Mémoire pour l'obtention du diplôme pour une

# Habilitation à Diriger des Recherches

Décernée par l'Institut National
Polytechnique de Toulouse
Spécialité : **Sciences**

## Understanding climate variability and predictability from observations, reanalysis and imperfect models

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Version du 26 avril 2016-04-20

*A Romain, merci pour ton aide dans ce petit coup de stress supplémentaire...*

*Tous gardèrent le silence pendant le décollage, Retancourt s'étant plongée dans une revue sans la lire.*
*— Ciel bleu limpide sur l'Islande, ai-je lu, dit Veyrenc.*
*— Mais là-bas, il suffit d'un éternuement pour que le temps change répondit Adamsberg.*
*— Oui.*
*— On ne verra même pas Rejkavik.*
*— Reykjavik.*
*— Je ne peux pas le prononcer.*
*— Façades des maisons rouges, bleues, blanches, roses, jaunes, continua Veyrenc. Lacs et falaises, montagnes noires et enneigées.*
*— Ça doit être beau.*
*— Sûrement.*

Fred Vargas dans 'Temps Glaciares"

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# 1 Introduction to climate variability and predictability

## 1.1 SOURCES OF CLIMATE VARIABILITY

A great part of the climate research is focused on the understanding of climate variability at a variety of spatial scales and timescales. "Climate variability" can be defined as the fluctuations of climate above or below a climatological reference or mean states, which are significant from a statistical point of view. Climate variations can be classified into two main categories: i) the intrinsic or internal variability, which originates from numerous interactions among all the components of the climate system (the atmosphere, the ocean, the biosphere, the land surface, and the cryosphere); and ii) the external forced variability, which is defined as the response of the climate system to the external forcings. The latter can have natural origin like volcanic eruptions, solar fluctuations, modifications in orbital parameters; and from human activities (greenhouse gases and anthropogenic aerosols emissions, land-use, etc).

Paleoclimate and historical records reconstructions show that climate has experienced important changes in the past. However, it has been scientifically proven that the increase of Greenhouse Gases (GHGs) emissions into the atmosphere as a consequence to human activities since the industrial development (mid 19$^{th}$ century), has induced an unprecedented global warming (IPCC2007[1], IPCC2013, http://www.ipcc.ch/). The human-induced temperature increase will undoubtedly impact our environment, society and economy, hence a key objective of climate science is to understand climate variability that results from anthropogenic and natural external forcings, and how they may be distinguished from changes and variability that result from internal climate processes.

### 1.1.1 Internal climate variability

The understanding of the mechanisms governing the purely intrinsic climate variability constitutes a hard task, since these can operate at multiple spatial scales and timescales, and can be generated by only one or several components of the climate system through coupled interactions (Hasselmann, 1976). Atmospheric processes creating internal variability are known to occur on spatial scales from several kilometers up to basin-wide, and time scales ranging from virtually instantaneous (condensation of water vapor in clouds) to months (troposphere-stratosphere or inter-hemispheric exchanges). Other components of the climate system, such as the ocean and sea-ice, tend to operate on much longer time scales (years,

[1] Intergovernmental panel on Climate Change

[2] Pacific North American Pattern

[3] Coupled Model Intercomparison Project Phase 5

[4] Atmospheric Chemistry and Climate Model Intercomparison Project

decades and millennia). The ocean and sea-ice produce their proper internal variability and also integrate variability from the rapidly varying atmosphere.

In the tropical regions, there is clear evidence of a strong coupling between the ocean and the atmosphere, which generates internal processes, such as the El-Niño Southern Oscillation (ENSO) in the Equatorial Pacific (Philander, 1989); or the Madden-Julian Oscillation (MJO, Madden and Julian, 1994), which is a tropical disturbance that propagates eastward around the global tropics with a cycle on the order of 30-60 days.

Coupled interactions have been identified trough a number of feedback mechanisms that modulate the spatial and temporal variations of tropical climate (Xie, 1994). These involve changes in cloud cover, surface evaporation, winds and ocean dynamical adjustments. The main tropical feedbacks are i) the mythic Bjerknes feedback (Bjerknes 1966; Wyrtki 1975), which explains the ENSO phenomenon in the Equatorial Pacific. This Bjerknes mode of coupled ocean atmospheric variability is also observed in the equatorial Atlantic and Indian Oceans on interannual timescales (Chang et al. 2006; Keenlyside and Latif, 2007); ii) the Wind-Evaporation-Sea Surface Temperature (WES) feedback (Xie 1994; Chang et al. 1997) responsible of the existence of meridional sea surface temperature (SST) gradients in the tropical Pacific and Atlantic; iii) the cloud feedback (Klein and Hartmann 1993) and the water vapor feedback (Hall and Manabe 1999). These mechanisms have been identified in observations and/or reanalysis products, and also in theoretical and conceptual models (Vimont et al. 2010). Some of them have been also investigated in climate models (Richter et al. 2012), though the latter present severe errors in simulating some of the physical processes involved (ocean thermocline adjustment, subtropical low clouds cover, low level winds), and model mean biases could affect the representation of the variability.

In contrast to tropical regions where the atmosphere and the ocean variability practically fluctuate at the same timescales, in midlatitudes areas more complex interactions have been identified, occurring at different spatial scales and timescales for the atmosphere, the ocean and sea-ice (Peng and Fyfe, 1996). From synoptic (2-7 days) to intra-seasonal timescales, the variability is mainly governed by the atmosphere dynamics. At these timescales, the atmosphere mainly drives the ocean trough a stochastic forcing, by local processes involving water, radiative and turbulent heat fluxes (Frankignoul and Hasselman 1977; Frankignoul 1985). Due to its thermal inertia, the ocean can integrate this high-frequency forcing from the atmosphere and responds at longer periods, influencing in turn the atmosphere. The ocean feedback onto the underlying atmosphere is not easily detectable, since the chaotic nature of the atmosphere makes it difficult to extract the signal from the noise. The midlatitude air-sea coupled processes, in particular those in the North Atlantic region, received special attention in the later 1990s and earlier 2000s. Focusing on seasonal to interannual timescales, a number of studies based on observational analysis (Rodwell et al. 1999; Czaja et Frankignoul 2000; Drevillon et al. 2001) and numerical modelling (Watanabe et Kimoto 2000; Sutton and Hodson 2003; Kushnir et al. 2002; Drevillon et al. 2002; Cassou and Terray 2001) showed that the ocean could influence atmosphere circulation by the so-called re-emergence process. In the latter mechanism, the atmospheric forcing can create SST anomalies that could be “tied” to a deep thermal anomaly within the mixed layer, which is re-exposed each winter (Alexander and Deser 1995; Alexander and Penland 1996; Timlin et al. 2002; Cassou et al. 2007). Then the SST anomaly can re-emerge year after year, and so might have a greater ability to alter, through anomalous heat fluxes, the overlying atmosphere.

At even longer timescales the mechanisms generating decadal and multi-decadal variability are connected to air-sea interactions, in which slow processes as ocean gyres adjustment, deep water masses and thermohaline circulation are at play. Ocean fluctuations at decadal and multi-decadal timescales were firstly detected from observations and modelling studies in the late 1990s, in the North Atlantic (Delworth et al. 1993; Kushnir 1994; Sutton and Allen 1997; Timmerman et al. 1998; Kerr 2000) and also in the Pacific oceans (Latif and Barnett 1994 and 1996; Mantua et al. 1997). Recently, this low frequency variability, named as Atlantic Multidecadal Variability (AMV) and Pacific Decadal Variability (PDV), has received particular attention for several reasons: i) It has been shown that the AMV and the PDV exert important impacts on the surroundings continents (Knight et al. 2006; Mantua et al. 1997) and have been related to a number of climate impacts of high societal importance like US droughts, Sahel rainfall, hurricane changes, shifts in ecosystems (Nigam et al. 1999; Enfield et al. 2001; Zhang and Delworth 2006; Knight et al. 2006; Trenberth and Shea 2006; Hakkinen et al. 2011). These low-varying fluctuations in the ocean could lead to predictable climate signals. The presence of this low-frequency variability has been simulated by models and observed not only in historical records, but also in proxy and paleoclimate reconstructions (Shen et al. 2006; Svendsen et al. 2014). Nevertheless, the period of these oscillations, about 60yr in the AMV and 20-70 years for the PDV, still remains very uncertain, even with the use of paleoclimate records, because the lack of agreement amongst them.

The mechanisms generating decadal and multi-decadal climate variability are not fully understood yet. In the Pacific, the PDV seems not to be a single phenomenon, but is instead the result of a combination of different physical processes, including both remote tropical forcing and local North Pacific atmosphere/ocean interactions, which operate on different timescales (Newman et al. submitted). In the Atlantic, several theories point to an ocean-atmosphere processes involving the North Atlantic Oscillation (NAO) that can yield to changes in the Atlantic Meridional Overturning Circulation (AMOC), and this can in turn alter the poleward heat transport and induces changes in the SSTs (Hodson et al. 2010; Gastineau et al. 2013; Omrani et al. 2014; Peings and Magnusdottir 2014; Keenlyside et al. 2015; Woollings et al. 2015). But the links NAO/AMV needs further investigation since no consensus is reached so far, principally because the mechanisms driving the AMV are still very unclear.

An interesting feature in the climate system is that climate anomalies generated over a certain region can influence remotely other areas of the globe. This phenomenon is known as “climate teleconnections”, and it can be defined as linkages between weather and climate anomalies that occur over relatively large distances. One of the most emblematic teleconnection is the one linking sea-level pressure (SLP) at Tahiti and Darwin (Australia), which happens during ENSO (Philander 1989). Through changes in the atmosphere deep convection, the occurrence of an ENSO phenomenon can alter the Hadley and Walker circulations, or even trigger atmospheric Rossby waves which can connect the Tropical Pacific to other tropical and extratropical regions by atmospheric bridges (Lau and Nath 1996; Klein et al. 1999; Alexander et al. 2002). Several studies have found a consistent and statistically significant ENSO signal in the North Pacific (Wallace and Gutzler, 1981) and North Atlantic-Europe sectors, especially in late winter and early spring seasons (Fraedrich and Müller 1992; Moron and Plaut, 2003; Pozo-Vazquez et al. 2001; Garcia-Serrano et al. 2011; Lopez-Parages and Rodriguez-Fonseca 2012). It is also well established that El Niño (La Niña) affects the tropical Atlantic and weakens (reinforces) the Atlantic Hadley circulation (Ruiz-Barradas et al. 2003). It has been also shown through observational and modelling studies, that Indian ocean anomalous SSTs can induce changes on the North Atlantic atmospheric circulation (Hoerling et al. 2001; Sutton and Hodson 2003; Hurrell et al. 2004; Bader and Latif, 2003; Selten et al. 2004; Bader and Latif 2005; Sanchez-Gomez et al. 2008b). In particular a warming over the Indian Ocean is associated to a positive phase of the NAO. It has been hypothesized that such a North Atlantic response is mainly eddy driven via a circumglobal pattern along the South Asian and North Atlantic Jets associated with changes along the local storm track (Hoerling et al. 2001). It appears though that the mechanisms are still very unclear and questionable (because of model dependence in particular).

According to these results, the knowledge of teleconnection mechanisms and impacts gives some amount of predictability in remote locations with an outlook sometimes as long as a few seasons. For instance, predicting El Niño could enhance the predictability of North American rainfall, snowfall, droughts or temperature patterns with a leadtime from a few weeks to several months.

### *Modes of variability*

The internal climate variability is not randomly distributed in space and time, but often appear to be organized into relatively coherent spatial structures that tend to preserve their shape, while their amplitude and phase change through time. These spatial structures are named as patterns or modes of variability. The literature is replete with descriptions of these modes, which cover a broad range of climatological variables and spatial (global to regional) and temporal scales. Several of these patterns have received considerable attention, and their names are now firmly established in the climatological lexicon (e.g. ENSO in the Equatorial Pacific, NAO in the North Atlantic, PNA[2] in the North Pacific, the AMV, the PDV, see Figure 1.1 for an illustration). The modes of variability generally affect regional climate, and are related to important features for human life, as agricultural yields and regional fish inventories, flash floods, droughts, frequency of tropical cyclones, storm-tracks. This paradigm of the "modes of variability" has allowed a considerable insight regarding the climate system, the air-sea interactions, teleconnections mechanisms and predictability. The importance of these patterns is that they combine different forcings and processes into single coherent responses. Because of these attributes and co-varying relationships, they provide one obvious advantage to search for predictable climate signals, amongst all the complexity of the climate system.

[2] Pacific North American Pattern

During my research, I have often used the concept of weather regimes, which can be described as large-scale modes of atmospheric variability operating on synoptic to interannual timescales (more details in Chapter 2).

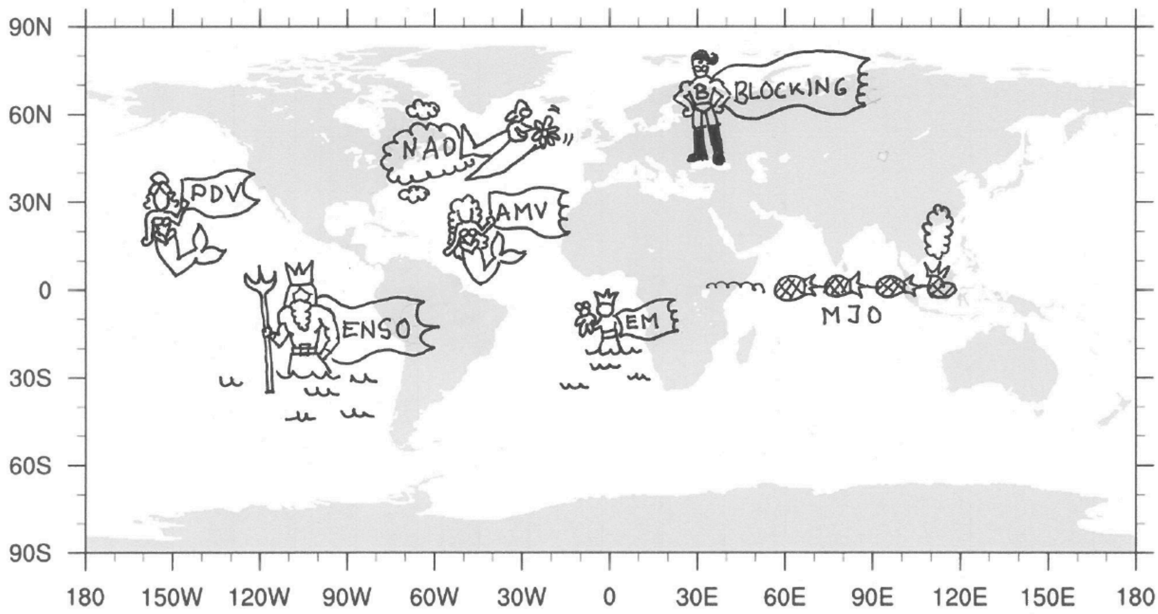


**Figure 1.1:** Illustration on the main models of variability and their approximate location described in the text. From left to right: PDV (Pacific Decadal Variability); ENSO (El Niño-Southern Oscillation); NAO (North Atlantic Oscillation); AMV (Atlantic Multi-decadal Variability); EM (Equatorial Mode or Atlantic Niño); BLOCKING (Scandinavian Blocking); MJO (Madden Julian Oscillation).

### 1.1.2 Forced climate variability

Some external influences, such as changes in solar radiation and volcanism, occur naturally and contribute to the total variability of the climate system. Other external factors, such as changes in the composition of the atmosphere that are the result of human activity, can also induce climate shifts. The scientific understanding of climate change is now sufficiently clear to show that anthropogenic global warming is already upon us, with a projected rate of change that exceeds anything seen in nature in the past 10,000 years.

