAM5 employs only 19 (31) vertical levels at a horizontal resolution of T31 (T63) and does not allow a simulation of the QBO for several reasons. There are many more examples of how better resolution helps to improve the simulation of the time-averaged circulations and variability in climate models. Many coarse-resolution ocean models, for instance, fail to simulate a realistic path of the North Atlantic Current, which gives rise to rather large SST biases in the North Atlantic when they serve as oceanic component in climate models (Fig. 9). As described by Bryan et al. (2007), improvements in the simulation of the North Atlantic Ocean circulation appear to represent a regime shift in the dynamics of the simulated flow as the horizontal resolution decreases to around 10 km. Such high resolution cannot be afforded in global climate models for the next years.

One final example is given in the following and concerns the role of mesoscale eddies in the ocean. While baroclinic eddies in the atmosphere are well resolved due to their large characteristic horizontal scale even in coarse-resolution AGCMs, they are not resolved by the ocean components used in most IPCC models. Biastoch et al. (2008) show in a modelling study that explicit simulation of Agulhas Current eddies affect the Atlantic AMOC and enhance its decadal variability. They used a two-way nest to increase horizontal resolution in the Agulhas Current region. Böning et al. (2008) find evidence that the Southern Ocean eddies may have stabilized the Antarctic Circumpolar Current (ACC) in the presence of intensifying winds during recent decades. Stronger westerlies over the Southern Ocean are projected by many not ocean eddy-resolving climate models in response to enhanced atmospheric greenhouse gas concentrations, and the ACC generally speeds up in these simulations, which may have profound implications for the oceanic carbon uptake. The explicit simulation of ocean eddies may considerably change the response. In summary, resolution matters when addressing model biases in both climatology and variability, which is a prerequisite to enhance the skill of decadal climate predictions.

Parameterizations

An alternative, but intellectually more challenging, way to include processes which are not resolved in a climate model is to parameterize them, i.e. they are represented in a concise manner given the information at the available grid points. The parameterizations of subgrid-scale physical processes are based on theoretical considerations and empirical evidence. Naturally, several assumptions have generally to be made about the process under consideration that cannot be rigorously justified, and this is a major source of uncertainty. Furthermore, parameterizations must be adjusted when moving to

higher resolution. Giorgetta et al. (2002), for instance, found that the QBO in their model depends equally on resolved wave mean-flow interaction and parameterized gravity wave drag.

However, physical parameterizations must be improved, not only in connection with changes in resolution, to allow for reliable and longer integrations and larger ensembles with coarse-resolution models. The convection parameterization, for instance, poses a major challenge in both atmosphere and ocean modelling. The strong warm bias in the Southeast Tropical and Equatorial Atlantic SST (Figure 8), for instance, is dependent in some models, at least partly, on too weak convection over South America (Richter and Xie 2008; Chang et al. 2008; Wahl et al. 2009): a too weak Walker Circulation is the consequence of this, with too weak easterlies along the equator, even in uncoupled mode. This error in turn leads to reduced upwelling of cold waters from below and to a warm SST bias in the east in coupled mode, which further weakens the easterlies. It is the coupled nature of the problem that makes it so difficult to reduce the Tropical Atlantic SST bias. Coupled feedbacks are also at the heart of the Equatorial Pacific cold bias problem, another major bias in virtually all climate models.

Efforts should be directed to the improvement of the large-scale circulations in the climate system by more refined parameterizations, and a joint approach is needed that brings together observations, theoretical concepts, process and large-scale models. Only such a comprehensive treatment of the processes will improve our understanding and eventually enable the development of “suitable” parameterizations. Concerning AMOC the overflow parameterization in coarse-resolution models may be of special interest, as shown in many studies (e. g., Redler and Böning 1997). A successful example of a parameterization is the eddy parameterization by Gent and McWilliams (1990), which pioneered ocean modelling at that time. Current attempts are directed toward a more unified theory of ocean

mixing. However, new theories must eventually produce better parameterizations, and these must be tested in the models run in climate mode. This requires the availability of large computer resources, since rather long integrations would have to be conducted to assess the usefulness of a parameterization in a climate model.

Coupling of additional climate subsystems

Some components of the climate system are not well represented or not at all part of standard climate models. One example is the stratosphere, which is generally represented only by a few vertical levels. As described above, the stratospheric QBO can be simulated only with a well resolved stratosphere. One reason is the important role of vertically propagating Kelvin waves in the generation of the QBO, which requires high vertical resolution. Recent studies indicate that the mid-latitude response to both tropical and extra-tropical SST anomalies over the North Atlantic Sector may critically depend on stratospheric feedbacks. Ineson and Scaife (2009) present evidence for an active stratospheric role in the transition to cold conditions in northern Europe and mild conditions in southern Europe in late winter during El Niño years. The response in European surface climate to the El Niño signal is large enough to be useful for seasonal forecasting. Such a mechanism may also operate on decadal timescales. A strong sensitivity of the NAO to decadal-scale North Atlantic SST anomalies, for instance, may only exist, if stratospheric processes are resolved, as suggested by e.g., Keenlyside et al. (2008b). It follows that low-frequency stratospheric change, of either natural or anthropogenic origin, may influence tropospheric circulation. Experiments by Scaife et al. (2005) showed that the observed strengthening of the stratospheric jet from 1965-1995 could reproduce the observed changes in the NAO and North Atlantic Sector climate. However, we have just started to recognize the importance of

the stratosphere in inter-annual and decadal variability. A detailed description of the mechanisms that link variations in the ocean to the atmosphere via the stratosphere is pending.

Other climate system components also suffer from significant shortcomings, as comparisons with observed decadal changes reveal. It was shown in several studies (e. g., Zheng et al. 1999) that decadal variations in Sahel rainfall critically depend on land-atmosphere interactions. It is a common shortcoming even in stand-alone integrations with AGCMs forced by prescribed observed SSTs that simulations fail to reproduce the correct magnitude of the decadal precipitation anomalies. The phase, however, is realistically simulated in most cases. This indicates on the one hand that Sahel rainfall is sensitive to SST. However, the models lack on the other hand important land-surface feedbacks associated with hydrological processes and/or dynamical vegetation.

Another example is Arctic sea ice. Stroeve et al. (2007) show that virtually all climate models considerably underestimate the observed Arctic sea ice decline during the recent decades in so called 20th century integrations with prescribed (known natural and anthropogenic) observed forcing. The Arctic sea ice cover in summer 2009 was the third-lowest extent recorded since satellites began measuring minimum sea ice extent in 1979. While the 2009 minimum extent was greater than the previous two years, it is still much below the long-term average, and presumably well outside the range of natural variability. The inability of most models to simulate the observed decline in the 20th century integrations even in individual realizations suggests that sea ice is not adequately incorporated: either the models underestimate the multidecadal sea ice variability and/or the sea ice sensitivity to polar warming.

Finally, atmospheric chemistry and aerosol processes are still not well incorporated into current climate models. The climatic effects of changed solar radiation, for instance, depend on both dynamical and chemical processes. The minimum of the 11-year cycle has become deeper during the last few cycles, and this may continue for some more cycles according to some studies, which may offset somewhat Global Warming (e. g., Lean and Rind 2009). Associated changes in ozone chemistry may play an important role in this context and can feed back on the large-scale atmospheric circulation, specifically the NAO. This may also be important for capturing the climate response to the 11-year solar cycle (Meehl et al. 2009). The effects of explosive volcanic eruptions that inject material directly into the stratosphere involve many aerosol processes (direct and indirect) and a large number of chemical reactions. Although the changes in both external factors, solar and volcanic activity, cannot be predicted, their long-lasting effects can be computed and should be considered in decadal prediction models. The climate effects of strong volcanic eruptions, for instance, can persist for about a decade.