Uncertainties remain, however, especially regarding how climate will change in the next decades ("near-term"), in particular at regional and local scales for which the internal and external variability are large. There are essentially two main sources of uncertainty for near-term climate change: the first one is the poor understanding of decadal internal variability and the degree to which it modulates anthropogenic climate change at continental to regional scales. The second concerns uncertainties related to past and future emissions of radiatively important trace gases (including GHGs, stratospheric ozone, and stratospheric ozone depleting substances) and pollutants affecting atmospheric aerosol composition, as well as our capability to accurately simulate the response of the climate system to that altered radiative forcing.

To differentiate the forced from the internal climate variability observed in the last decades, Detection and Attribution (D&A) approaches used idealized numerical experiments combined with objective statistical tests to assess whether observations contain evidence of the expected responses to external forcing, that is distinct from variation generated within the internal variability of the climate system (Hegerl et al. 2007; Ribes and Terray 2013). These methods attempt to identify in observations the responses to one or several forcings, by exploiting the time and/or spatial pattern of the expected responses. Even if a significant progress has been achieved in D&A, the discrimination between internal versus external factors (GHG, volcanoes, solar, aerosols) is still quite challenging. Nevertheless, D&A studies and analysis of numerical experiments performed with climate models has considerably improved our understanding on the role of different external influences on climate. In particular:

i) The GHG forcing leads to increased surface temperature and an amplified hydrologic cycle, which modify the surface heat and freshwater fluxes between the ocean and the atmosphere (Held and Soden, 2006). Atmospheric dynamics are also affected: in a world where GHG are increased, midlatitude westerlies move polewards especially in the southern hemisphere where signals are more robust (Lorenz and DeWeaver 2007; Chavaillaz et al 2013), midlatitude storminess intensifies due to increased baroclinicity (Yin, 2005) and tropical circulations weaken (Vecchi and Soden, 2007; Gastineau et al. 2008). Other changes have also been reported regarding ocean dynamics. The AMOC concurrently slows down in most climate models due to the alteration of both wind and surface fluxes (Cheng et al. 2013), but the details of the involved processes are still lacking.

ii) The direct effect caused by the stratospheric injection of volcanic aerosols is a decrease of the incoming solar radiation at the surface, which decreases tropospheric temperatures while the lower stratosphere warms (Robock et al. 2000). Minimum solar cycles in contrast lead to a weak cooling of the entire atmospheric column. Both natural forcings influence the lower-stratospheric meridional temperature gradient by altering the ozone photochemistry in the stratosphere, which in turn alters the troposphere by Rossby-wave propagation (Shindell et al. 2001). At decadal timescale in the Atlantic, Swingedouw et al. (2013) found a strong relationship between volcanic eruptions and the AMOC variability in CMIP5[3] historical simulations. In the Pacific, Meehl et al (2009a) suggest an influence of the 11-yr solar cycle, whose weak forcing is amplified through ocean-atmosphere coupling.

iii) Even if they have been identified as drivers of climate change and low-frequency variability, the role of aerosols concentrations on the radiative forcing of climate is not completely understood (Carslaw et al. 2013). This is mainly due large uncertainties linked to various aspects of the aerosol modelling, in particular the lack of understanding of the physical processes involved in aerosols effects on cloud droplet concentrations (the so called indirect effect) and in the radiative properties. Over the last 20 years or so, aerosol models have progressed tremendously and the global estimation of the direct aerosol radiative forcing has been much better quantified. More recently, the ACCMIP[4] community has put together an

[3] Coupled Model Intercomparison Project Phase 5

[4] Atmospheric Chemistry and Climate Model Intercomparison Project

experimental design aimed at supplementing the CMIP5 aerosol experiments (Taylor et al. 2012) to better understand and tackle the large uncertainties linked to various aspects of the aerosol modelling (Lamarque et al. 2012, Shindell et al. 2013).

Because the coupled system is complex it is often difficult to understand its variability without breaking it into its individual components. In such a framework, the oceanic surface is considered as a boundary forcing for the atmosphere, while the atmosphere is considered as a boundary for the ocean, and practically it is treated as external forcing. For example, the SST anomalies in the Equatorial Pacific associated to the ENSO phenomenon can be considered as an external forcing of the atmosphere in the Pacific and also in the remote regions as in the North Atlantic. This paradigm is often implemented by the design and performance of idealized numerical experiments in which one on the subsystem acts as a boundary forcing for other (e.g. Li, 2006). In this case a certain anomalous SST pattern imposed to the underlying atmosphere. These experimental setups are the base of some of the MIPs[5] within the CMIP, as AMIP[6] and OMIP[7].

## 1.2 DRIVERS OF CLIMATE PREDICTABILITY

Climate predictions on seasonal-to-decadal timescales (s2d hereinafter) hinge on determinism in the low-frequency evolution of the climate system, in time and space. Such determinism can arise from both the influence of external forcings or from the internal variability. The atmospheric internal processes are, for the most part, chaotic (Lorenz 1963), resulting in a so-called "climate noise" which is inherently unpredictable. However, the atmosphere interacts with the slower components of the climate system, such as the ocean, sea-ice and land surface, which can yield to modes of variability that have either a quasi-periodic evolution or a large persistence (e.g. the ENSO phenomenon at seasonal scale, or the AMV and PDV at decadal scale). Hence, the physical basis for climate prediction arises from the influence of predictable seasonal-to-decadal timescale signals from the ocean, and to a lesser extent the land surface, on the underlying atmosphere (Palmer and Anderson 1994; Meehl et al. 2009b). The key paradigm for seasonal forecasting is the ENSO phenomenon, which is predictable six months and more ahead (Jin et al. 2008; Weisheimer et al. 2009). In the case of longer prediction timescales, multiannual or decadal, the potentially predictable signals arise from the ocean and are localized in the North Atlantic, North Pacific and Southern oceans (Boer 2004, 2012). Climate s2d forecasting has been possible thanks to the recent improvements in the ocean observational networks and the development of data assimilation systems that provide ocean reanalysis products of higher quality (Wijffels et al. 2008; Ishii and Kimoto 2009; Corre et al. 2012; Ferry et al. 2010; Balmaseda et al. 2012).

[5] Model Intercomparison Project

[6] Atmospheric Model Intercomparison Project

[7] Ocean Model Intercomparison Project

Starting from coupled atmosphere–ocean models of intermediate complexity and spanning the tropical domain, the science of predicting seasonal-timescale fluctuations in climate started as fundamental research topic (Cane et al. 1986; Perigaud and Dewitte, 1996; Dewitte and Perigaud, 1996). It has become a routine operational activity in a number of meteorological forecast services using comprehensive coupled ocean–atmosphere models spanning the global domain (Stockdale et al. 1998; Arribas et al. 2011; Saha et al. 2013, among others). The aim of seasonal predictions is to provide estimates of seasonal-mean statistics of weather, typically up to three months ahead of the season in question. Despite large efforts, seasonal predictions still have limited forecast skill and reliability, especially over extratropical and polar regions, where the internal chaotic variability is large (Weisheimer et al. 2011). Unfortunately, progress in seasonal forecasting seems to be very slow, despite the international efforts that have been deployed in projects like PROVOST[8], DEMETER[9] (Palmer et al. 2004) or ENSEMBLES[10] (Doblas-Reyes et al. 2010). In those projects, retrospective forecasts (or *hindcasts*) emulating real-time seasonal forecast situations for the past were performed as coordinated experiments, since multi-model ensembles are useful to address uncertainties mainly due to model systematic errors. In this direction, state-of-the-art models still exhibit severe errors in some regions of the globe, which affect the reliability of the forecasts.

For the past few years, the climate research community has been facing a scientific challenge with the emergence of predictability studies at decadal timescales. Focus lies on near term future ranging from 1-year to 10-year horizon (Smith et al. 2007, Keenlyside et al. 2008, Hurrell et al. 2010; Meehl et al. 2009a; Pohlmann et al. 2009; Mochizuki et al. 2010), and complementing the traditional long term future climate projections based on GHGs aerosols emission scenarios. Decadal or so-called "near-term" climate forecast is a research topic relatively new, compared to the seasonal forecast. Similarly to seasonal prediction, several coordinated exercises have been proposed at the European level within the ENSEMBLES (Doblas-Reyes et al., 2011; Van Oldenborgh et al. 2012; Garcia Serrano and Doblas-Reyes, 2012) and COMBINE (Bellucci et al. 2014) projects for instance. Recently, in a more international context, near-term future climate changes have been included in the 5th IPCC report (Kirtman et al. 2013) based on simulations proposed within CMIP5 (Taylor et al. 2012). These coordinated experiments relied mostly on retrospective climate predictions over the 1960-2005 period to evaluate the predictability of the climate system at decadal timescale. As an extension, Smith et al. (2012) have performed quasi-real time decadal forecasts in a multi-model framework using most of the climate prediction systems that participated in CMIP5.

The most recent studies from CMIP5 (see Kirtman et al 2013 and Meehl et al. 2014 for a review) confirm that a large fraction of the decadal predictability comes from the external forcings, either anthropogenic (worldwide) or natural ones (e.g. role of volcano radiative forcings over the Indian Ocean, Guemas et al. 2013). Added-value from ocean initialisation

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[8] Prediction of Climate Variations on Seasonal Timescales

[9] Development of a European Multimodel Ensemble system for seasonal to inTERannual predictions

accounting for the phase of the modes of natural variability, such as the AMV, increases the regional forecast skill for SST compared with non-initialised experiments, in particular over the North Atlantic and western Pacific oceans up to 8-9 year leadtimes (Mochizuki et al. 2010; Msadek et al. 2014; Mochizuki et al. 2012; Bellucci et al. 2012; van Oldenborgh et al. 2012; Hazeleger et al. 2013a; Doblas-Reyes et al. 2013; Ham et al. 2014). Despite improved performance over the latter basins, the impact of ocean initialisation on the predictive skill over land, even over the areas adjacent to the North Atlantic and Pacific oceans, remains very limited (Goddard et al. 2012).

The relative importance of internal versus external variability changes depending on the timescale considered in the climate prediction or projection. Predicting climate on seasonal time scales requires accurate estimates of the initial conditions (internal variability) mainly from the ocean, with less dependence on changes in external forcing, also called boundary condition in the forecasters' jargon, over the period of forecast. At longer time scales, decadal predictions rely on both the knowledge of the internal variability (initial conditions) and the external forcing (boundary condition). In a climate projection, the main role is exerted by the boundary condition. In summary: at short timescales the evolution is largely dominated by the initial climate state, while at longer timescales the influence of the initial conditions decreases and the importance of the external forcing increases, as illustrated in Figure 1.2.

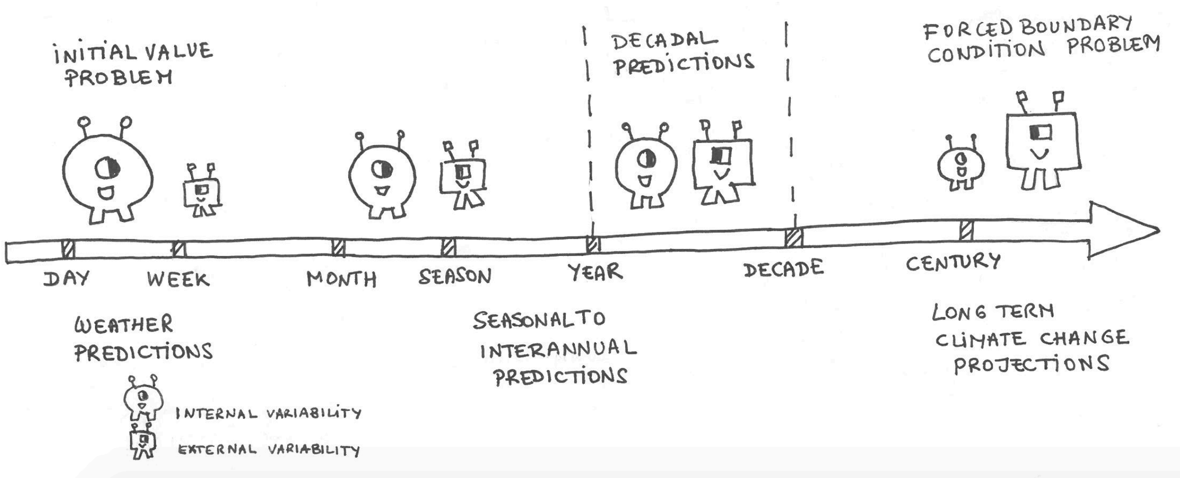


**Figure 1.2:** An illustration of the progression from an initial-value based prediction at short timescales to the forced boundary problem on climate projection at long timescales. Decadal prediction is located in the middle grown between the two (Based on Box 11.1, Figure 2, from WG1-AR5 report).

We cannot finish this section without mentioning the purely statistical approaches to study the predictability and also to perform and evaluate empirical forecasts (Barnett and Preisendorfer 1987; Barston and Ropelewski 1992; Johansson et al. 1998; Vautard et al. 1998). These techniques, mainly based on discriminant analysis, determine statistical links between two or more climate variables to built empirical models based on these relationships. Statistical s2d forecast models have the advantage of requiring very few computational resources, comparing to numerical-based forecasts. In general, these statistical models are used as a benchmark to assess the forecast skill of climate models. Some of the work done during my PhD was focused on this kind of statistical approach (Sanchez-Gomez et al. 2001, 2002, 2003, Chapter 3).

## 1.3 NUMERICAL MODELLING

To achieve all the progress summarized in the previous sections and to continue our advance in the understanding of the physics of climate, the research made by the climate scientists basically relies on two main tools. The first is the statistical analysis, that allows reducing the information from huge databases that we have to deal with, extracting the main features contained in data (observations or numerical simulations). The statistical analysis itself is not sufficient to understand climate, a good knowledge of the physics underneath is essential to interpret the results obtained through the statistical approaches. In climate, statistics and physics must be linked. The second tool are the climate models, that in general terms, can defined as a mathematical representation of the climate system based on physical, biological and chemical laws and principles. Basically a climate model solves numerically the physical equations of the general circulation. As a consequence of the numerical approaches, climate models provide a solution that is discrete in space and time, meaning that the results obtained represent averages over regions, whose size depends on the grid considered or model resolution, and for specific times. Due to this discretization of the space and time, small-scale processes, such as turbulence in the atmosphere and the ocean, or clouds microphysics cannot be represented. Furthermore, many processes are still not sufficiently well known to include their detailed behavior in models**.** To overcome these problems, researchers have designed and develop so-called parameterisations, which are based on empirical evidence and/or on theoretical arguments, to account for the large-scale influence of these processes that are not explicitly represented.

Since the development of digital computers in the 1950s, progress made on numerical models is striking. Starting from very simple and conceptual models, global circulation models (GCMs) operate worldwide in most of the research laboratories and they have become the indispensable tools of climate science. From the 1990s to the present, a trend toward increasingly comprehensive coupled climate models considering more and more complex interactions within the entire climate system has emerged. Climate model evaluation and inter-comparison is changing modeling into a more standardized framework, joining efforts to improve models performance, not only in terms of accuracy in simulating the climate features, but also on technical and engineering aspects as rapidity and efficiency in the numerical operations are key.

The GCMs constitute our research laboratory; they are formidable tools to improve our knowledge of the climate system, to understand the causes of climate variations and also to perform climate predictions. However, climate models exhibit deficiencies and biases that challenge the reliability of climate predictions and projections (Wang et al., 2014). More recently, international efforts have been developed in order to identify, understand and reduce model biases. This topic is crucial but it is not an easy task, since it needs several stages of increasing complexity: the first step is to identify the error of a climate feature by comparing the model output to the observations. The second step is to understand the mechanisms leading to a particular model bias. This stage can be of high complexity, since model errors can be due either to local causes, or to remote influences, and often to both. The third stage is a main concern for climate modelers: once the error and its mechanism are identified, how can we improve the model to reduce the error on this particular feature without affecting other regions?

## 1.4 SCIENTIFIC QUESTIONS ADRESSED IN THIS REPORT

After this “maybe quite long” description of the climate science status in 2016, the reader may wonder: What has been her contribution to the challenges and progress made by climate scientists? Since the end of my PhD (focused on North Atlantic climate variability and predictability with empirical methods), I have held several (~5) post-doctoral positions. These have allowed me to learn about different topics of climate sciences. The fact of being constrained to post-doctoral fellow requirements every approximately 2 years is that this maybe has prevented me from becoming a specialist on a single scientific topic. This is not regrettable, since I believe that in turn, I have got a broader view of climate science status.

My main interests and scientific challenges will be described in the coming chapters and can be summarized as follows:

***Chapter 2: Using Weather regimes to characterize and understand climate variability at local scale***

- Weather regimes are useful tools to represent the large-scale dynamics of atmospheric internal variability in the North Atlantic region. Are they linked to surface variables as temperature and precipitation at local scale? Are they linked to the occurrence of extremes of temperature and precipitation? In the North Atlantic, how are they linked to the storm-tracks?
- Could the atmospheric dynamics internal variability be potentially predictable? Can we define some kind of atmospheric oscillations in which the weather regimes are the phase?
- Can we use the weather regimes paradigm to identify climate teleconnections?
- Are the intrinsic weather regimes affected by external forcings, in particular by GHGs increasing?

***Chapter 3: From statistical to dynamical climate forecast***

- Given the midlatitudes air-sea interactions described in section 1.1, are the anomalous climate conditions near the surface in the North Atlantic predictable from anomalies of SSTs? To what extent?
- Can we design an initialisation method in decadal forecasting to minimise the initial shock in a decadal prediction system? What are the main mechanisms characterising this initial shock?

***Chapter 4: Evaluating and Understanding biases in climate models***

- What can we learn from a multi-model assessment?
- How can our understanding of our climate models be improved? Is the analysis of drifts in a climate prediction protocol that uses initialised numerical experiments a useful approach for that purpose?

# 2 Using weather regimes to characterize and understand climate variability at regional scale

The main idea is to characterize the large-scale atmospheric circulation by a few spatial patterns called weather regimes. They are defined as the peaks in the probability distribution function of all the possible states of the atmospheric circulation, characterized by various properties such as persistence (they are active for several days), recurrence and quasi-stationarity. This paradigm is a very useful approach, since it allows for decomposing the complex large-scale atmospheric dynamics into a few "objects" with determined features. These modes of variability are usually obtained from classification techniques or cluster analysis of a field representative of the near surface or middle tropospheric dynamics (e.g sea level pressure or geopotential height field). Previous works based on reanalysis and observed data have established links between weather regimes and surface variables at regional scale, and even local extreme episodes of temperature and precipitation over different regions of the Northern Hemisphere (Robertson and Ghil, 1999; Plaut and Simmonet 2001; Yiou and Nogaj 2004; Sanchez-Gomez and Terray 2005). These links have been also identified in numerical simulations performed with climate models (Goubanova et al. 2010; Cattiaux et al. 2013).

I have extensively used weather regimes in a great part of my research to address scientific topics such as links between large-scale atmospheric dynamics and climate extremes (Sanchez-Gomez and Terray 2005); low-frequency atmospheric oscillations (Sanchez-Gomez et al. 2008a); tropical-extratropical teleconnections (Sanchez-Gomez et al. 2008b); air-sea interactions (Guemas et al., 2009ab); I have also used weather regimes in statistical downscaling schemes (Piazza et al., 2013); and even for regional climate models evaluation (Sanchez-Gomez et al. 2008c). This chapter provides a short selection of the main results found by means of the weather regimes approach.

## 2.1 HOW ARE THE WEATHER REGIMES OBTAINED?

In general, weather regimes are determined from a daily anomalous field representative of the large-scale atmospheric dynamics (sea level pressure (SLP) or the 500 hPa geopotential height (Z500)). In my work, the decomposition of the large-scale flow has been performed using the *k–means* clustering algorithm. This approach is used when we wish a partition from the original data into a small number of groups or clusters, whose identities are not known in advance. In climate sciences, there are a great variety of cluster algorithms, than roughly can be divided in *hierarchical* and *non-hierarchal* methods (Wilks, 2011). The main difference is that for the former, the classification procedure starts with a small number of clusters that can be divided into new groups, to form something similar to a genealogic tree. For the non-hierarchical methods, the data are divided into a number of groups that is known *a-priori*. The k-means is a *non-hierarchical* iterative clustering algorithm, which classifies data into a prescribed number of clusters. Given *k* clusters set *a priori*, the goal is to find a partition P = $C_1$, $C_2$, …, $C_k$ so as to minimize the sum of the squared intra-group distances by an iterative procedure, achieving the best separation between the data points. The *k-means* method has shown to be efficient in obtaining robust and physically interpretable clusters in atmospheric sciences. It has been used to determine weather regimes in the North Atlantic (Michelangeli et al. 1995; Cassou et al. 2004; Sanchez-Gomez and Terray 2005) and Mediterranean regions (Sanchez-Gomez et al. 2008a), and in other interesting applications, like model biases classification (López-Parages et al. 2015).

Before the classification, an EOF[11] analysis is often conducted on the daily anomalies of the atmospheric field maps for the targeted season. After this, a certain number of EOFs is retained, such as the 90% of the total variance is captured. Finally the *k–means* approach is applied in the space spanned by these leading principal components. In the North Atlantic basin, four weather regimes have been identified (Vautard 1999; Michelangeli et al. 1995), which are represented in Figure 2.1 in terms of anomalous SLP. These patterns are: 1) The Zonal regime (ZO), also considered as the positive phase of the NAO, is characterized by an enhanced zonal flow crossing the North Atlantic basin due to a concomitant reinforcement of the Icelandic Low and the Azores High; 2) The Greenland Anticyclone (GA) pattern which is dominated by a strong positive anomaly centered over west of Greenland, and which is frequently referred to as the negative phase of the NAO; 3) the Atlantic Ridge (AR) regime, with a positive anomaly over the North Atlantic basin and low pressure over Northern Europe; and finally 4) the Blocking regime (BL), which displays a strong anomalous persistent high over Scandinavia. Other weather regimes have been identified in the Mediterranean region (Sanchez-Gomez et al. 2008a) by the same methodology.

There is an important issue concerning the large-scale atmospheric variable used for obtaining the weather regimes. In the present climate (from models or reanalysis) either using SLP or Z500 leads to similar results, and the differences concerning the daily classification are non significant (in a statistical sense). From the more purist point of view of at atmospheric scientist, the Z500 field would seem more convenient to describe the large-scale dynamics, since this variable is not affected by surface and boundary layer physics. However, in the global warming context and when dealing with future climate scenarios, if one decides to use the Z500 anomalies, the thermal expansion due to surface warming must be first corrected. This is very important, since the inhomogeneous thermal expansion (the warming is stronger over the continents than over the oceans) can lead to a spurious weather regimes classification in a scenario simulation. This is done for example in Cattiaux and Cassou (2015), to investigate the changes in the NAM[12] in CMP3/CMIP5 simulations. The method for correcting the thermal expansion is straightforward: it consists of removing the temporal trend of the spatial average pattern within the domain. However, this correction is not necessary in the case of SLP anomalies; hence many statistical downscaling methods use SLP to characterise future changes in the large-scale atmospheric circulation (Boe et al. 2006).

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[11] Empirical Orthogonal Functions

[12] Northern Annular Mode

Another important issue comes from the fact that CMIP5 projections at the end of 21st century reveal an opposite response of the NAM between SLP (positive trend) and Z500 (negative trend) anomalous circulation, as shown by Cattiaux and Cassou (2015). This discrepancy is not present in CMIP3 simulations. The authors of that study explain these differences by two phenomena: a local consequence of faster Arctic sea ice loss in CMIP5 than in CMIP3 models, and a stronger warming in the western tropical Pacific simulated in CMIP5 compared with CMIP3, which can remotely influence midlatitude dynamics. These considerations should be taken into account when defining atmospheric modes of variability and addressing warming trends in future climate.

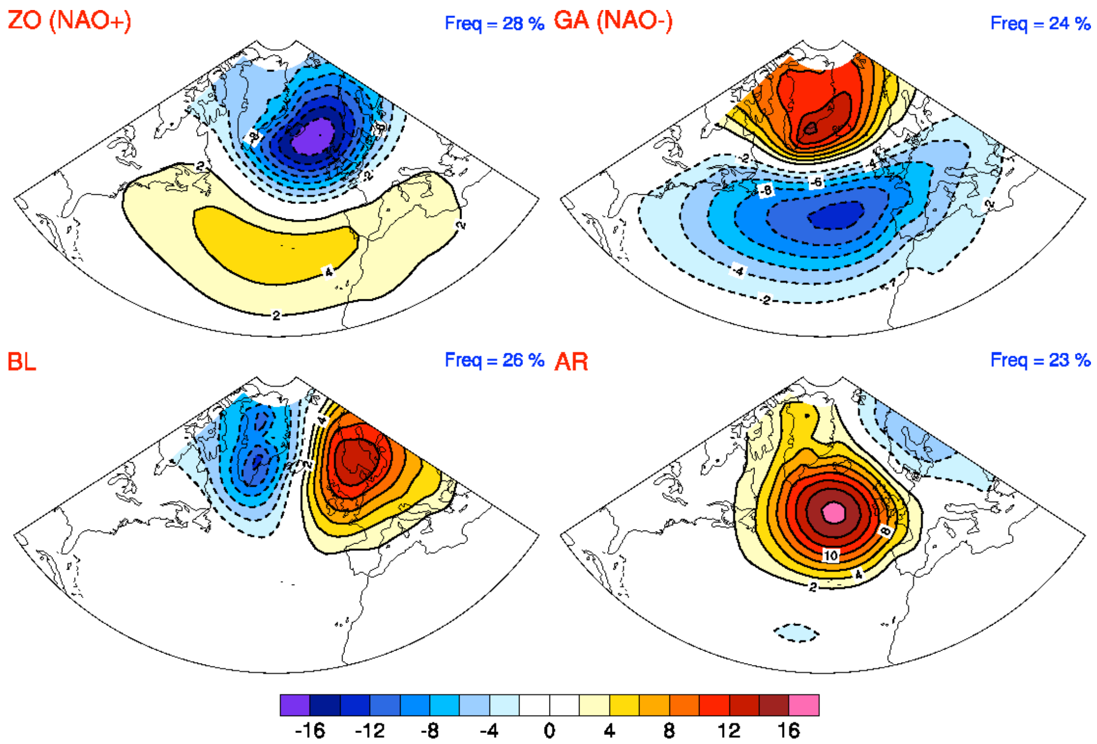


**Figure 2.1:** Four North Atlantic weather regimes (units in hPa) for the winter season (December-March). These have been determined by using the k-means clustering algorithm applied to anomalous daily sea level pressure from NCEP reanalysis, for the period 1958-2014.

When analysing numerical experiments, it is legitimate to ask the question: do the atmospheric models correctly represent weather regimes? The response is yes in general, though some biases are present and they depend on the model. For example, the ARPEGE model, largely used in my studies, which is the atmospheric component of the CNRM-CM coupled models, presents the following bias: the day attribution is not statistically robust when we consider 4 centroids in the k-means algorithm. We need to add a supplementary centroid in ARPEGE data, which turns out to be the so-called East Atlantic Pattern (Wallace and Guztler 1981) or Atlantic Low (AL hereinafter). This is considered in the work by Piazza et al. 2015 to study, trough numerical modelling, the influence of small-scale SST patterns in the Gulf Stream on the large scale North Atlantic dynamics simulated by the ARPEGE model.

When dealing with multi-model approaches, the classification applied on individual models become tedious, and the comparison is not possible, since one model can lead to different number of clusters for a given domain. In a multi-model study, Sanchez-Gomez et al. 2008b, proposed the following solution: the weather regimes centroids are first determined from an atmospheric reanalysis. Then for each model, daily maps are attributed to the respective centroids by a minimization of a similarity criterion (spatial correlation, Euclidean distance, etc). In this way, we ensure that the anomalous patterns we are analysing correspond to the same spatial structures for all the models.

This approach can also be used when we want to study the influence of external forcings on the intrinsic weather regimes of a coupled model. For this, we need a non perturbed or control simulation that represents the internal variability, and weather regimes centroids are determined from the anomalous daily maps from this simulation. These centroids represent the intrinsic patterns of the model, which in this case are fixed. Then, the classification can be performed on daily maps from the perturbed simulation, in which a given forcing has been prescribed. For example, this methodology allows determining trends in weather regimes under global warming (Boe and Terray, 2008). The important underlying hypothesis assumes stationarity in the number of weather regimes, as well as in the spatial structure of the centroids. It is then expected that external forcing would affect the frequency of occurrence of some or all weather regimes (see section 2.5).

## 2.2 WEATHER REGIMES AND THE ATMOSPHERIC OSCILLATIONS

Through statistical analysis techniques, intra-seasonal atmospheric oscillations have been identified in the North Atlantic region (Plaut et Vautard, 1994). Interestingly, the phases of these oscillations seem to be related to the weather regimes occurrence; hence the intra-seasonal large-scale atmospheric variability can be characterized by the alternation between the weather regimes and their transitions. It is well known that the quasi-stable flow associated to weather regimes may be responsible for climate extremes as droughts, heat waves, deep freezes and even excessive precipitation if they are sufficiently persistent. However, the quasi-equilibrium can be broken up by an atmospheric disturbance, inducing the onset and break of weather regimes.

In Sanchez-Gomez and Terray (2005), we propose a methodology to identify weather regimes transitions patterns and their probability of occurrence. After the daily classification, firstly we remove the first two and last two days of each season, to avoid spurious weather regimes episodes concatenated between two consecutive years. Second, we consider as weather regime event those episodes lasting at least 4 days. For ranges of more or equal to 4 days we also remove the onset (break) day, which is the first (last) day of each weather regime event. At the end, we eliminate approximately about 20% of the days in the whole data set, which can be considered as transition days. For four weather regimes, there are twelve possible transitions (if we do not consider the transitions between the same weather regime). The probability of occurrence of transitions can be defined as the ratio between the number of cases observed for one transition and the total number of transitions found for a particular regime. We find that, although the probability changes for each transition, the mean duration of the transition phase remained almost constant, between 2 and 3 days. Statistical significance of transitions can be addressed by a Monte Carlo test consisting of randomly reordering the sequence of weather regimes episodes lasting at least 4 days (Table 1 from Sanchez-Gomez and Terray, (2005)).

One may wonder what happens during the development or break of a weather regime episode. Sanchez-Gomez et Terray, (2005) observed that a non negligible percentage of intense precipitation events (IPE hereinafter) in western France can occur during the transition from the ZO to GA weather regimes (ZOtoGA transition). A useful tool to analyse whether a particular weather pattern is associated to the IPE occurrence is the so-called Discriminating Power (DP, Plaut et al. 2000). Given a weather pattern, the DP measures the percentage of probability of finding those IPE days that exhibit similar large-scale spatial structure to the selected weather pattern. DP is determined by a distance between all the daily maps in the data set and the spatial pattern of the given weather regime or transition. This distance ($d_c$) is defined as the spatial correlation between the weather pattern (WP) and any day (Day), both preferably represented as vectors in the space spanned by the first EOFs:

$$d_c = 1 - corr(\mathrm{WP}, Day) \tag{2.1}$$

Note that $d_c$ ranks from 0 (perfect correlation) to 2 (completely uncorrelated); and $d_c > 1$ implies a negative correlation. The daily values of $d_c$ can be organized into different categories to build a distance histogram. For each of the categories in the histogram, we determine the probability of finding an IPE (that is, the ratio between the number of IPE and the total number of days belonging to the same category). In the case that a weather pattern presents a high DP, the shape of the histogram would correspond to a decreasing function. Figure 2.2 shows the ZOtoGA spatial pattern (2.2.a) obtained from Z500, the composite variance (2.2.b) and the DP shape associated to IPE in western France (2.2.c). From this Fig. 2, it is clear that a high IPE probability of occurrence is associated to this large-scale spatial structure. Curiously, the ZOtoGA transition is reminiscent of the East Atlantic pattern or Atlantic Low (Wallace and Guztler, 1981).