5. Discussion

Decadal climate prediction is of socio-economic importance and has a potentially important role to play in policy making. While seasonal prediction is an initial value and centennial climate projections are basically boundary value problems, decadal prediction is a joint initial/boundary value problem. Thus, both accurate projections of changes in radiative forcing and initialisation of the climate state, particularly the ocean, are required. Although the first promising steps towards decadal prediction have been made, much more work is required. Two problems deserve special attention. First, a sufficient understanding of the mechanisms of decadal-to-multidecadal variability is lacking. The atmospheric response to mid-latitude SST anomalies, for instance, is still highly controversial and future research

should treat this as a key topic. Second, model development is still an issue. On the one hand, state-of-the-art climate models suffer from large biases. On the other hand, they are incomplete and do not incorporate potentially important physics.

The decadal predictability potential appears to be rather large in the North Atlantic Sector. Although the mechanisms behind the decadal to multidecadal variability in the North Atlantic Sector are still controversial, there is some consensus that some of the longer-term multidecadal variability is driven by variations in the AMOC. We expect that the next few decades will be strongly influenced by such multidecadal variations, although the effects of anthropogenic climate change are likely to introduce trends. Several impacts of the variations of the AMOC on the atmosphere have been demonstrated in some studies, so that useful decadal predictions with economic benefit may be possible. However, unpredictable external forcing through explosive volcanic eruptions and/or anomalous solar radiation originating from internal solar dynamics may offset the internal variations and introduce an additional source of uncertainty.

Many coupled ocean-atmosphere-sea ice models simulate decadal variability that is consistent in some respects with the available observations. Yet, the mechanisms differ strongly from model to model, and the poor observational database does not allow a distinction between “realistic” and “unrealistic” simulations. An attempt should be made to identify key regions for long-term intensive observations that will eventually help to understand the fundamental mechanisms of decadal variability in the real world. Key indices should be defined which (hopefully) can be reconstructed from paleo-climatic data to extend the record backward in time as much as possible. Furthermore, we need to define and deploy a “suitable” climate observing system to initialize our climate models for decadal predictions. For the past,

not many sub-surface ocean observations were available, which hindered initialization and verification of decadal hindcasts (retrospective forecasts). Whether the current observing system (including satellites and the ARGO fleet) is “suitable” remains to be shown. However, much more research is needed to define what “suitable” really means for decadal prediction. Dunstone and Smith (2010) conclude that the ARGO array provides a good basis for predicting AMOC variations.

Finally, we need to improve our models. Experience gained from numerical weather and seasonal prediction shows that reduction of systematic bias helps to considerably improve forecast skill. Biases are still large in state-of-the-art climate models. Typical errors in surface air temperature, for instance, can amount up to 10°C in certain regions in individual models. Hotspots in this respect are, for example, the eastern tropical and subtropical oceans exhibiting a large warm, and the North Atlantic and North Pacific generally suffering from a large cold bias. Likewise significant discrepancies to observations exist concerning the variability. Many models, for instance, still fail to simulate a realistic El Niño/Southern Oscillation. Thus it cannot be assumed that current climate models are well suited to realize the full decadal predictability potential. Much higher resolution is certainly one important step to improve models, as has been shown in numerous studies. However, this requires a significant increase in the computing capacity available to the world’s weather and climate centres in order to accelerate progress in improving models and eventually predictions. The World Modelling Summit for Climate Prediction in 2008 (WCRP, 2009) recommended computing systems dedicated to climate research at least a thousand times more powerful than those currently available.

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References

- Alvarez-Garcia, F., M. Latif, and A. Biastoch, 2008: On multidecadal and quasi-decadal North Atlantic variability. *J. Climate*, **21**, 3433–3452.
- Bader, J., and M. Latif, 2005: North Atlantic Oscillation response to anomalous Indian Ocean SST in a coupled GCM. *J. Climate*, **18**, 5382-5389.
- Bengtsson, L. et al., 2007: How may tropical cyclones change in a warmer climate? *Tellus*, **59A**, 539–561.
- Biastoch, A., C. Böning, and J. Lutjeharms, 2008: Agulhas leakage dynamics affects decadal variability in Atlantic overturning circulation. *Nature*, **456**, doi:10.1038/nature07426.
- Biasutti, M. and A. Giannini, 2006: Robust Sahel drying in response to late 20th century forcings. *Geophys. Res. Lett.*, **33**, L11706, 10.1029/2006gl026067.
- Bjerknes, J., 1964: Atlantic air-sea interaction. *Advances in Geophysics*, Academic Press, **10**, 1-82.
- Böning, C. W., A. Dispert, M. Visbeck, S. R. Rintoul, and F. U. Schwarzkopf, 2008: The response of the Antarctic Circumpolar Current to recent climate change. *Nature Geoscience*, **1**, doi:10.1038/ngeo362.
- Boer, G., 2000: A study of atmosphere-ocean predictability on long time scales. *Clim. Dynamics*, **16**, 469-472.
- Boer, G. J., 2004: Long timescale potential predictability in an ensemble of coupled climate models. *Climate Dynamics*, **23**, 29-44.
- Boer, G. J., and S. J. Lambert, 2008: Multi-model decadal potential predictability of precipitation and temperature. *Geophys. Res. Lett.*, **35**, L05706, doi:10.1029/2008GL033234.

- Broccoli, A. J., K. W. Dixon, T. L. Delworth, T. R. Knutson, R. J. Stouffer, et al., 2003: Twentieth-century temperature and precipitation trends in ensemble climate simulations including natural and anthropogenic forcing. *J. Geophys. Res. (Atmos)*, **108**, doi: 10.1029/2003jd003812.
- Bryan, F. O., M. W. Hecht, and R. D. Smith, 2007: Resolution convergence and sensitivity studies with North Atlantic circulation models. Part I: The western boundary current system. *Ocean Modelling*, **16**, 141–159.
- Chang, P., L. Ji, and H. Li (1997): A decadal climate variation in the tropical Atlantic Ocean from thermodynamic air-sea interactions, *Nature*, **385**, 516-518.
- Chang, C.-Y., S. Nigam, and J. A. Carton, 2008: Origin of the Springtime Westerly Bias in Equatorial Atlantic Surface Winds in the Community Atmosphere Model Version 3 (CAM3) Simulation. *J. Climate*, **21**, 4766–4778.
- Collins, M., 2002: Climate predictability on interannual to decadal time scales: the initial value problem. *Clim. Dynamics*, **19**, 671-692.
- Collins, M., and B. Sinha, 2003: Predictability of decadal variations in the thermohaline circulation and climate, *Geophys. Res. Lett.*, **30**(6), 1306, doi:10.1029/2002GL016504.
- Curry, R.G., M.S. McCartney, and T.M. Joyce, 1998: Oceanic transport of subpolar climate signals to mid-depth subtropical waters. *Nature*, **391**, 575-577.
- Davis, R. E., 1976: Predictability of Sea Surface Temperature and Sea Level Pressure Anomalies over the North Pacific Ocean. *J. Phys. Oceanogr.*, **6**, 249–266.
- Delworth, T.L., and R.J. Greatbatch, 2000: Multidecadal thermohaline circulation variability driven by atmospheric surface flux forcing. *J. Climate*, **13**, 1481-1495.

Delworth, T., S. Manabe, and R.J. Stouffer, 1993: Interdecadal variations of the thermohaline circulation in a coupled ocean-atmosphere model. *J. Climate*, **6**, 1993-2011.

Delworth, T. L. and M. E. Mann, 2000: Observed and simulated multidecadal variability in the Northern Hemisphere. *Climate Dynamics*, **16**, 661-676, 10.1007/s003820000075.

Deser, C. and M.L. Blackmon, 1993: Surface climate variations over the North Atlantic Ocean during winter: 1900-1989. *J. Climate*, **6**, 1743-1753.

Dommenget, D. and M. Latif, 2008: Generation of Hyper Climate Mode. *Geophys. Res. Lett.*, **35**, L02706, doi:10.1029/2007GL031087.

Dunstone, N. J. and D. M. Smith, 2010: Impact of atmosphere and sub-surface ocean data on decadal climate prediction. *Geophys. Res. Lett.*, **37**, L02709, doi:10.1029/2009GL041609

Eden, C., and T. Jung, 2001: North Atlantic Interdecadal Variability: Oceanic response to the North Atlantic Oscillation (1865-1997). *J. Climate*, **14**, 676-691.