In another work, Sanchez-Gomez et al. (2008a) identified 6 weather regimes in the Euro-Mediterranean region from the Z500 daily anomalies (i.e. WR1, ..., WR6). This study showed a link between these large–scale patterns and IPE in some regions over the Mediterranean basin during the late summer and autumn season. The most important highlight of this work was that these 6 weather regimes were related to the phases of an intra-seasonal atmospheric oscillation. For this, the MSSA[13] statistical technique was applied (Plaut and Vautard, 1994; Kondrashov et al. 2004). More precisely, the methodology used was the following: First, the daily Z500 anomalies from January to December were previously filtered by a PCA, retaining the first leading modes. The associated coefficients, the principal components, are called here the channels. The MSSA consists of diagonalizing the lag-covariance matrix of the

[13] Multi-Channel Singular Spectrum Analysis

multichannel time series, with lags (L) ranging between 0 to L -1, where $W = L * \Delta t$ is called the window length with $\Delta t$ the sampling interval. We used as window length W = 90 days.

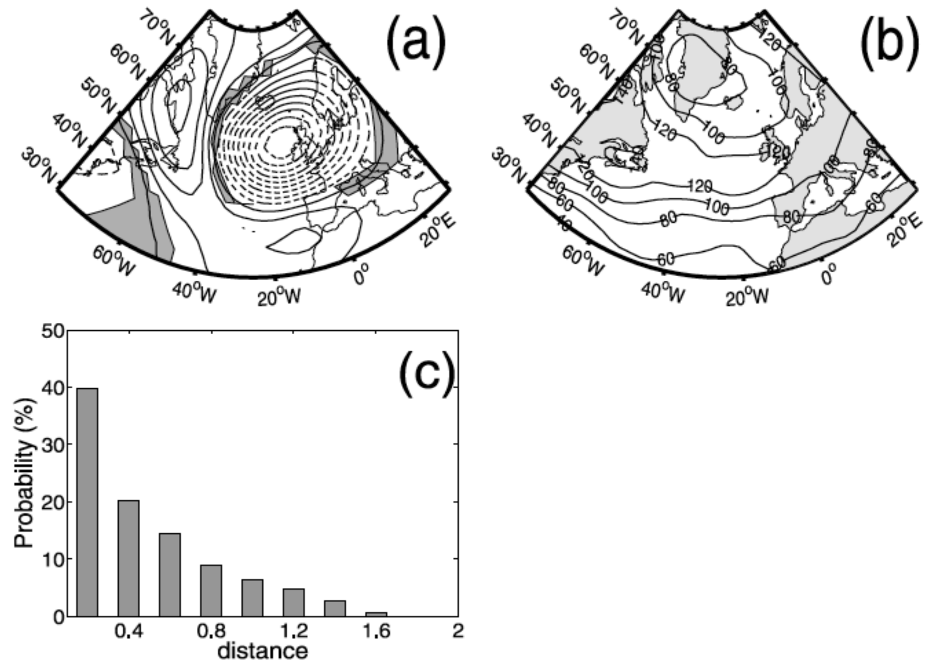


**Figure 2.2:** (a) Zonal to Greenland Anticyclone transition pattern. The isolines are the Z500 composite (solid lines are positives values and dot dashed are negative values). Contour interval is 20 gpm. Non significant areas at 95% level are indicated by the gray shading. Statistical tests for the robustness of the composite have been carried out following Terray et al. (2003). (b) Standard deviation of the Z500 composite for this pattern. Units are in gpm. (c) Discriminant power (DP) of the ZotoGA transition pattern for the western part of France.

By MSSA, we identified a 50-day European-Mediterranean atmospheric oscillation, characterized by a sequence of negative and positive Z500 anomalies moving from east to west. This oscillation may be associated to the westward traveling perturbations, which were described by Doblas-Reyes et al. (2001), who determined an oscillatory mode of 20-40 days period over the European-Mediterranean sector. These east-to-west perturbations are governed by Rossby waves dynamics and their variance is stronger in regions where the mean zonal flow is weak (e.g. the Mediterranean region). Analysing the correspondence with the European-Mediterranean weather regimes, we found the transition WR1 -> WR3 -> WR2 -> WR5 to be consistent with the phases of the identified oscillation trough MSSA (Sanchez-Gomez et al. 2008a). Figure 2.3 shows the probability of occurrence of an IPE over two different boxes within the southern Mediterranean domain as a function of the phase of this oscillation (8 phases are considered here).

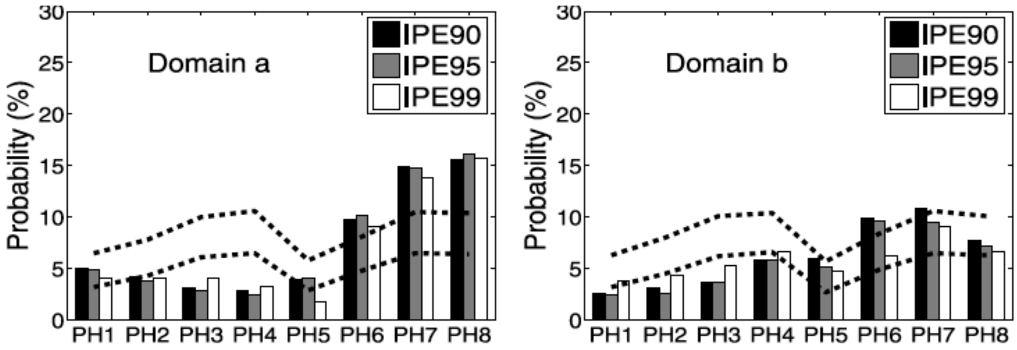


**Figure 2.3:** Probability of IPE occurrence (threshold values 90%, 95%, 99%) over two selected domains (domain a: Gulf of Lyon, domain b: Balkans Peninsula) in the Mediterranean region for the eight phases of the intra-seasonal European-Mediterranean oscillation. Dotted lines represent the upper and lower 5% significance limits. The statistical significance is assessed by a Montecarlo technique.

These results thus confirm the links between episodic (weather regimes) and oscillatory approaches. Weather regimes can then be viewed as being part of an oscillatory and thus a potentially predictable phenomenon. Further work would be needed to investigate whether the interactions between the tropical phenomena and the atmospheric dynamics on the European-Mediterranean region play a role in generating or modulating these intra–seasonal oscillations. In a latter work, Cassou 2008, showed that the tropical conditions, in particular the Madden-Julian Oscillation (MJO), modulate the North Atlantic weather regime sequence, which has strong implications for the medium-range and intra-seasonal-to seasonal climate forecasting.

## 2.3 WEATHER REGIMES AND TROPICAL-EXTRATROPICAL TELECONNECTIONS

Through teleconnections, the tropical climate can affect the atmospheric circulation in the North Atlantic region (Chapter 1). By using the weather regimes approach, Sanchez-Gomez et al. 2008b investigated the influence of the Indian and western Pacific Ocean warming over the 1950-2000 period, on the frequency of occurrence of North Atlantic weather regimes. Here, a multi-model approach was adopted, in which five different atmospheric general circulation models (ARPEGE, HadAM3, GAMIL, ECHAM5, CAM3) were forced with idealized SST patterns, mimicking the Indo-Pacific (IP hereinafter) warming after 1970s. We adopted the numerical approach that assumes that the ocean surface is acting as an external or boundary forcing on the atmosphere. For this, two twin experiments were performed by prescribing warmer and cooler than normal SST anomalies over the IP region. A control run, by prescribing climatological SSTs, was also performed.

Using the methodology described in section 2.1, the four North Atlantic weather regimes were first determined in winter (DJF) anomalies of Z500 in ERA40 reanalysis. For each model, daily Z500 anomalies were projected on the 4 clusters centroids from ERA40, and daily maps were attributed to the respective centroids by a minimization of a similarity criterion (spatial correlation). Despite some discrepancies, three models out of five suggested a stronger occurrence of the ZO regime when the IP region is warmer, compensated by less frequent GA regime, which was consistently with the observed positive trend of the North Atlantic

Oscillation during 1990s. The other two models simulated instead an increase in the frequency of occurrence of the AR regime (Figure 2.4).

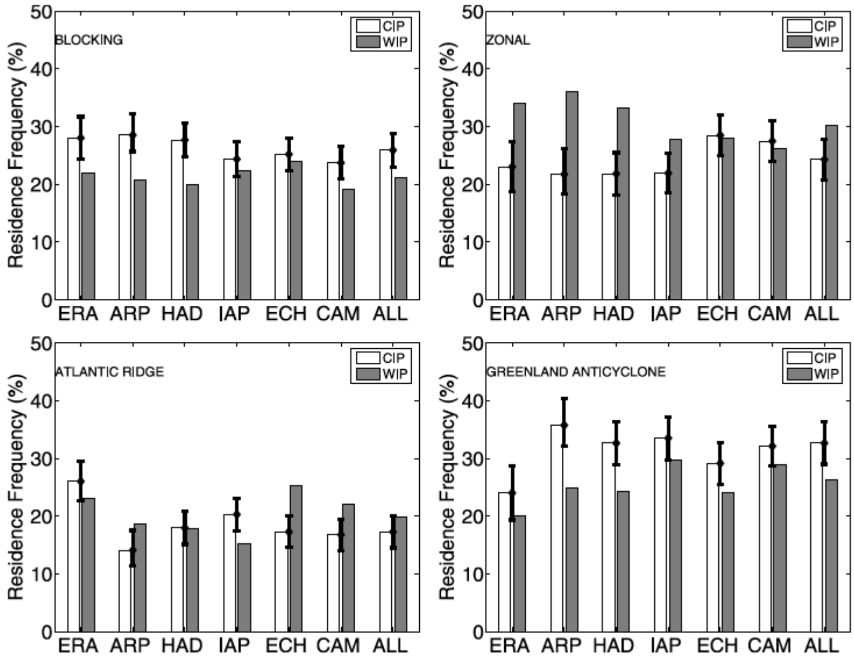


**Figure 2.4:** Relative changes in the frequency of occurrence for the North Atlantic weather regimes in the boreal winter season (DJF). Error bars represent the significance levels of the difference between CIP (colder SST over IP) and WIP experiments (warmer SST over IP), determined by building a probability distribution function of frequencies from a number (1000) of weather regimes random classification. Horizontal axis indicates the model: ARP (ARPEGE), HAD (HadAM3), ECH (ECHAM5), IAP (GAMIL) and CAM (CAM3). ERA40 (ERA) reanalysis is also shown.

In summary, based on weather regimes responses, the five atmospheric models were classified into two groups: ARPEGE, HadAM3 and GAMIL together giving a positive ''ZO response'' and ECHAM5 and CAM3 leading to increased AR. Differences in the upper level meridional winds showed that the AR pattern was in fact associated with a Northern Hemisphere wave activity along the waveguide (Branstator, 2002) in ECHAM5 and CAM3; but not in the three other models. The ''Pacific route'' is thus dominant in ECHAM5 and CAM3, whose response is best explained by disturbances associated with transient atmospheric waves propagating eastward along the jet guide from the North Pacific to the North Atlantic. To further test this hypothesis, we decomposed the total space-time variance of Z500 from the control run into stationary and transient waves, by using the wave number-frequency spectral analysis or space-time spectral analysis technique (Hayashi 1979; Doblas-Reyes et al. 2001). Through this decomposition, we showed that ECHAM5 and CAM3 present the highest values of the variance of the synoptic scale transient activity, whereas ARPEGE, HadAM3 and GAMIL were less energetic, corroborating for ECHAM5 and CAM3 the strong possibility of Rossby waves propagation along the waveguide following Branstator's paradigm. For the other three models, ARPEGE, HadAM3 and GAMIL, the ZO regime excitation is probably explained by changes in the Walker cell: Anomalous potential velocity at 200 hPa showed a strong subsidence over a broad tropical Atlantic in response to the IP warming.

## 2.4 WEATHER REGIMES AND EXTRATROPICAL STORMS

The studies performed during the national IMFREX[14] project showed that the North Atlantic weather regimes were a powerful tool to describe the large-scale environments associated to the trajectories and intensity of extra-tropical storms (Déqué et al. 2005). I actively participated in these analyses and in the recent years I have considered to overtake this research line, by using new reanalysis products and coupled model simulations. First the weather regimes and storm tracks from different atmospheric reanalysis products (ERA40, ERAI, NCEP, 20CR) have been determined. Storm tracks have been characterized through a tracking tool (Ayrault and Joly, 2000), which is based on the detection of maxima of relative vorticity at 850 hPa ($\zeta_{850}$). The first step consists on identifying the cyclone centers, defined as local maxima of $\zeta_{850}$ within a radius of 380 km, determined every 6 hours from the numerical experiments. A smoothing of the $\zeta_{850}$ field is first performed using a 9-grid points spatial filter, obtained by weighting by the inverse of the distance from the central point. In the second stage, trajectories are built by pairing the cyclone centers previously determined for consecutive time steps, through three criteria: i) the first takes into account the absolute vorticity field and its variation from the given cyclone center. If the variation between two cyclone centers is important (more than 40%), the two centers are considered to belong to a two different cyclones systems. ii) The second criterion uses the mean flow in the middle troposphere represented by the wind at 700 hPa. From winds at 850 hPa and 700 hPa levels, two trajectory possible positions are determined and compared. iii) The third criterion ensures the trajectory coherence by minimizing the acceleration, in order to avoid the abrupt changes in the wind speed and direction of the movement.

In the following, my analysis on the links between intrinsic weather regimes and storm-tracks are summarized. Figure 2.5 shows the composite patterns of the daily density of tracks in winter (DJFM) for the four North Atlantic weather regimes. The density of tracks (D hereinafter) is computed for each grid point as the density of cyclones trajectories in a radius of ~200 km. A kernel density estimator methodology has been applied to build the density field. Figure 2.5 corroborates the expected result: a higher storm-tracks density over the Northern Europe is associated to the ZO regime, whereas trajectories are located southwards in the case of GA regime. During the BL regime, extra-tropical storms are deviated towards eastern Greenland and Arctic Sea, and AR regime exhibits a small tracks density over the center North Atlantic, the storm-tracks get around the anti-cyclone and are deviated towards the southern Greenland. AR regime is also associated to the passage of more cyclones over the western Mediterranean. We can also show that weather regimes are related to extra-tropical cyclones intensity, for example, in northern France, with the strongest storms occurring when the ZO regime is excited (Joly et al. 2005).

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[14] IMpact des changements anthropiques sur la FRéquence des phénomènes EXtrêmes de vent de température et de précipitations http://imfrex.sedoo.fr/web/

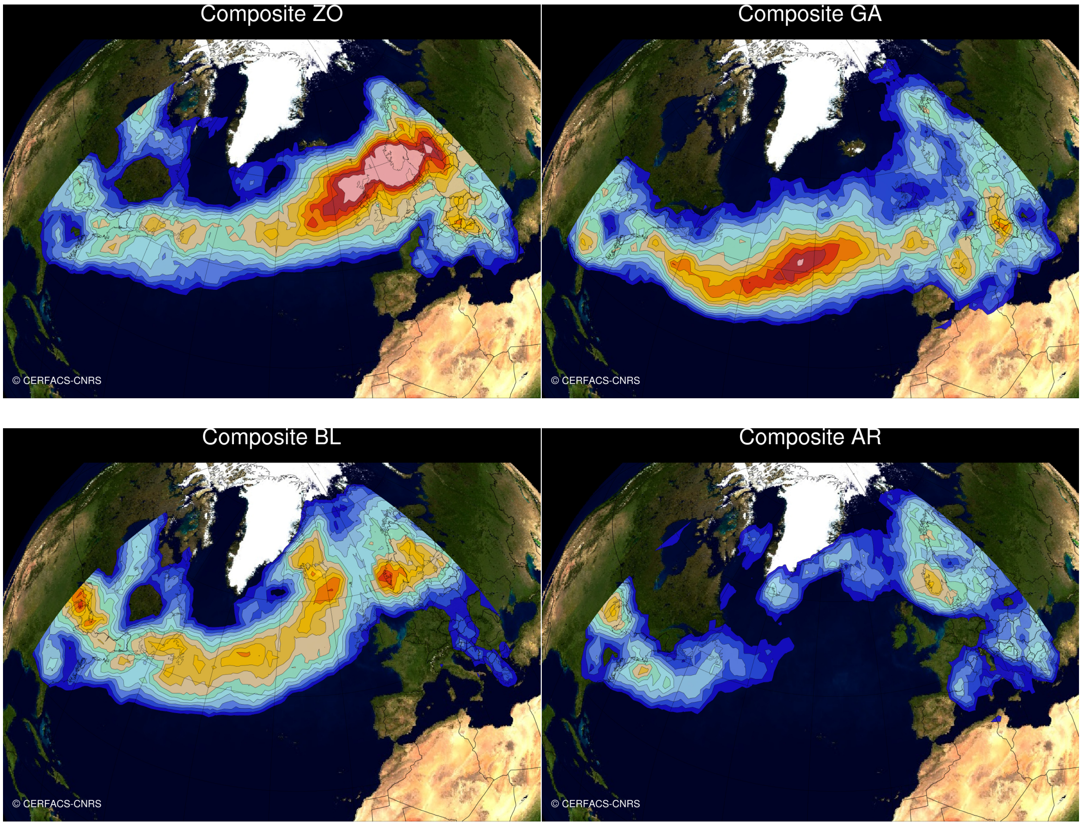


**Figure 2.5:** Composite patterns of the daily density of tracks for the four North Atlantic weather regimes during winter. The patterns have been obtained by averaging all the days corresponding to the same weather regime. Units are in tracks/season, colors are shown from 20 tracks/year every 1 track/year.

It is interesting to quantify the contribution of the large-scale dynamics to changes in the density of tracks D. This can be addressed following the methodology described in Driouech et al. (2010;) to estimate the contribution of weather regimes to changes in Moroccan precipitation; and in Goubanova et al. (2010) and Cattiaux et al. (2013), to determine changes in cold events over Europe. Following this approach we consider the linear decomposition of the tracks density D:

$$\overline{D} = \sum_{k=1}^{NWR} f_k d_k \qquad (2.2)$$

where $\overline{D}$ represents the average of the density over a certain time period, $f_k$ the frequency of occurrence of the weather regime $k$ (with $k=1, \ldots, NWR$, NWR=number of weather regimes) and $d_k$ the regime's conditional mean (or composite, as in Figure 2.5), computed by averaging the ensemble of $N_k$ days of D classified in the $k$th regime. Let's suppose that under the influence of an external forcing, $\overline{D}$ may be altered between two time slices (named F and P periods). We can then investigate the changes in $\overline{D}$ under global warming induced by GHGs increase, F and P periods indicating present and future climate.

Following equation 2.2, this change can be written in the form:

$$\Delta^{F-P}\overline{D} = \overline{D}^F - \overline{D}^P \quad = \sum_{k=1}^{NWR} f_k^F d_k^F - \sum_{k=1}^{NWR} f_k^P d_k^P =$$

$$= \sum_{k=1}^{NWR} \Delta f_k * d_k^P + \sum_{k=1}^{NWR} f_k^P * \Delta d_k + RES = FRC + CMC + RES \qquad (2.3)$$

The first term (in red) in equation 2.3 represents those changes in the mean state due to changes in the frequency of occurrence of weather regimes; the second term (blue) stands for changes in the conditional mean state of the variable (changes in the composite mean state). We call the first term FRC (from frequency of occurrence change) and the second term CMC (conditional mean change). A residual term is also considered, following Cattiaux et al. (2013). It is important to mention that a particular care should be taken on the interpretation of these terms, in particular the CMC term, because $\Delta d_k$ terms can contain changes induced by both dynamical and non-dynamical sources. Indeed, the conditional means or composite $d_k$ may differ between present and future, either due to a slight shift of the mean centroid k or to changes in other physical processes. In addition, the relationship between D and weather regimes may also be modified in the future.

To apply equation 2.3 three important hypothesis are assumed: i) the number of weather regimes are supposed to be constant between F and P periods; ii) their centroids are unchanged under global warming (see below), iii) the statistical links between D and weather regimes are conserved. These hypotheses, which most of the statistical downscaling methods rely on, are difficult to verify and often are assumed without further considerations. However, the work of Cattiaux et al. (2013) addresses this problem and proposes a solution by using an alternative approach based on distances to the centroids and analogues.

We have computed the terms of the equation 2.3 from numerical simulations performed with the coupled model CNRM-CM5 (Voldoire et al. 2013), whose atmospheric component is the ARPEGE (V4) model. The simulations analysed here are those of the historical ensemble (HIST hereinafter), which represents the present climate; and those of the scenario RCP8.5[15], which include future climate projection. Two 30 years time slice periods are considered: 1961-1990 (P) for HIST, and 2071-2100 (F) for RCP8.5. The ensemble size is 5 members for both HIST and RCP8.5. We focus on the winter season, from December to March. Weather regimes are determined as explained in section 2.1, assuming that the number of centroids is invariant in a warmer climate. As also mentioned in section 2.1, taking into account the ARPEGE model biases, we consider here 5 North Atlantic weather regimes, by including the AL mode. First the

[15] Relative Concentration Pathway 8.5

centroids are identified from daily SLP anomalies from a long control simulation, and then days in HIST and RCP8.5 are classified according to a similarity criterion (Euclidean distance).

To verify hypothesis iii) we have compared for the P (1961-1990) and F (2071-2100) periods, the spatial pattern correlations computed between the frequency of occurrence of each weather regime and D (Figures A1 and A2 from the annexe). By averaging across ensemble members we obtain the forced response to the external forcing. Hence, the ensemble mean over the 5 correlation maps are considered here. The uncertainty due to internal variability (inter-members spread) is estimated from the confidence interval $t_\alpha * std/\sqrt{n}$ , where *std* in the inter-members standard deviation and *n* the number of years. For the parameter $t_\alpha$ we have consider the 95% confidence level. Results indicate that the spatial structures are quite similar between P and F periods, which allows using equation 2.3. However, there are two interesting features emerging from Figures A1 and A2: First the correlations between D and $f_k$ seem to be stronger for ZO and GA regimes, which indicates that the linear relationship assumption applies better for these patterns. Indeed, a straightforward ANOVA analysis shows that $f_k$ for ZO and GA would be the best predictors for D in a multiple-linear regression model. Second, event if the statistical links are conserved between F and P, correlations are slightly stronger in the F period, suggesting that maybe the relationship between large-scale dynamics and density of cyclones will become stronger in a warmer climate. But this is a non-achieved result and further investigation would be needed to make a conclusion.

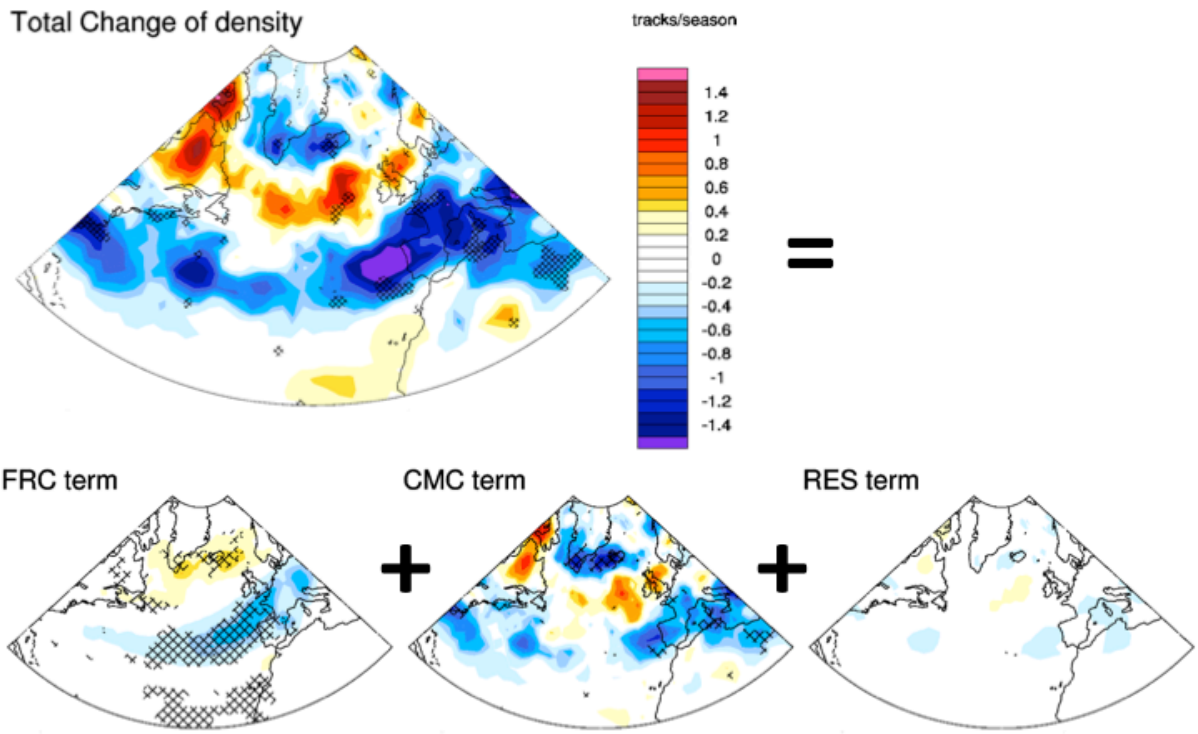


**Figure 2.6:** Expansion of the different terms of equation 2.3: total change in the density of tracks field between future (2071-2100) minus present (1961-1990) time slices (top panel); FRC, CRC and RES terms contributions (low panel). Units are in tracks per season, considering DJFM. In this figure the ensembles mean is shown. Black hatching indicates those grids points where the signal-to-noise ratio, estimates as the ensembles mean divided by the confidence interval $t_\alpha * std/\sqrt{n}$, is greater than 1.

Figure 2.6 shows the terms computed from equation 2.3: the total difference $\overline{D^F} - \overline{D^P}$ and the contribution of the FRC, CMC and RES terms. We analyse here the ensembles mean, which represents the signal or forced response to external forcing. We notice that there are few significant areas in Fig. 2.6, except for FRC terms, indicating that the response is not detectable from the noise, which leads to questioning if 5 members are enough to assess changes in the North Atlantic storm-tracks. Even if not significant, changes in the D field (term on the left in eq. 2.3) show a tripole pattern: a decrease in the number of tracks in the southern North Atlantic, in the latitudinal belt encompassing from the eastern coast of USA, near the Cap Hatteras to the western coast of southern Europe and western Mediterranean; an increase in the latitudinal band from the Baffin Island, Labrador Peninsula and Scandinavia; and a decrease in the polar regions: south of Greenland and Iceland. This tripolar pattern points to a poleward shift of the North Atlantic storm-tracks. This tripole has already been identified in Zappa et al. (2013), who analysed the extra-tropical cyclones response in CMIP5 models. Eichler et al. (2013) also reported a decrease in the southern North Atlantic and Greenland. Note that only the density of trajectories in investigated here, and not the cyclones properties like the associated winds or precipitation. This will be included in my prospect work (see chapter 5).

Concerning the right terms in equation 2.3, the FRC term points to a northward shift of the Atlantic storm-tracks, with a decrease of cyclones in eastern Atlantic and western Europe; and an increase south of Greenland and around Iceland. This is coherent with the projected changes in the frequency of occurrence of weather regimes, which indicate an increase of ZO regime (NAO+) of ~6%, which is statistically significant, between P and F periods. The other regimes do not show detectable changes. The increase of ZO (NAO+) has been also reported from CMIP5 models (5th IPCC report), though this signal is less evident than the one documented in the previous IPCC report.

The strongest contribution corresponds to the CMC term, which explains most of the tripolar pattern described above, and which suggests that the large-scale dynamics would play a secondary role in changes of D. We can further investigate this issue by analysing the CMC term for each individual weather regime (Figure A3, annexe A). This decomposition indicates that, even if they are compensating effects, the weather regimes contributing most to the D changes are the AL for a decrease of D in western Europe and southern North Atlantic, the AR and ZO regimes for the decrease south of Greenland/Iceland, and for the increase over the west coast of UK. Nevertheless these changes are not statistically significant, and further investigation would be needed.

Recently a number of groups developed and applied tracking tools for cyclone identification and that gave rise to the IMILAST[16] project (Neu et al. 2013). The objectives of this project are i) to gain in our understanding of observed extra-tropical cyclones as represented in the reanalysis, ii) to diagnose how models simulate the extra-tropical cyclones and their properties, and iii) to analyse the extra-tropical cyclones response to global warming. Ulbrich et

[16] Intercomparison of Midlatitude storm diagnostics (http://www.proclim.ch/imilast/index.html)

al. (2013) shows that a great degree of uncertainty resides in how the cyclones are detected, since the different tracking tools can lead to different conclusions, in particular to weaker extra-tropical cyclones. However, it seems that under global warming, the signal is robust (decrease in the Mediterranean, Greenland/Barents Seas, and North America), regardless the tracking algorithm. Unfortunately I have not participated still to the IMILAST initiative, but this is something that would form part of my prospect as a future work.

One more source of uncertainty is the internal variability. In this chapter we show that the signal-to-noise ratio is too large to be able to detect significant signals in extra-tropical cyclones. This suggests that approaches using large ensembles will be welcome to robustly estimate the role of internal versus external variability on extratropical cyclones (Chapter 5).

# 3 From statistical to dynamical climate forecast

Climate prediction at seasonal-to-decadal timescales (s2d hereinafter) is a great challenge for climate sciences. We could say that climate prediction is the ultimate goal, for which all our efforts are focused, and that it requires first understanding how the climate functions. Apart from its scientific interest, s2d climate predictability may have significant social, economic and environmental implications. Besides, there is an important demand from decision makers who need to know at best the information provided by climate forecasts in order to plan adaptation strategies for areas of high vulnerability and sensitivity to climate changes (Meehl et al. 2009 and 2014; Hurrell et al. 2010; Means et al. 2010).

During my career, I have contributed to the climate prediction topic by two research lines, the first dealing with empirical methods applied to seasonal forecasting (Sanchez-Gomez et al., 2001, 2002, 2003), and the second, on numerical predictions at near term or decadal timescales (Bellucci et al. 2014; Germe et al. 2014; Sanchez-Gomez et al. 2015).