Eden, C., and J. Willebrand, 2001: Mechanism of interannual to decadal variability of the North Atlantic circulation. *J. Climate*, **14**, 2266-2280.

Eden, C. and R. J. Greatbatch, 2003: A damped decadal oscillation in the North Atlantic Ocean Climate System. *J. Climate*, **16**, 4043-4060.

Frankignoul, C. and R. W. Reynolds, 1983: Testing a dynamical model for midlatitude sea surface temperature anomalies, *J. Phys. Oceanogr.*, **13**, 1131-1145

Frankignoul, C., P. Muller, E. Zorita, 1997: A simple model of the decadal response of the ocean to stochastic wind forcing. *J. Phys. Oceanogr.*, **27**, 1533-1546.

- Frankignoul, C. and K. Hasselmann, 1977: Stochastic climate models. Part II: application to sea surface temperature anomalies and thermocline variability, *Tellus*, **29**, 284–305.
- Gent, P. R. and J. C. McWilliams, 1990: Isopycnal mixing in ocean circulation models. *J. Phys. Oceanogr.*, **20**, 150-155.
- Giorgetta M. A., E. Manzini E., and E. Roeckner, 2002: Forcing of the quasi-biennial oscillation from a broad spectrum of atmospheric waves. *Geophys. Res. Lett.*, **29**, 10.1029/2002GL014756.
- Griffies, S. M., and E. Tziperman, 1995: A linear thermohaline oscillator driven by stochastic atmospheric forcing. *J. Climate*, **8**, 2440-2453
- Griffies, S.M. and K. Bryan, 1997a: A predictability study of simulated North Atlantic multidecadal variability. *Clim. Dynamics*, **13**, 459-488.
- Griffies, S.M. and K. Bryan, 1997b: Predictability of North Atlantic multidecadal climate variability. *Science*, **275**, 181-184.
- Grötzner, A., M. Latif, A. Timmermann, and R. Voss, 1999: Interannual to decadal predictability in a coupled ocean-atmosphere general circulation model. *J. Climate*, **12**, 2607-2624.
- Gu, D. and S. G. H. Philander, 1997: Interdecadal Climate Fluctuations that depend on Exchanges between the Tropics and Extratropics, *Science*, **275**, 805-807.
- Hall, A. and S. Manabe, 1997: Can Local, Linear Stochastic Theory Explain Sea Surface Temperature and Salinity Variability? *Climate Dynamics*, **13**, 167-180.
- Hasselmann, K., 1976: Stochastic climate models. Part I: Theory. *Tellus*, **28**, 473-485.

Hawkins, E. and R. Sutton, 2009: The potential to reduce uncertainty in regional climate predictions. *Bull. Am. Meteorol. Soc.*, in press.

Hawkins, E. et al. 2010: Evaluating the potential for statistical decadal predictions of SSTs with a perfect model approach, *Climate Dynamics*, submitted.

Herterich K. and K. Hasselmann, 1987: Extraction of mixed layer advection velocities, diffusion coefficients, feedback factors, and atmospheric forcing parameters from the statistical analysis of the North Pacific SST anomaly fields. *J. Phys. Oceanogr.*, **17**, 2145–2156.

Hoerling, M. P., J. W. Hurrell, and T. Y. Xu, 2001: Tropical origins for recent North Atlantic climate change. *Science*, **292**, 90-92.

Hurrell et al., 2010: Decadal Climate Prediction: Opportunities and Challenges. Community White Paper, *OceanObs '09*, in press.

Ineson, S. and A. A. Scaife, 2009: The role of the stratosphere in the European climate response to El Niño. *Nature Geoscience*, **2**, 32 – 36. doi:10.1038/ngeo381.

IPCC, 2007: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon, et al., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jacobs, G. A., H. E. Hurlburt, J. C. Kindle, E. J. Metzger, J. L. Mitchell, W. J. Teague, and A. J. Wallcraft, 1994: Decade-scale trans-Pacific propagation and warming effects of an El Niño anomaly. *Nature*, **370**, 360 – 363.

Keenlyside, N. S., M. Latif, J. Jungclaus, L. Kornblueh, and E. Roeckner, 2008a: Advancing decadal-scale climate prediction in the North Atlantic sector. *Nature*, **453**, 84-88 doi:10.1038/nature06921.

Keenlyside, N. S., N.-E. Omrani, K. Krüger, M. Latif, and A. Scaife, 2008b: Decadal predictability: How might the stratosphere be involved? *SPARC Newsletter*, **31**, 23-27.

Kirtman, B. P. and J. Shukla, 2002: Interactive coupled ensemble: A new coupling strategy for GCMs. *Geophys. Res. Lett.*, **29**(10), 1367, doi:10.1029/2002GL014834.

Kleeman, R., J. P. McCreary, Jr., and B. A. Klinger, 1999: A mechanism for generating ENSO decadal variability. *Geophys. Res. Lett.*, **26**, 1743-1746, 10.1029/1999gl900352.

Knight, J. R., R. J. Allan, C. K. Folland, M. Vellinga, and M. E. Mann, 2005: A signature of persistent natural thermohaline circulation cycles in observed climate. *Geophys. Res. Lett.*, **32**, L20708, doi:10.1029/2005GL024233

Kushnir, Y. W. A. Robinson, I. Bladé, N. M. J. Hall, S. Peng, and R. Sutton, 2002: Atmospheric GCM Response to Extratropical SST Anomalies: Synthesis and Evaluation. *J. Climate*, **15**, 2233–2256.

Latif, M., 1998: Dynamics of interdecadal variability in coupled ocean-atmosphere models. *J. Climate*, **11**, 602-624.

Latif, M. (2001): Tropical Pacific/Atlantic Ocean interactions at multi-decadal time scales. *Geophys. Res. Lett.*, **28**, 539-542.

Latif, M., 2006: On North Pacific Multidecadal Climate Variability. *J. Climate*, **19**, 2906-2915.

Latif, M., and T.P. Barnett, 1994: Causes of decadal climate variability over the North Pacific and North America. *Science*, **266**, 634-637.

Latif, M. and N. Keenlyside, 2008: El Niño/Southern Oscillation response to global warming. *Proc. Nat. Ac. Sci.*, doi:10.1073/pnas.0710860105.

Latif, M., E. Roeckner, U. Mikolajewicz and R. Voss (2000): Tropical stabilisation of the thermohaline circulation in a greenhouse warming simulation. *J. Climate*, **13**, 1809-1813.

Latif, M., E. Roeckner, M. Botzet, M. Esch, H. Haak, S. Hagemann, J. Jungclaus, S. Legutke, Marsland, S., U. Mikolajewicz, and J. Mitchell, 2004: Reconstructing, Monitoring, and Predicting Multidecadal-Scale Changes in the North Atlantic Thermohaline Circulation with Sea Surface Temperature. *J. Climate*, **17**, 1605-1614.

Latif, M. M. Collins, H. Pohlmann, and N. Keenlyside, 2006a: A review of predictability studies of the Atlantic sector climate on decadal time scales. *J. Climate*, **19**, 5971-5987.

Latif, C. Böning, J. Willebrand, A. Biastoch, J. Dengg, N. Keenlyside, U. Schweckendiek, and G. Madec, 2006b: Is the thermohaline circulation changing? *J. Climate*, **19**, 4631-4637.

Latif, M., W. Park, N. Keenlyside, and H. Ding, 2009: Internal and External North Atlantic Sector Variability in the Kiel Climate Model. *Meteor. Zeitschrift*, **18**, 433-443.

Lean, J. L., and D. H. Rind, 2009: How will Earth's surface temperature change in future decades? *Geophys. Res. Lett.*, **36**, L15708, doi:10.1029/2009GL038932.

Lemke, P., E. W. Trinkl, and K. Hasselmann, 1980: Stochastic dynamic analysis of sea ice variability. *J. Phys. Oceanogr.*, **10**, 2100-2120.

Mann, M.E. and Emanuel, K.A. 2006: Atlantic Hurricane Trends Linked to Climate Change. *Eos Trans.*, **87**, 233.