## 3.1 EMPIRICAL SEASONAL FORECASTS OF NORTH ATLANTIC ANOMALOUS CONDITIONS

In parallel to dynamical seasonal forecasting, prediction schemes based on statistical analysis were developed many years ago. Theoretically, dynamical models can provide more "realistic" forecasts, since they include the physical interactions of the climate system that can be non-stationary in time. Empirical models are based on statistical relationships between a so-called predictor and predictand (variable to predict or target) variables. These links are determined from the information of the past, and the important assumption is that they are assumed to be constant in time (which is not necessarily accurate for the climate system). To assess the problem of the non-stationarity in the relationships between predictor and predictand, and to avoid misleading interpretations, one should implement adapted statistical methods to test the significance of results. Empirical prediction models are often designed to operate over a certain region in the world, over which the statistical parameters are established.

Empirical models have been developed and used to complement dynamical predictions for several reasons: First, the GCMs can present severe biases (see chapter 1 and 4) in specific regions in the globe, which makes the climate forecasts not reliable in those regions (i.e. The Tropical Atlantic). Second, there is a need for a number of independent predictions to assess the forecast skill (Brankovic and Palmer 2000), this makes the task of producing numerical hindcasts (or retrospective forecasts) for several decades very expensive from a computational point of view. Third, before the design of an empirical prediction scheme, a detailed analysis of the observed climate on the target domain is necessary, and this provides a further understanding of the phenomena to predict.

Nowadays statistical and dynamical schemes are two complementary lines of research in climate prediction. The analysis of these long empirical forecasts can assist GCM predictions, either by identifying the main sources of interannual variability within a given region or by assessing the effect of remote low-frequency signals on the forecast skill. Concerning the performances in terms of skill, seasonal empirical models have shown levels of skill similar to those of numerical models. In the tropical areas statistical predictions have exhibited useful skill values (Penland and Magorian 1993; Penland and Matrosova 1998; Ruiz de Elvira et al. 2000). Unfortunately, the skill of empirical forecasts for the midlatitudes, (Shabbar and Barnston 1996; Johansson et al. 1998; Vautard et al. 1999; Sanchez-Gomez et al. 2001, 2002, 2003) is only modest.

The empirical forecast scheme that I developed during my PhD was intended to be a benchmark to assess the GCM forecast skill in the European Union funded project PROVOST[17]. This statistical model was based on discriminant analysis, which allows decomposing the multivariate climate data into a few empirical variables explaining the most prominent features. Mathematically, the discriminant approach is based on the algebra theory, and the basic idea is to decompose linearly the data, in order to change the reference basis in which it is expressed. Even if this technique relies on linear assumptions, the decompositions obtained are often physically robust and have allowed for a relevant progress in climate sciences. In a statistical scheme, the goal is to retain the coupled variability between two fields: the predictor field X and the predictand field Y. The most frequently used technique is the Maximum Covariance Analysis (MCA), which is based on the Singular Value Decomposition (SVD) of a non-squared cross-covariance matrix. The MCA has been extensively used in climate research (Bretherthon et al. 1992; Sanchez-Gomez et al. 2001; Rodriguez-Fonseca et al. 2002; Sanchez-Gomez et al. 2002; Sanchez-Gomez et al. 2003; Haarsma and Hazeleger 2007; Lopez-Parages et al. 2014).

Let $x_j$ and $y_j$ be the values of two geographical fields, named respectively predictand and predictor fields, at the point j of the spatial grid (or station) and at time $t$ ($t=1, \ldots, N$). Let's assume that the spatial dimensions of X and Y are p and q respectively, with $p \leq q$. By SVD, the lagged cross-covariance matrix C at lag $l$ between X and Y can be written in the following way:

$$c_{ij} = \sum_{t=1+l}^{N} (y_i(t-l) - \overline{y_l}) * (x_j(t) - \bar{x}_j) = \sum_{k=1}^{p} \sigma_k * u_{ik} * v_{kj} \qquad (3.1)$$

where $u_{ik}$ and $v_{kj}$ are the components of the spatial singular vectors ($\boldsymbol{u_k}$ and $\boldsymbol{v_k}$) of the predictand and predictor field respectively, and $\sigma_k$ are the singular values of the lagged covariance matrix, associated to the singular mode $k$. These spatial patterns ($\boldsymbol{u_k}$, $\boldsymbol{v_k}$) can be ordered by decreasing order according to the singular value. The percentage of covariance explained by each mode $k$ can be computed as the squared of the matrix $\Sigma$. Through the projection of each field onto the

[17] Prediction of Climate Variations on Seasonal to Interannual Timescales http://cordis.europa.eu/news/rcn/9609_en.html

corresponding vector, we obtain the empirical coefficients $a_k(t)$ and $b_k(t)$, that give the time evolution of each singular pattern. Through this approach, X and Y can be reconstructed in a linear expansion as:

$$\tilde{x}_j(t) = \sum_{k=1}^{p} a_k(t) * u_{kj} \qquad \tilde{y}_j(t) = \sum_{k=1}^{p} b_k(t) * v_{kj} \tag{3.2}$$

The idea is that the temporal coefficients $a_k$ and $b_k$ can be related trough the relationship:

$$a_k(t) = e_k * b_k(t-l)$$

where $e_k$ are empirical coefficients determined by the least-squares criterion. In this way, the prediction of X, named $\widehat{x_p}$(t), when the field Y is known $l$ time-steps in advance, can be expressed as:

$$\widehat{x_p}(t) = \sum_{k=1}^{p} e_k * b_k(t-l) * u_k \tag{3.3}$$

In practice, in equation 3.3 only the first singular modes, and not the total number $p$, are used in predicting $\widehat{x_p}$(t). The choice for the truncation can be done by selection rules or by using Monte Carlo methods (Preisendorfer 1988). In my seasonal scheme, the predictor field and predictand are separated into four sets of 3 months each, according to the seasons: DJF, MAM, JJA, OND. Each season in the predictor field will be used to forecast all the seasons ahead in the predictand. In this way, the winter months (December, January, February) of the predictor will be used to predict the spring season (MAM) 3 months ahead; the summer (JJA) 6 months ahead; the autumn (SON) 9 months ahead and so on. The covariance matrix in equation 3.1 is computed following this seasonal scheme for the different lags. Both the predictand and predictor fields are divided into two segments: training sample and validation period. For a forecast $l$ months ahead, the training sample is formed with the observations from all the years preceding the start of the forecast period. In the empirical forecast schemes used in Sanchez-Gomez et al. 2001, 2002, 2003, two predictors fields were considered: anomalous SSTs in the North Atlantic and sea-ice fraction in the Arctic sea. As predictand I used the North Atlantic air temperature at 850 hPa and the SLP fields.

Forecast skill was assessed by comparing the reconstruction $\tilde{x}$ versus the forecast $\hat{x}$ using several measures: the anomaly correlation coefficient, the root mean squared error and the LEPS scores, the latter being based on a conditional probability distribution of the predictand. A simple persistence model was also taken into account to compare and validate our prediction scheme. As the number of spatial patterns used to forecast is not small (more than 10), the problem of an artificial skill obtained by overfitting had to be accounted for. The levels of the artificial skill were estimated using a bootstrap procedure (Efron and Tibshirani 1993).

The main results of that study that I conducted showed that for the air temperature at 850 hPa, the highest skill values were found in the subtropics, near Bermuda and around the Iberian Peninsula, whereas on North America and Europe, the levels of skill were quite low, though increased skill values was found near the U.S. coast in autumn. In most of the domain, the skill values beat those obtained just by assuming persistence. Figure 3.1 shows an example for a NAO index forecasts 3 months ahead, predicted from SSTs in DJF (winter). Even if the skill measured as correlation is low, the sign of the NAO index is forecasted up to 60% of the time.

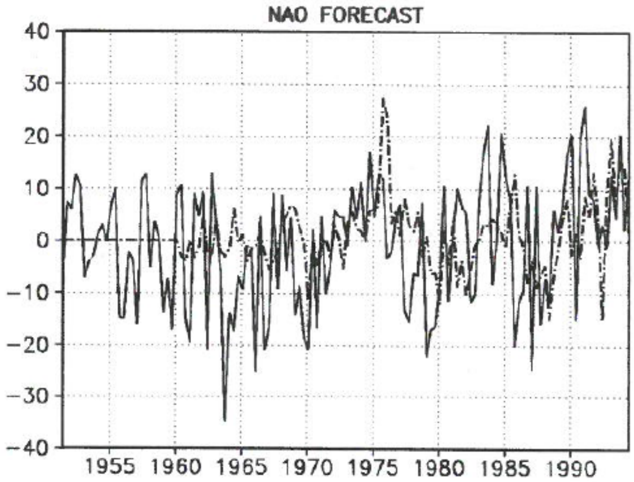


**Figure 3.1:** Observed (solid line) versus predicted (dashed line) NAO index in spring (MAM, units in Pa) obtained from the empirical scheme described in the text. The predictor field is the North Atlantic SSTs one season ahead (winter, DJF).

## 3.2 NEAR TERM NUMERICAL FORECASTS: INITIALISATION METHODOLOGY

In the recent years, an important part of my research has been focused on the recent challenge of decadal forecasting (Chapter 1, section 1.2), in particular, on the development and implementation of initialisation methodologies and on the analysis of model drifts (Sanchez-Gomez et al. 2015).

To produce a decadal forecast, the models need to be initialised (in particular the ocean component) from an observed state. Initialising climate models offers the potential to predict internal variability in addition to externally forced climate change, and this is thought to be at the heart of the s2d prediction problem. The deal is to investigate whether the model, trough the knowledge of its initial conditions (chronology of internal variability) and external forcing, is capable of predicting the evolution of the climate of the following seasons or years. Obviously, the initialisation issue is not trivial, and the way climate model will respond when initialised from observed conditions is not anodyne. Further, often the presence of model drift can alter the solution (see chapter 4). In climate numerical forecast, there are basically two initialisation strategies: “full field initialisation” in which the raw ocean reanalysis is used as initial conditions for the coupled forecast model (Mochizuki et al. 2010; Doblas-Reyes et al. 2012), and the “anomaly initialisation” (Schneider et al. 1999) in which anomalies for the reanalysis are first computed and are then added to the model climatology to produce the ocean initial conditions (Smith et al. 2007, Keenlyside et al. 2008; Pohlmann et al. 2009; Smith et al. 2010). The latter is viewed as a technique to minimize the strong model drift when initialised close to observations in full field. In both cases, the model drift must be removed *a posteriori* in order to estimate the forecast skill. Some studies have compared the two methods using the same forecast system and concluded that both lead to a similar level of predictive skill (Smith et al. 2013; Magnusson et al. 2012; Hazeleger et al. 2013). Hence, no consensus has been found so far on the best practice in model initialisation. Beyond full-field versus anomaly strategies, choice also lays between tri-dimensional versus surface-only initialisations as adopted by some groups (Swingedouw et al. 2012).

In a recent paper, Sanchez-Gomez et al. 2015, document a novel protocol for ocean initialisation, which was adopted by the CNRM-CERFACS modelling group in the CMIP5 decadal forecasting framework. In their protocol, initial conditions for the decadal hindcasts produced with the CNRM-CM5 coupled model (Voldoire et al. 2013) were obtained from a preliminary simulation (hereafter referred to as NUD4IC) over 1958-2008, where the ocean component is nudged towards the NEMOVAR ocean reanalysis (Balmaseda et al. 2010), while the other components (atmosphere, sea-ice, continents) are freely coupled. The choice for NEMOVAR instead of other reanalysis products was motivated by the fact that i) NEMOVAR and CNRM-CM5 share the same ocean model version (NEMO[18] v3.2) and grid, which avoids spurious effects introduced by interpolation, especially over the vertical dimension, and ii), they are integrated with the same physical and dynamical assumptions set in the "namelist". The rationale for NUD4IC is to try to minimize the initial shock when forecasts begin but also, on a practical side, to get an initial state for other components for which there is no available reanalyses such as land and sea-ice (thickness, surface albedo, etc).

Two different approaches are combined for nudging in the NUD4IC experiment. At the surface, a restoring is applied in terms of heat and fresh water fluxes, by using a flux derivative term as follows:

$$Q_{ns} = Q_{ns}^{0} + \frac{dQ}{dT} * (T_{k=1} - SST_{NEMOVAR})$$

$$EMP = EMP^{0} + \gamma^{-1} * e_{3t} * \frac{(S_{k=1} - SSS_{NEMOVAR})}{S_{k=1}} \qquad (3.4)$$

where $Q_{ns}$ and $Q^{o}_{ns}$ are the net non solar flux at the surface, T is the sea surface temperature of the model and $SST_{NEMOVAR}$ for the reanalysis, and dQ/dT is a feedback coefficient between flux and temperature set to -40W/m$^2$/K as diagnosed from Barnier et al. 1995. EMP

[18] Nucleus for European Modelling of the Ocean, www.nemo-ocean.eu

and $EMP_o$ are the fresh water budget at the surface, S and $SSS_{NEMOVAR}$ are the sea surface salinity of the model and reanalysis respectively, $e_{3t}$ is the vertical weighting scale factor, and $\gamma_s$ is the feedback parameter which here is set to -167 mm/day. The dQ/dT coefficient plausibly represents corrections to real physical feedbacks involving net non-solar flux at the atmosphere, whereas there is little feedback of surface salinity on the atmosphere and hence $\gamma_s$ is rather an ad-hoc measure to prevent surface salinity drift and also tentatively conserve the density. Flux derivative terms are preferred to Newtonian damping for surface fields because they indirectly account for the prognostic evolution of the mixed layer depth ensuring more dynamical/physical coherence throughout the ocean column (Servonnat et al. 2015).

Below the mixed layer that is not affected by the surface restoring, a 3D Newtonian damping in temperature and salinity (see Madec et al. 2008 for details) is implemented following the equations:

$$\frac{\partial T}{\partial t} = \ldots - \frac{1}{\beta}\left(T - T_{NEMOVAR}\right)$$

$$\frac{\partial S}{\partial t} = \ldots - \frac{1}{\beta}\left(S - S_{NEMOVAR}\right) \tag{3.5}$$

where T and S are the model temperature and salinity, $T_o$ and $S_o$ are from NEMOVAR, and $\beta$ is a timescale parameter. To conserve as much as possible the ocean properties and in order to avoid spurious effects on ocean currents let free in our case, the values of parameter b must be carefully chosen as a function of depth and location. Here, no damping ($1/\beta = 0$) is applied within the mixed layer that is free to evolve. Below the thermocline down to 800m depth, the $\beta$ parameter is set to 10 days and for the deep ocean below, a weak restoring is chosen ($\beta = 360$ days). In addition, nudging is equal to 0 ($1/\beta = 0$) along the coastline, considering a distance of 300km from the coast.

Several tests were performed to determine the optimal set of surface/subsurface parameters detailed above, but also to determine the geographical locations where the subsurface damping terms is applied. Our reference configuration in the following is the one where the subsurface nudging is only applied *outside* the 15°S - 15°N latitudinal band; the latter has been retained for initializing the decadal hindcasts for the CNRM-CERFACS group as archived in CMIP5. This experiment is called NOTROP_IC. Another configuration named NOEQ_IC is used, here the subsurface nudging is applied everywhere except within the 1°S - 1°N band. Nudging right at the equator is indeed problematic because it leads to spurious vertical velocity in the ocean that is clearly unrealistic. Note that whatever the configuration, the sea surface restoring is performed everywhere and a 5° buffer zone is considered between the no-nudged zone and the rest of the ocean where full nudging is applied.

As a illustration of the nudging application, we compute the differences between the initial conditions and a historical simulation performed from CNRM-CM5 model, named here as HIST. Figure 3.2a-b shows the zonal mean of the whole Pacific Ocean temperature as a function of depth for NOTROP_IC – HIST (a) and NOEQ_IC – HIST (b) differences. NOTROP_ICs are characterized by an excess of heat with respect to HIST in a broad tropical band between 30°S – 10°N and down to 300-400m depth; this is indicative for shallower thermocline of the model attractor with respect to the observations. The warmer ocean subsurface is straddled by cooler temperature in HIST around 45°S and 15°N with maximum loading between 100m and 500m. South of 45°S, NOTROP_IC temperatures are considerably colder than HIST from surface to bottom of the ocean (differences ranging between 0.5°C and 2.5°C). Relatively homogeneous differences there over the whole water column are indicative of poor representation in the CNRM-CM5 model of the Austral deep-water formation that feeds the deepest ocean. The Northern Pacific basin is characterized by a vertical dipole with warmer conditions in the mixed layer down to 150 m in NOTROP_IC versus HIST and colder conditions below down to about 1500 m. NOEQ_ICs show that the excess of heat stored in the subsurface is greater than for NOTROP_ICs where the model thermocline and surface winds are more in a balanced state. This can then potentially reduce the shock when the model is set free in a forecast mode; and we show here that this is the case.

Following the CMIP5 protocol, we have performed 10 members of 10 years initialised at the 1st of January at starting dates between 1961 and 2006 at years 1 and 6 of each decades, namely 1961, 1966, 1971, …, 1996, 2001, 2006 (Taylor et al. 2012). To build the decadal ensembles, only the atmosphere is perturbed by random selection of initial states within the January month produced in NOTROP_IC for the corresponding starting date. These hindcasts are called here DEC. A similar protocol has been followed for the NOEQ_ICs to generate the DEC_NOEQ retrospective predictions. External forcings (GHGs concentration, aerosols, solar irradiance and observed volcanic eruptions) are prescribed in the model and are the exact same ones as in the so-called historical experiments (HIST) corresponding to the non-initialised runs (Taylor et al 2012). In the following analyses, we make the hypothesis that the model attractor can be estimated by HIST over the same period as the forecasts (1960-2010). Hence, the DEC simulations drift away to reach the HIST climate. Most of the diagnostics are thus presented through differences between the decadal predictions (DEC, DEC_NOEQ) minus HIST as a function of the leadtime.

If we focus on the Equatorial Pacific, the evolution in DEC of the ocean subsurface from the initial state (NOTROP_IC) until the forth year in the forecast (Yr4) is investigated. Figure 3.2c-d shows a time versus longitude Hovmöller diagram of the DEC-HIST (c) and DEC_NOEQ-HIST (d) differences for equatorial 10 meters wind and for 20°C isotherm depth averaged between 2°S and 2°N. Considering the importance of the annual cycle in the equatorial Pacific, seasonal means (JFM, AMJ, JAS, OND) are preferred to annual means. NOTROP_IC – HIST differences in OND of Yr0 are also included in the graph for the ocean field. Figure 3.2c shows that, at the beginning of the forecast (OND Yr0 and JFM Yr1) consistent with Figure 3.2a, the thermocline is considerably deeper (by around 40m) in DEC especially on the western and central part of the basin. Westerly wind anomalies develop concurrently at the west of the dateline at the beginning of the forecast from AMJ Yr1, and persist up to the following fall. The latter maintain the initial deepened thermocline and simultaneously trigger equatorial downwelling Kelvin waves crossing the basin in about 3 months. A first one reaches the eastern basin in AMJ as materialized by a deepening thermocline depth compared to previous JFM Yr1 and OND Yr0. A second Kelvin wave of lower amplitude appears in JAS Yr1 with maximum amplitude in the east in late OND Yr1 and JFM Yr2. The latter is explained by the prevalence of westerly wind anomalies west of 200°E. This yields indeed to positive SSTs anomalies in the eastern Equatorial Pacific, reminiscent of the formation of an El Niño event following the Bjerknes feedback mechanism (Bjerknes 1966). Discharge occurs in late Yr1 in the western Pacific and during Yr2, while anomalous westerlies disappear and a weak La Niña tends to pop up in the central Pacific. After one ENSO cycle, the model has reached the HIST state, i.e. the model intrinsic equilibrium. The latter mechanism is much more pronounced in retrospective forecasts DEC_NOTE (Figure 3.2d), for which the ENSO flip-flop is still detectable at leadtime 4 year.

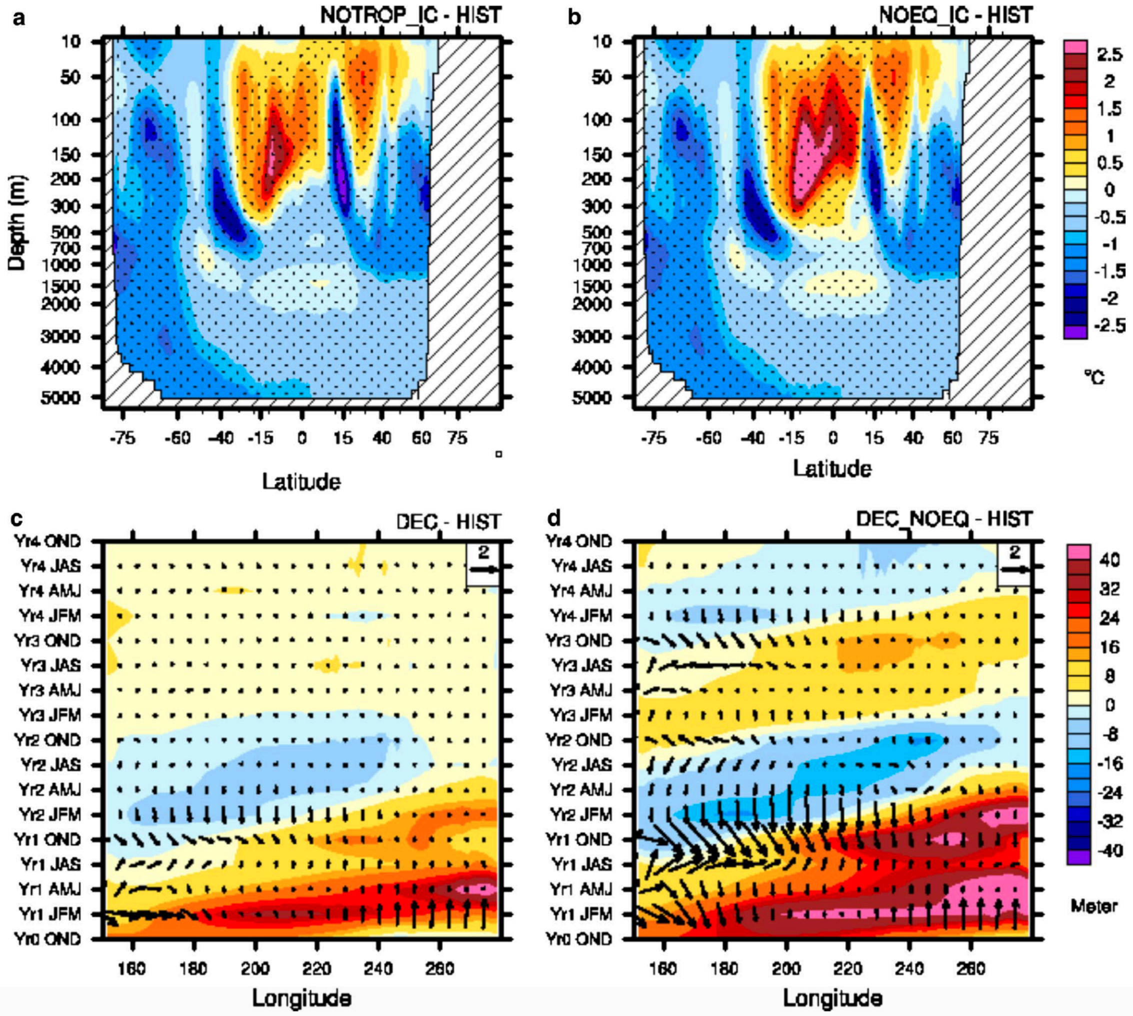


**Figure 3.2:** (a) NOTROP_IC–HIST and (b) NOEQ_IC–HIST zonal mean differences for temperature annual means as a function of depth in the Pacific Ocean. Contour interval is every 0.5 °C. HIST is represented here by one member among the historical ensemble of CNRM-CM5 model. Leadtime (from OND Yr0 to OND Yr4) versus longitude plots for (c) DEC–HIST and (d) DEC_NOEQ–HIST seasonal means differences of the 20 °C isotherm depth (filled colors) and 10-m winds (arrows) averaged over 2°S–2°N. Yr0 OND represents the (c) NOTROP_IC–HIST and (d) NOEQ_IC–HIST differences that are present one season before the forecast starts. Contour interval is every 2 m and arrow units are given in the upper-right corner of the panel in m s−1.

In summary, we show that the first year of the forecasts is characterized by a quasi-systematic excitation of El Niño – Southern Oscillation (ENSO) warm events whatever the starting dates. This, through ocean-to-atmosphere heat transfer materialized by diabatic heating, can be viewed for the coupled model as an efficient way to rapidly adjust to its own biased climate mean state. Weak La Niña events tend to occur the second year of the forecast due to the so-called discharge-recharge mechanism, while the spurious oscillatory behavior is progressively damped. Based on this analysis, we decided to retain the DEC configuration for CMIP5 archive because of the minimized initial shock in the Pacific.

# 4 Evaluating and understanding biases in climate models

Evaluating climate models and understanding the source of errors is crucial since most of our science relies on numerical modeling. Indeed, it is important to identify the limits of the models we use to provide climate predictions and projections to increase the confidence of our scientific results. In the climate community, multi-model studies have been conducted in order to identify and understand sources of errors in climate models, focusing often on climate simulations from the CMIP archive (Richter and Xie 2008; Guilyardi et al. 2009; Li and Xie 2012; Richter et al. 2012; Flato et al. 2013; Wang et al. 2014, among others). During my research, I have also been interested in evaluating, analyzing and understanding model biases. My work has been focused either on one component of the GCM (i.e. stand-alone atmospheric model or ocean model) or on the whole climate system (coupled model). To summarize my work, I present in the next sections three issues that are to me of increasing complexity: : 1) the influence of model errors in the representation of climate mean state, 2) the influence of model errors in the representation of climate variability and 3) the existence of climate drift and its usefulness in understanding the causes of model errors.

## 4.1 INFLUENCE OF MODEL ERRORS ON THE MEAN STATE

The model mean state evaluation consists, for a certain variable, of comparing model averages over a period of time, to observed averages of the same variable and over the same time period (if observations are available). Even if it may seem a very simple diagnostics, the evaluation of the model mean state requires several conditions to be satisfied: i) A mean state must be determined from an equilibrium state, implying that this diagnostic has to be compute, after the so-called spin-up protocol. ii) A long model integration is needed for a robust estimate of the model mean state or model climate. To evaluate model mean state versus the observations, it is advisable to use simulations that replicate the observed climate conditions over the 20st century, that is, when all the external forcings are prescribed in the model (i.e. the historical simulations of CMIP5). Nevertheless, in some cases, pre-industrial runs have been used for model evaluation. Comparing these to present day observations would introduce a small error due to the different GHGs concentrations, but in some regions, as the Tropical Atlantic, this error is negligible in most models due to the severity of the biases (Richter and Xie 2008; Richter et al. 2012). (iii) Homogeneous and high quality observational records are also required over the region and period of study, to avoid misleading interpretations. In some cases, the observed records are not available over a long period of time (e.g. the sea level height is available since the altimetry development: from 1992 to present). This is a limitation for model evaluation, and in this case I would recommend the use of statistics to estimate the observed uncertainty due to the short period of time considered in the observations. Considering only one source of data for a given variable can also be misleading and for this reason, it is also recommendable to use several observational datasets (when available) to generate an observational spread and account for the uncertainty.

In the following I present two examples of model mean state evaluation, the first based on a multi-model approach and the second for a specific coupled model.

## *Evaluation of the water budget over the Mediterranean Sea*

In this work, Sanchez-Gomez et al. (2011) assessed the ability of an ensemble of Regional Climate Models (RCMs) from the FP6-EU ENSEMBLES[19] database, to simulate the various components and net values of the Mediterranean water budget (MWB hereinafter). To produce this multimodel ensemble, all RCM experiments were performed for the time period 1961–2000 using six hourly lateral boundary conditions provided by the ERA40 reanalysis (Uppala et al. 2004). SSTs and sea-ice concentration are also from ERA40 dataset. Models domain covered the European-Mediterranean area. The RCMs used their own model setup as well as grid specifications like rotation and number of vertical levels, but similar horizontal resolution (~25km). In a preliminary and necessary analysis, we compared estimates of MWB from a range of observational datasets and discussed the main differences between them. One highlight of this study was the high degree of uncertainty that exists in the MBW observed and modelled estimates. Obtaining accurate estimates of every term in the MWB is crucial for understanding the Mediterranean ocean circulation and climate, and their evolution under climate change.

Taking into account the closure hypothesis at the Gibraltar Strait, we built several observational estimates of MWB by combining different observational components. Figure 4.1 shows the annual cycle for the different components of the MBW for RCMs and observations averaged over the whole Mediterranean Sea. In the case of the Black Sea input, this has been estimated by considering averages over the Black Sea. In this work not all the models provided the runoff variable, so the net MWD was validated only for a sub-ensemble of RCMs. The common period of integration for RCMs was 1961-2000. However, observations were available for different periods. To evaluate the uncertainties associated with the interannual variability in the MWB estimates, we provide an error bar estimated as $t_\alpha * std/\sqrt{n}$, where *std* is the standard deviation of the interannual time series, and *n* is the number of years.

From Figure 4.1, most of the RCM Mediterranean basin means are within the range spanned by the observational estimates of the different budget components, though in some cases the RCMs have a tendency to overestimate the latent heat flux (or evaporation) with respect to observations. One important conclusion here is, even if they operate at higher resolution (25 km), the RCMs do not show significant improvements of the total water budget estimates compared to the lateral boundary forcing (ERA40). Moreover, given the large spread found in observational estimates of precipitation over the sea, it is difficult to draw conclusions on the performance of RCM for the freshwater budget and this underlines the need for better

[19] http://ensembles-eu.metoffice.com/

precipitation observations.

This work provided an important result for the regional modelling community over the Mediterranean region. After the ENSEMBLES project, this was the first multi-model study on the MWB. From this study, other works have emerged and now the MWB studies and estimates constitute one of the main topics of the HyMeX[20] program.