Meehl, G. A. and A. X. Hu, 2006: Megadroughts in the Indian monsoon region and southwest North America and a mechanism for associated multidecadal Pacific sea surface temperature anomalies. *J. Climate*, **19**, 1605-1623

Meehl G.A., J.M. Arblaster, K. Matthes, F. Sassi and H. van Loon, 2009: Amplifying the Pacific Climate System Response to a Small 11-Year Solar Cycle Forcing, *Science*, 325, **1114**, DOI: 10.1126/science.1172872

Mikolajewicz, U. and E. Maier-Reimer, 1990: Internal secular variability in an ocean general circulation model. *Climate Dynamics*, **4**, 145-156.

Miller, A. J., and N. Schneider, 2000: Interdecadal climate regime dynamics in the North Pacific Ocean: Theories, observations and ecosystem impacts. *Prog. Oceanogr.*, **47**, 355–379.

Minobe S., A. Kuwano-Yoshida, N. Komori, S.-P. Xie, and R. J. Small, 2008: Influence of the Gulf Stream on the troposphere. *Nature*, **452**: 206-209.

Mochizuki T, et al., 2010: Pacific decadal oscillation hindcasts relevant to near-term climate prediction. *Proc. Natl. Acad. Sci.*, **107**:1833–1837.

Palmer, T. N., U. Andersen, P. Cantelaube, M. Davey, M. Deque, F. J. Doblas-Reyes, H. Feddersen, R. Graham, S. Gualdi, J.-F. Gueremy, R. Hagedorn, M. Hoshen, N. Keenlyside, M. Latif, A. Lazar, E. Maisonave, V. Marletto, A. P. Morse, B. Orfila, P. Rogel, J.-M. Terres, and M. C. Thomson, 2004: Development of a European Multi-Model Ensemble System for Seasonal to Interannual Prediction (DEMETER). *Bull. Am. Meteorol. Soc.*, **85**, 853–872.

Power, S.B., and R. Colman, 2006: Multi-year predictability in a coupled general circulation model. *Climate Dynamics*, **26**, 247-272.

Ottera, O. H., M. Bentsen, H. Drange, and L. Suo, 2010: External forcing as a metronome for Atlantic multidecadal variability. *Nature Geosci.*, advance online publication.

Okumura, Y., S.-P. Xie, A. Numaguti, and Y. Tanimoto, 2001: Tropical Atlantic air-sea interaction and its influence on the NAO. *Geophys. Res. Lett.*, **28**, 1507-1510.

Park, W., and M. Latif, 2005: Ocean Dynamics and the Nature of Air-Sea Interactions over the North Atlantic. *J. Climate*, **18**, 982-995.

Park, W., and M. Latif, 2008: Multidecadal and Multicentennial Variability of the Meridional Overturning Circulation. *Geophys. Res. Lett.*, **35**, L22703, doi:10.1029/2008GL035779.

Park, W., N. Keenlyside, M. Latif, A. Ströh, R. Redler, E. Roeckner, and G. Madec, 2009: Tropical Pacific climate and its response to global warming in the Kiel Climate Model. *J. Climate*, **22**, 71-92, DOI: 10.1175/2008JCLI2261.1.

Pohlmann, H., and M. Latif, 2005: Atlantic versus Indo-Pacific influence on Atlantic-European climate. *Geophys. Res. Lett.*, **32**, L05707, doi:10.1029/2004GL021316.

Pohlmann, H., M. Botzet, M. Latif, A. Roesch, M. Wild, and P. Tschuck, 2004: Estimating the Long-Term Predictability Potential of a coupled AOGCM. *J. Climate*, **17**, 4463-4472.

Pohlmann, H., J. Jungclaus, A. Koehl, D. Stammer, and J. Marotzke, 2009: Improving climate predictability through the initialization of a coupled model with the GECCO oceanic synthesis. *J. Climate*, **22**, 3926-3938.

Randall, D. A. et al., 2007: Climate Models and Their Evaluation. In: *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Richter, I., and S.-P. Xie, 2008: On the origin of equatorial Atlantic biases in coupled general circulation models. *Climate Dynamics*, **31**, 587–598.

Rodgers, K., P. Friedrichs and M. Latif, 2004: Tropical Pacific Decadal Variability and its relation to decadal modulations of ENSO. *J. Climate*, **17**, 3761-3774.

Saenger, C., A. L. Cohen, D. W. Oppo, R. B. Halley, and J. E. Carilli, 2009: Surface-temperature trends and variability in the low-latitude North Atlantic since 1552. *Nature Geosci.*, **2**, 492-495, Doi 10.1038/Ngeo552.

Saravanan, R., and J. C. McWilliams, 1997: Stochasticity and spatial resonance in interdecadal climate fluctuations. *J. Climate*, **10**, 2299–2320.

Scaife, A. A., J. R. Knight, G. K. Vallis, and C. K. Folland, 2005: A stratospheric influence on the winter NAO and North Atlantic surface climate. *Geophys. Res. Lett.*, **32**, L18715.

Schneider, N., and B. Cornuelle, 2005: The forcing of the Pacific Decadal Oscillation. *J. Climate*, **18**, 4355-4373.

Schmittner, A., M. Latif, and B. Schneider, 2005: Model projections of the North Atlantic thermohaline circulation for the 21st century assessed by observations. *Geophys. Res. Lett.*, **32**, L23710, doi:10.1029/2005GL024368.

Schneider, N., A. J. Miller and D. W. Pierce, 2002: Anatomy of North Pacific decadal variability. *J. Climate*, **15**, 586-605.

Semenov, V. A., Latif, M., Dommenges, D., Keenlyside, N.S., Strehz, A., Martin, T. and Park, W. 2010: The Impact of North Atlantic-Arctic Multidecadal Variability on Northern Hemisphere Surface Air Temperature, *J. Climate*, in press.

Smith, D. M., S. Cusack, A. W. Colman, C. K. Folland, G. R. Harris, and J. M. Murphy, 2007: Improved surface temperature prediction for the coming decade from a global climate model. *Science*, **317**, 796-799.

Stommel, H. M., 1961: Thermohaline convection with two stable regimes of flow. *Tellus*, **13**, 224–230.

Stroeve, J., M. M. Holland, W. Meier, T. Scambos, and M. Serreze, 2007: Arctic sea ice decline: Faster than forecast. *Geophys. Res. Lett.*, **34**, L09501, doi:10.1029/2007GL029703.

Sutton, R. T., and M.R. Allen, 1997: Decadal predictability of North Atlantic sea surface temperature and climate, *Nature*, **388**, 563-567.

Teng, H. and G. Branstator, 2010: Initial-value Predictability of Prominent Modes of North Pacific Subsurface Temperature in a CGCM. *Climate Dynamics*, in press.

Timmermann, A., M. Latif, R. Voss, and A. Grötzner, 1998: Northern Hemisphere interdecadal variability: A coupled air-sea mode. *J. Climate*, **11**, 1906-1931.

Ting, M. F., Y. Kushnir, R. Seager, and C. H. Li, 2009: Forced and Internal Twentieth-Century SST Trends in the North Atlantic. *J. Climate*, **22**, 1469-1481, Doi 10.1175/2008jcli2561.1

Vimont, D. J., D. S. Battisti, and A. C. Hirst, 2001: Footprinting: A seasonal connection between the tropics and mid-latitudes. *Geophys. Res. Lett.*, **28**, 3923-3926, 10.1029/2001gl013435.

Wahl, S., M. Latif, W. Park, and N. Keenlyside, 2009: On the Tropical Atlantic Warm Bias in the Kiel Climate Model. *Climate Dynamics*, DOI 10.1007/s00382-009-0690.

WCRP, 2009: World Modelling Summit for Climate Prediction, Reading UK, 6-9 May 2008, No. 131, WMO/TD No. 1468, http://wcrp.wmo.int/PG_Reports_WCRPSeries.html.

White, W. B., and R. Peterson, 1996: An Antarctic circumpolar wave in surface pressure, wind, temperature, and sea ice extent. *Nature*, **380**, 699-702.

Weisse, R., U. Mikolajewicz, and E. Maier-Reimer, 1994: Decadal variability of the North Atlantic in an ocean general circulation model, *J. Geophys. Res.*, **99**(C6), 12,411–12,421.

Weisse, R., U. Mikolajewicz, A. Sterl, and S. S. Drijfhout, 1999: Stochastically forced variability in the Antarctic Circumpolar Current, *J. Geophys. Res.*, **104**(C5), 11,049–11,064.

Xie, S.-P., 2004: Satellite observations of cool ocean-atmosphere interaction. *Bull. Amer. Meteor. Soc.*, **85**, 195-208.

Yeh, S.-W., and B. P. Kirtman, 2004: The North Pacific Oscillation–ENSO and internal atmospheric variability. *Geophys. Res. Lett.*, **31**, L13206, doi:10.1029/2004GL019983.

Zhang, R., T. L. Delworth, and I. M. Held, 2007: Can the Atlantic Ocean drive the observed multidecadal variability in Northern Hemisphere mean temperature? *Geophys. Res. Lett.*, **34**, L02709, doi:10.1029/2006GL028683

Zheng, N., J. D. Neelin,, K.-M. Lau, K.-M., and C.J. Tucker, 1999: Enhancement of inter-decadal climate variability in the Sahel by vegetation interaction. *Science*, **286**, 1537-1540.

Figure Captions

Fig. 1: The upper panel shows the Northern Hemisphere averaged annual SAT together with the linear trend (red) and the 21-year running mean (blue), the lower panel the annual AMV index and its 11-year running mean (dashed lines indicate plus and minus one standard deviation).

Fig. 2: From top to bottom: Annual mean European SAT (5°W-10°E, 35-60°N), linearly de-trended annual mean European SAT, linearly de-trended North Atlantic SST (0-60°N), summer Sahel rainfall, Atlantic hurricane activity (ACE index), and North Atlantic SST repeated from above. The bottom three panels show northwestern United States SAT, the linearly de-trended version, and the PDO index. The latter is defined as the linearly de-trended timeseries of the leading Empirical Orthogonal Function (EOF) of SST north of 20°N. All timeseries are deviations from the long-term mean. All temperature timeseries are in units of [°C]. The Sahel rainfall and the ACE index were normalized with the long-term standard deviation.

Fig.3.: The relative importance of each source of uncertainty in decadal mean surface temperature projections is shown by the fractional uncertainty (the 90% confidence level divided by the mean prediction), for (A) global mean, relative to the warming from the 1971-2000 mean, and (B) British Isles mean, relative to the warming from the 1971-2000 mean. Internal variability grows in importance for the smaller region. Scenario uncertainty only becomes important at multi-decadal lead times. The dashed lines in (A) indicate reductions in internal variability, and hence total uncertainty, that may be possible through proper initialisation of the predictions through assimilation of ocean observations (Smith et al., 2007). The fraction of total variance in decadal mean surface air temperature predictions

explained by the three components of total uncertainty is shown for, (C) a global mean, (D) a British Isles mean. Green regions represent scenario uncertainty, blue regions represent model uncertainty and orange regions represent the internal variability component. As the size of the region is reduced, the relative importance of internal variability increases. From Hawkins and Sutton (2009).

Fig. 4: Hierarchy of stochastic climate models. A feedback from the ocean onto the atmosphere is not considered, but could be easily included. See text for coupled feedbacks.

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11-yr running mean filter (thick line). Multidecadal changes of the MOC as indicated by the dipole index lag those of the NAO by about a decade, supporting the notion that a significant fraction of the low-frequency variability of the MOC is driven by that of the NAO. Shown in red are annual data of LSW thickness (m), a measure of convection in the Labrador Sea, at ocean weather ship Bravo, defined between isopycnals $\sigma_{1.5} = 34.72\text{--}34.62$, following (Curry et al. 1998). (b, lower) Correlation of an MOC index (overturning streamfunction at 30°N) with North Atlantic SST as a function of the time lag computed from a multimillennial control integration with the Kiel Climate Model (KCM). Redrawn after Latif et al. (2009).

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Figures

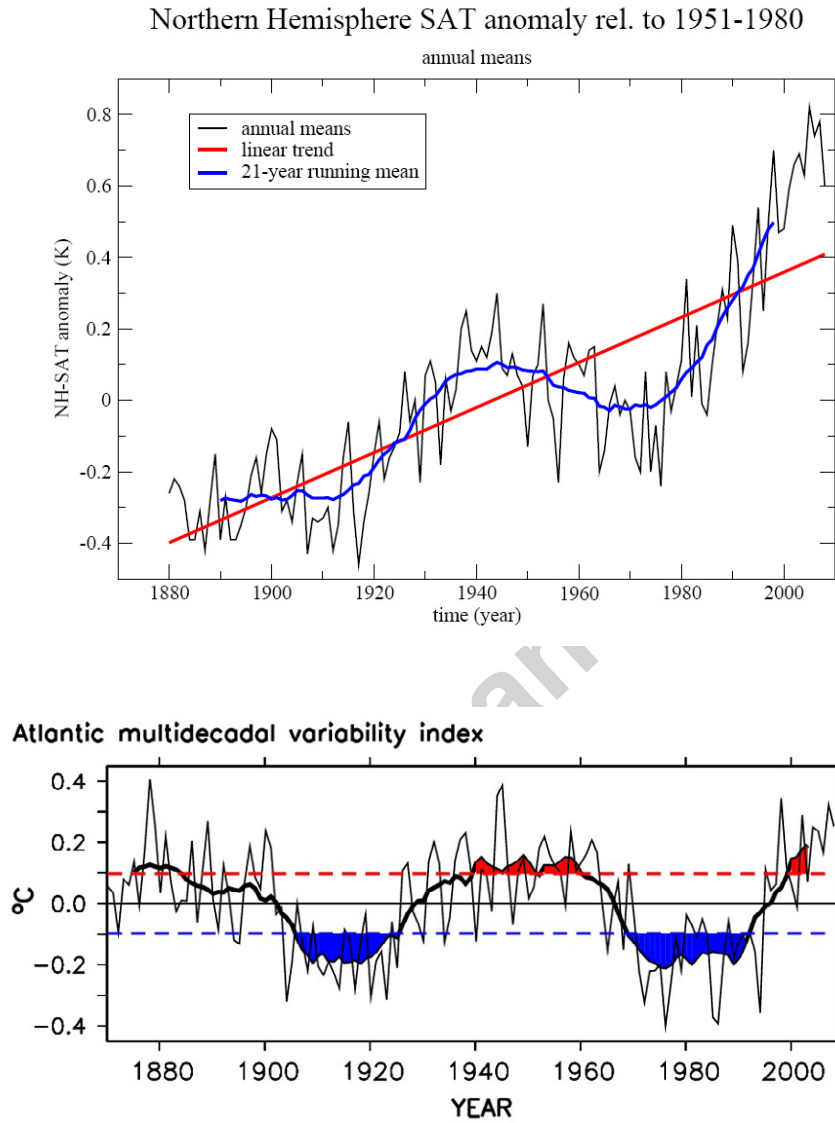


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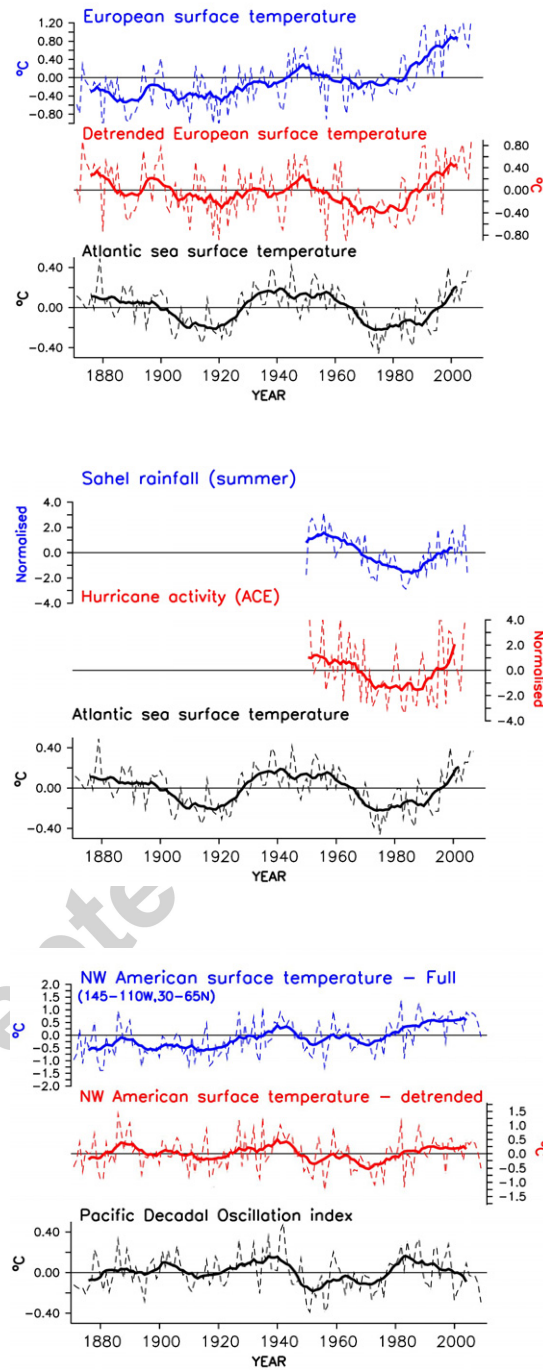


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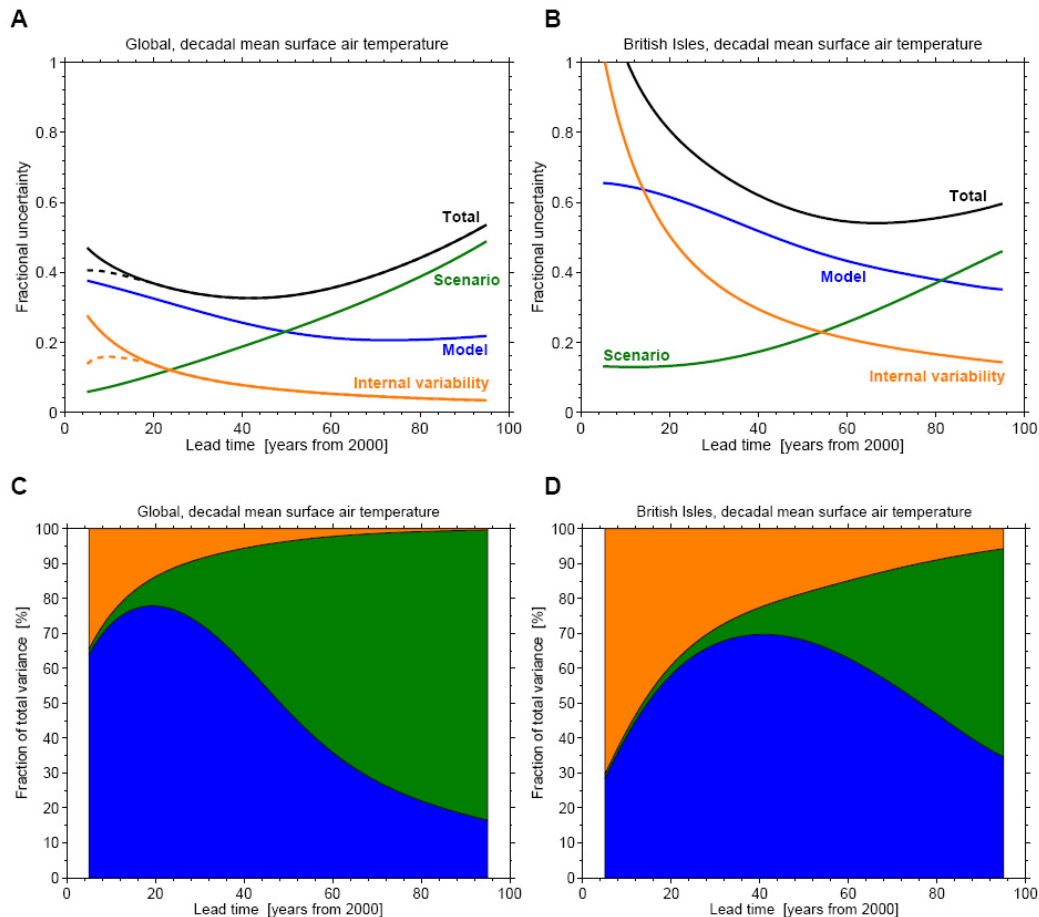


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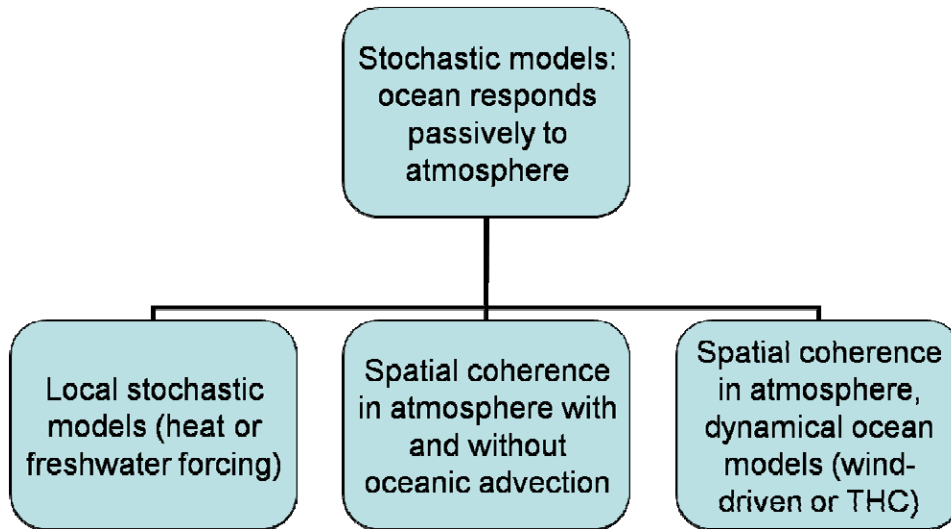
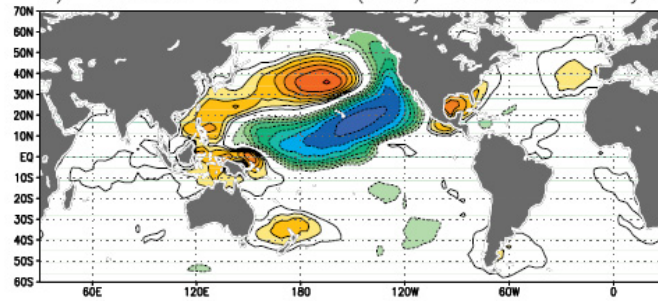
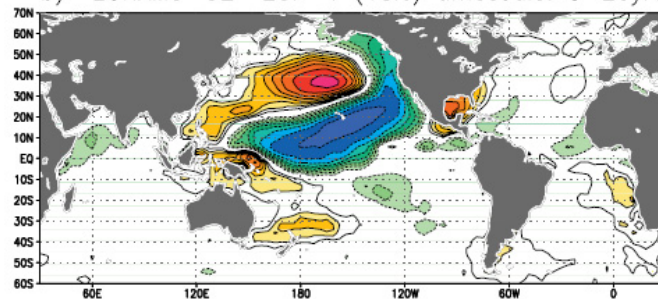


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b) ECHAM5-OZ EOF-1 (18%) timescale: 5–20yrs



c) ECHAM5-OZ EOF-1 (29%) timescale: >40yrs

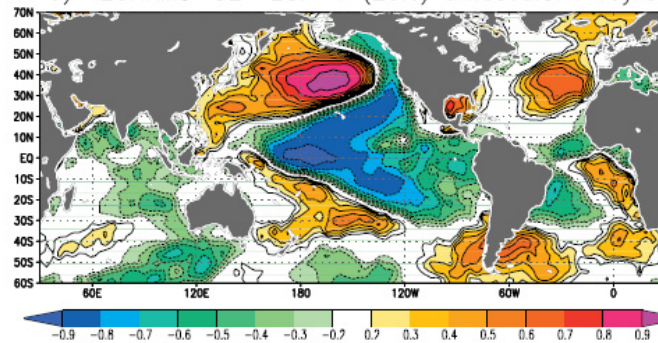


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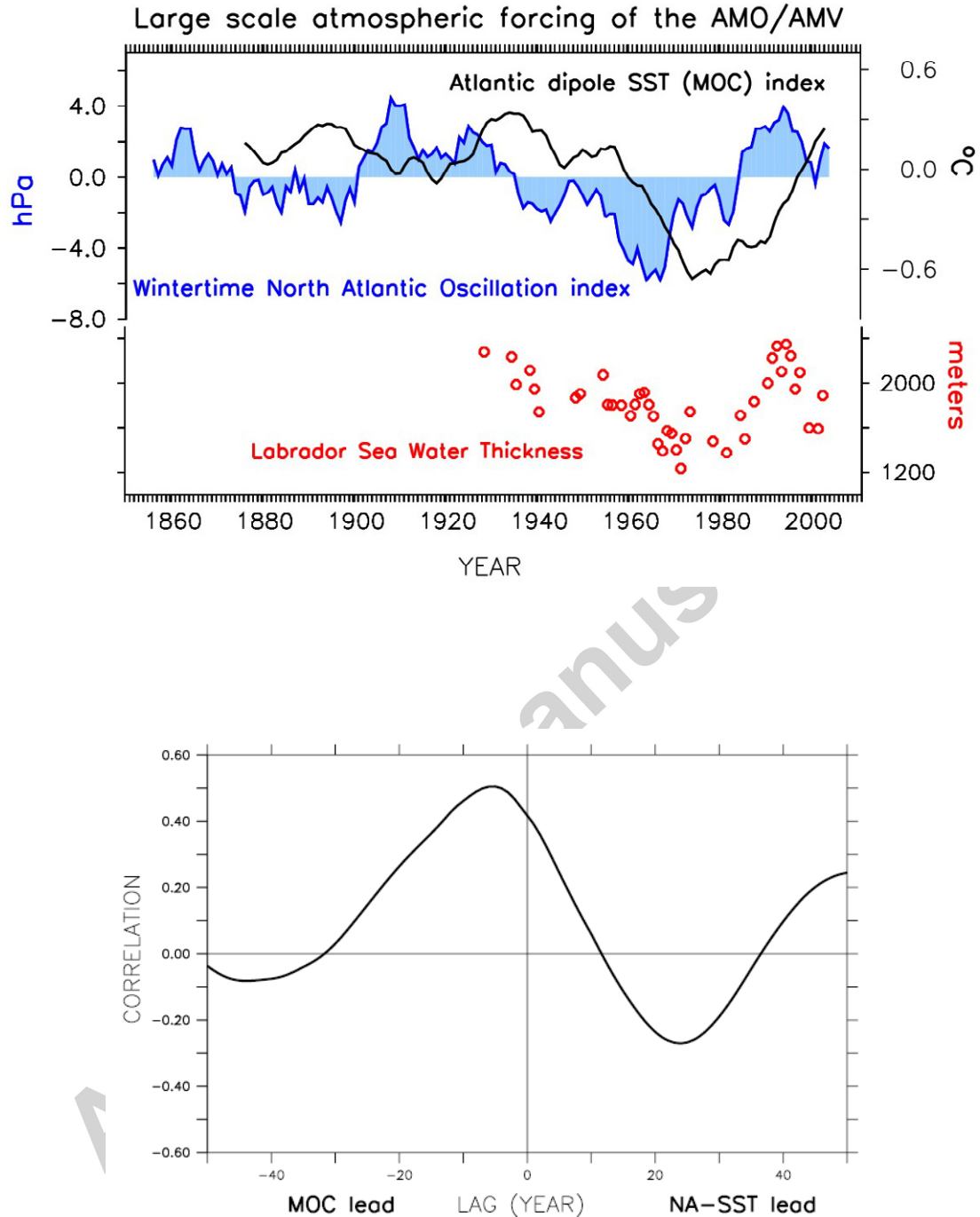


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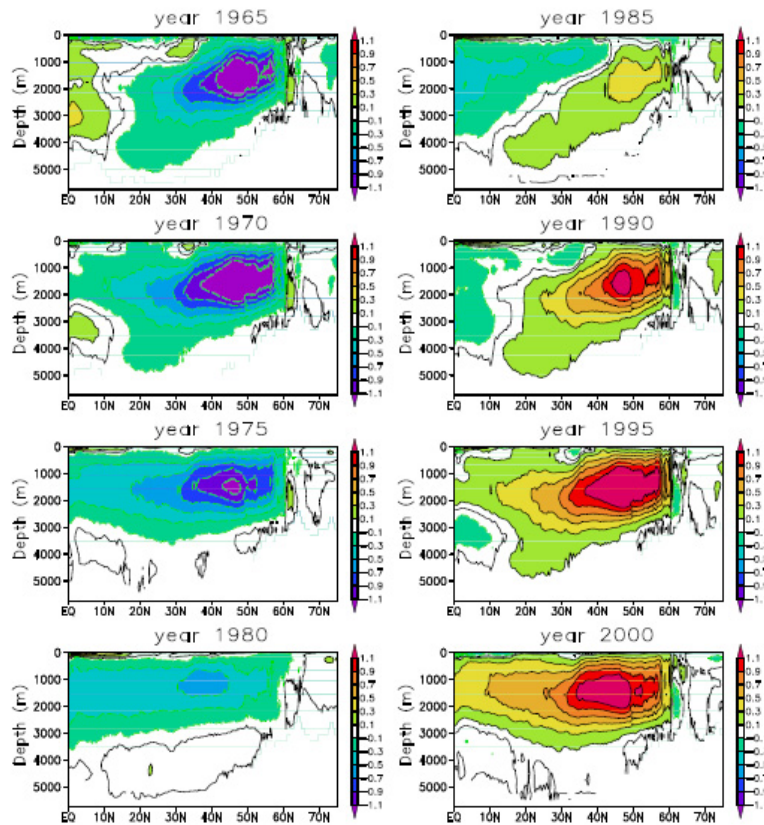


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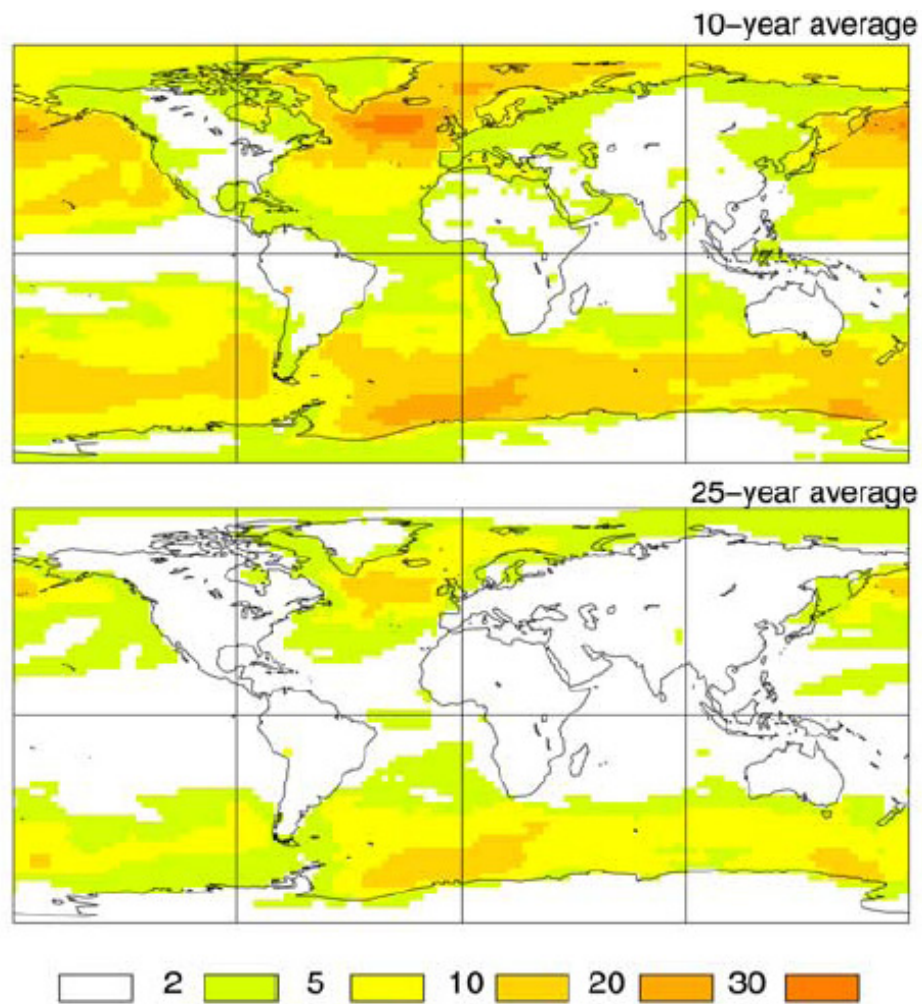


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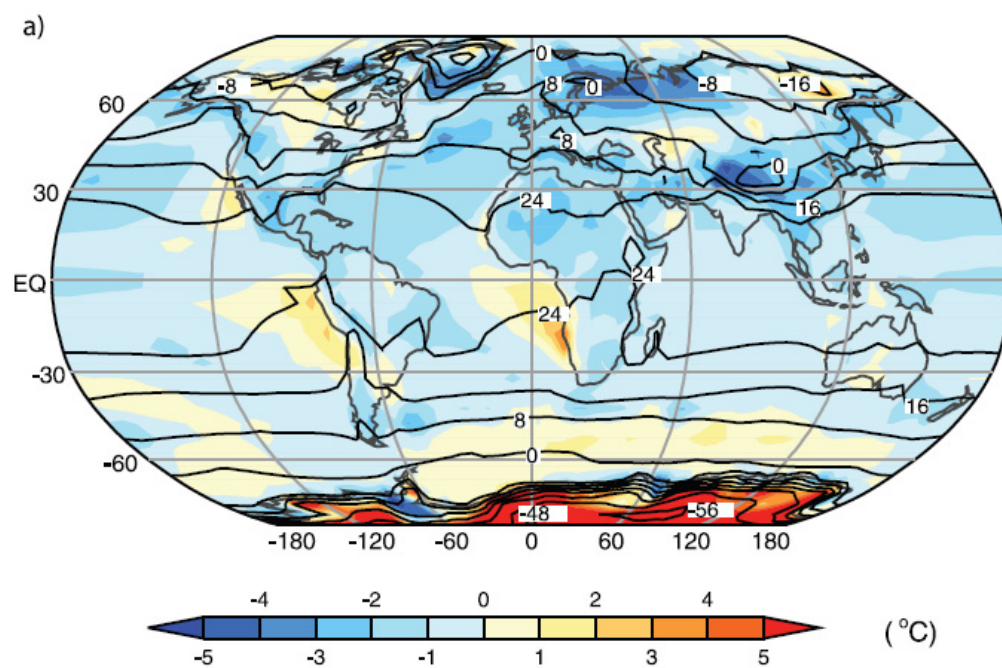


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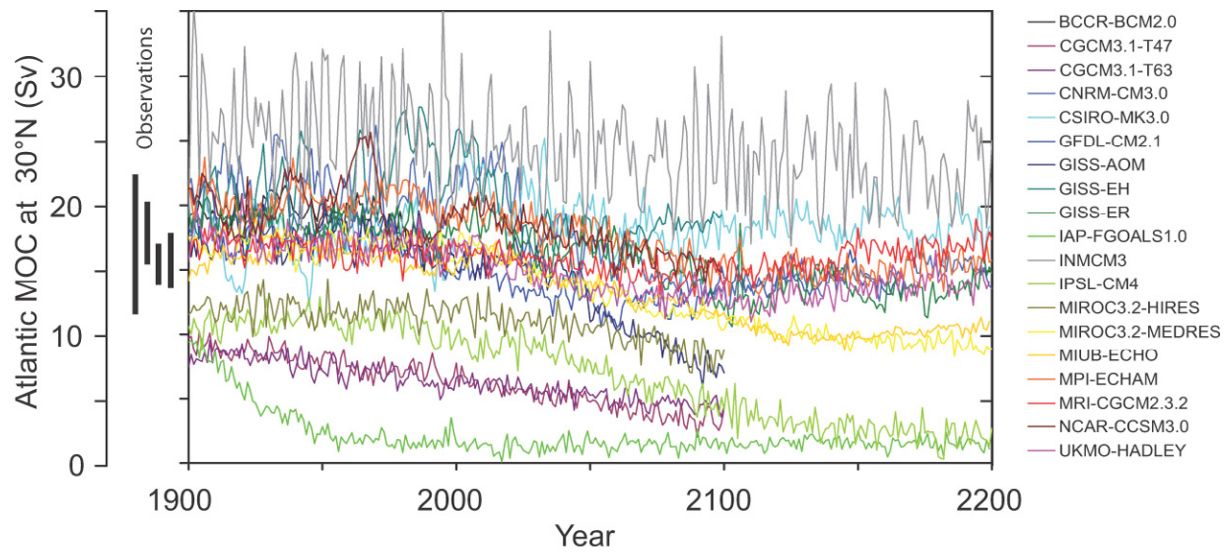


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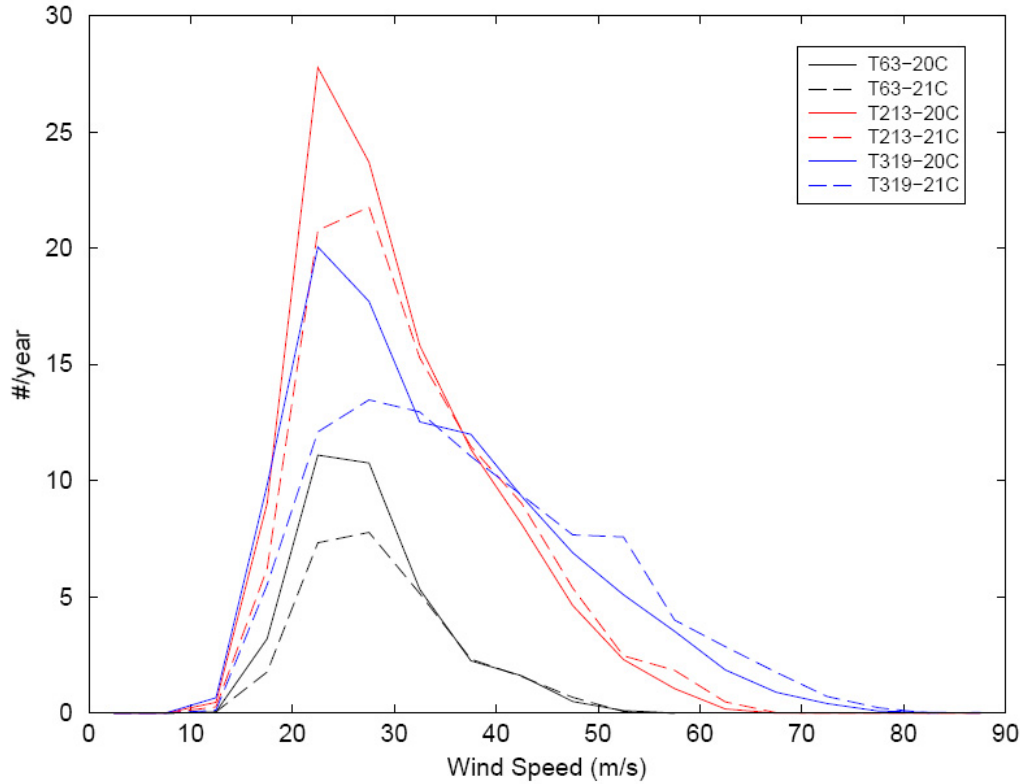


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