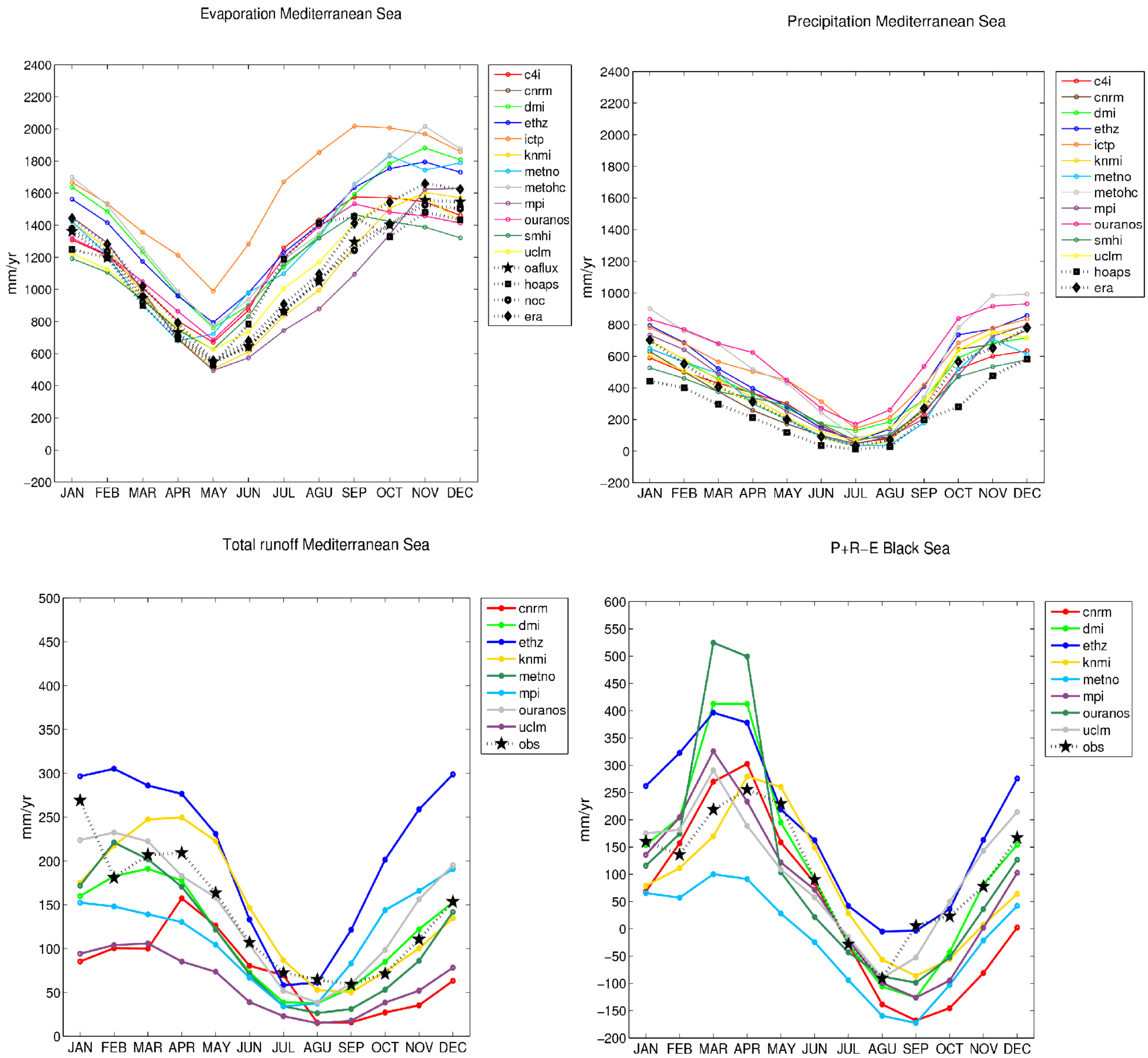


**Figure 4.1:** Annual cycle for the components of the MWB averaged over the whole Mediterranean basin. Evaporation from RCMs, OAFlux and HOAPS data; Precipitation from RCMs, GPCP and HOAPS data; River discharge from RCMs and Ludwig et al. 2009 and Black Sea (P+R-E) input from RCMs and Stanev et al. 2000. Models names are indicated in the legends.

[20] Hydrological Cycle in Mediterranean Experiment) program (http://www.hymex.org/)

## *Evaluation of the Atlantic Meridional Overturning circulation of the CNRM-CM5 model*

Within the CNRM-CERFACS modelling group, I participated actively in the evaluation of the ocean component of the coupled model CNRM-CM5. The description of the main features of this model and a preliminary assessment of its performance were published in the paper by Voldoire et al. 2013. This work provided an exhaustive study of the model's mean state, and constitutes a guide providing all the diagnostics that should be included in a model climatology assessment, allowing to get an idea of the “model’s health”.

The ocean component of CNRM-CM5 is the NEMO model version 3.2 on an ORCA1 grid, coupled to the sea ice model GELATO (Salas y Melia, 2002). To evaluate the ocean component, one of the most important diagnostics is the thermohaline circulation represented by the AMOC, which is characterized by warmer and saltier water flowing northward in the upper Atlantic Ocean and by cooler and fresher water flowing southward in the deep ocean. The AMOC is crucial to the northward heat transport by the ocean circulation. Recently, Wang et al. 2014 found that regional SST biases are commonly linked with the AMOC biases in CMIP5 models.

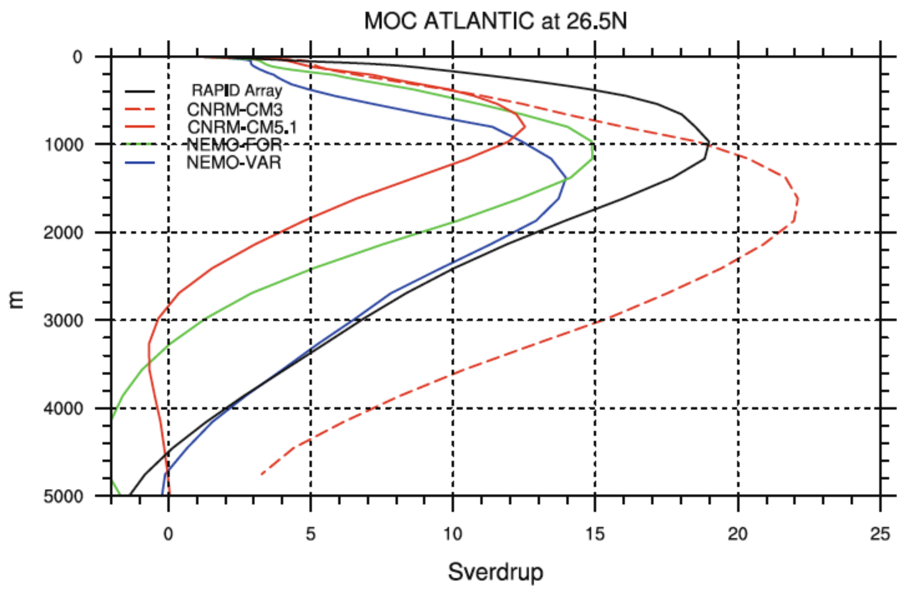


**Figure 4.2:** Meridional overturning stream function (Sv, 1 Sv = $10^6$ $m^3s^{-1}$) for the Atlantic ocean at 26.5°N for Rapid Moored array estimations, and averaged over the period 1960–2000 for CNRM-CM3, CNRM-CM5, NEMO-FOR and NEMO-VAR (see text for more details).

Figure 4.2 shows the mean vertical profile of the AMOC, in the previous version CNRM-CM3, CNRM-CM5, NEMO-FOR and NEMO-VAR averaged over 1960–2000, together with the mean observational estimate from moored array instruments through the RAPID section at 26.5°N (Cunningham et al. 2007) averaged over 2004–2009. NEMO-FOR and NEMO-VAR are respectively issued from a stand-alone ocean experiment forced by the so-called DFS4 dataset

(Brodeau et al. 2009) and for the NEMOVAR ocean reanalysis produced by ECMWF (Balsameda et al. 2010). From figure 4.2, AMOC observational estimates from RAPID reach a maximum value of around 19 Sv at 1.000 m depth approximately. CNRM-CM3 (CNRM-CM5) simulates a stronger (weaker) AMOC equal to 22 Sv (13–14 Sv) located at deeper (lower) levels (1.600 m, 800 m). It is interesting to highlight here that the AMOC absolute values in NEMO-FOR and NEMO-VAR, though stronger than for CNRM-CM5, also underestimate RAPID. This suggests that this NEMO configuration (1$^o$ resolution, mixing scheme parameters) may set the AMOC absolute value at first order; the depth for the maximum may be more dependent on the forcing. Figure 4.2 shows that in the coupled model CNRM-CM5 the AMOC is relatively weak, which can be due to both, biases in the ocean component and in the atmospheric component. In the last section of this chapter we analyse the origins of this bias in the AMOC and its relationship with the atmospheric component.

## 4.2 ROLE OF MODEL ERRORS IN REPRESENTING CLIMATE VARIABILITY

The model evaluation must be completed by an assessment of how the climate variability is simulated. The requirements for computing this diagnostic are the same to those mentioned in the previous section: the model must have reached its equilibrium state (no drift present); the period of time of the simulation and observations must be long enough (at least longer than 30 years) to obtain robust estimates of the variability. Nevertheless, even if long integrations are available, the observational period remains too short or inexistent for several variables (derived satellite products as winds, heat fluxes; subsurface ocean data as the AMOC, deep ocean data…), hence one should be always cautious when interpreting the results.

The Tropical Atlantic is a difficult region to get right in the models both in term of climatology and variability. Its variability can be assessed partly by looking at the Atlantic Meridional Mode (AMM) or inter-hemispheric mode. In the recent years and in the framework of the FP7 EU PREFACE[21] project, I have studied the representation of the AMM by the CMIP5 models. The AMM is an inter-hemispheric meridional SST gradient associated to cross-equatorial surface winds (Carton et al 1996; Chang et al 1997; Servain et al. 1999; Ruiz-Barradas et al 2000; Chiang and Vimont 2004). For this evaluation, we have used the historical experiments to compare more properly to the observations, which are represented in this case by NCEP/NCAR (Kalnay et al. 1996) and 20CR reanalysis (Compo et al. 2011). To compute the AMM we have followed the methodology described in Chiang and Vimont, (2004), which is based on a Maximum Covariance Analysis (MCA) between the SSTs and 10 m wind fields (both zonal and meridional components). The analysis is performed for each season separately, considering JFM (winter), AMJ (spring), JAS (summer) and OND (autumn). We remove the climate trends for both models and observations by using the least-squares fit technique. All the models have been interpolated to the same common grid 1.5$^o$ x 1.5$^o$ for comparability. The period selected for this analysis is 1950-2005.

[21] Enhancing prediction of Tropical Atlantic climate and its impacts (http://preface.b.uib.no/)

A preliminary analysis reveals that the AMM spatial structure and percentage of covariance explained can be different amongst the members or realisations of one model. This highlights the fact that internal variability is very important in the processes governing the AMM and that model assessment would depend on the member considered. This important consideration has to be taken into account when interpreting model biases computed only from one member. To avoid misleading interpretations, we have recomputed the AMM by including only models with at least 3 members in the historical experiments. This leads to an ensemble of 17 models. In order to increase the statistical robustness, only 3 members have been selected and concatenated before computing MCA.

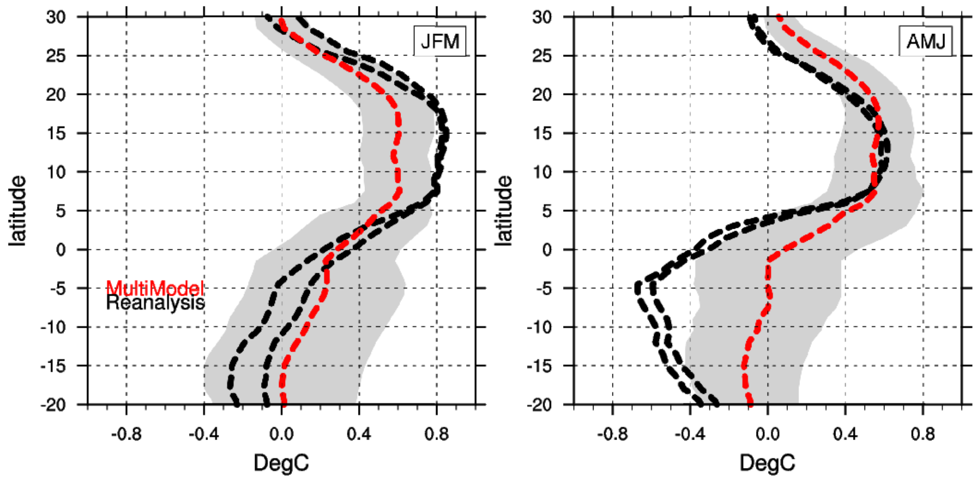


**Figure 4.3:** Zonal means of SST anomalies corresponding to the AMM in 17 CMIP5 models and atmospheric reanalysis. The models are represented by the ensemble mean (red line) and the inter-model spread (gray shading) computed from one standard deviation. The reanalysis are represented by the black dashed lines.

Figure 4.3 shows for JFM and AMJ seasons the zonal means of SST anomalies associated to the AMM for both models and reanalysis. The models are represented by the ensembles mean (red line). The inter-models spread (gray shading) is calculated as one standard deviation. It can be noticed that the model uncertainty is larger in the Southern Hemisphere, reaching up to 0.3-0.4°C. In the spring season, when the AMM peaks, models underestimate clearly the strength of the SST meridional gradient, with anomalies in SST much lower in the Southern Hemisphere than in reanalysis. This indicates that there are some deficiencies in the models to represent the inter-hemispheric SST gradient associated with the AMM. The questions that arise after this result are: Why do models underestimate the SST meridional dipole? Is there a link to the strong warm SSTs biases documented in the south-eastern Tropical Atlantic? Answering these questions is not straightforward. Coupled models exhibit common errors in the Tropical Atlantic: the warm bias SSTs in the south-eastern part of the basin; the too southward location of the ITCZ[22] that leads to a weaker surface wind speed in the south of equator. Intuitively,

[22] Inter-Tropical Convergence Zone

warmer SSTs in the southeast Tropical Atlantic would inhibit the anomalous cooling and the formation of an inter-hemispheric SST gradient. At the same time, a weaker wind speed in the southern hemisphere, would decrease the SST cooling by latent heat loss. Whatever the bias that is the source of discrepancy, the hypothesis that means state errors are affecting the AMM representation should be verified trough the use of numerical experiments, like the anomaly coupling technique. This method consists on replacing the climatological part of the fields exchanged in the model components by those from observations, while leaving free the anomalous parts without modifications (Kirtman et al. 1997). Currently I am working to implement the anomaly coupling technique on the CNRM-CM5 model, to investigate the influence of the mean state on the representation of the Tropical Atlantic Variability, in particular the AMM. This will be done in collaboration with some of my colleagues from the EU PREFACE project.

## 4.3 DRIFT ANALYSIS TO UNDERSTAND MODEL ERRORS

One interesting approach aimed at understanding the physical mechanisms causing models systematic errors is the analysis of drifts. This can be defined as the sequence of physical processes by which the model reaches its equilibrium state or attractor. Drifts are always present in coupled models when initialised from observed conditions because of intrinsic model errors (see Figure 4.4 for an illustrative point of view of the model drift). Moreover, they can potentially affect any type of climate predictions based on numerical experiments. Model drifts are usually removed through more or less sophisticated techniques for skill assessment, but they are rarely analysed. Beyond statistical predictability issues, the dynamical study of model drift and associated bias adjustment is also crucial, since, as pointed out by Meehl et al. 2014 and Hawkins et al. 2014, the rate of the bias development and its spatial pattern can provide a useful information on physical processes connected to model systematic errors that potentially affect the skill scores. Furthermore, this can give some clues to understand the model behavior, which can provide some guidance for model improvements.

The systematic analysis of bias adjustment in hindcasts appeared only recently in few studies: Vanniere et al. 2013 tracked back the origin of cold biases in the Pacific equatorial cold tongue from several seasonal forecast systems; Huang et al. 2015 examined the drift mechanism yielding to a weakening of the AMOC in the CFSv2 decadal prediction system; Voldoire et al. 2014 analysed the role of atmospheric systematic errors in initiating seasonal SSTs biases in the Tropical Atlantic in the CNRM-CM5 model; and Tonniazzo and Woolnough 2013 studied the development of Tropical Atlantic errors as well but based on multi-model decadal predictions from CMIP5. Lately, Hawkins et al. 2014 investigated the importance of the methodology used for removing model biases estimates for global temperature in decadal hindcasts, using a toy model and CMIP5 experiments. The analysis of drift has also become a coordinated protocol in the EU-PF7 PREFACE project, in order to make progress in understanding the local and remote causes for SSTs biases in the Tropical Atlantic. Myself, with the CERFACS team are participating in this coordinated experiment.

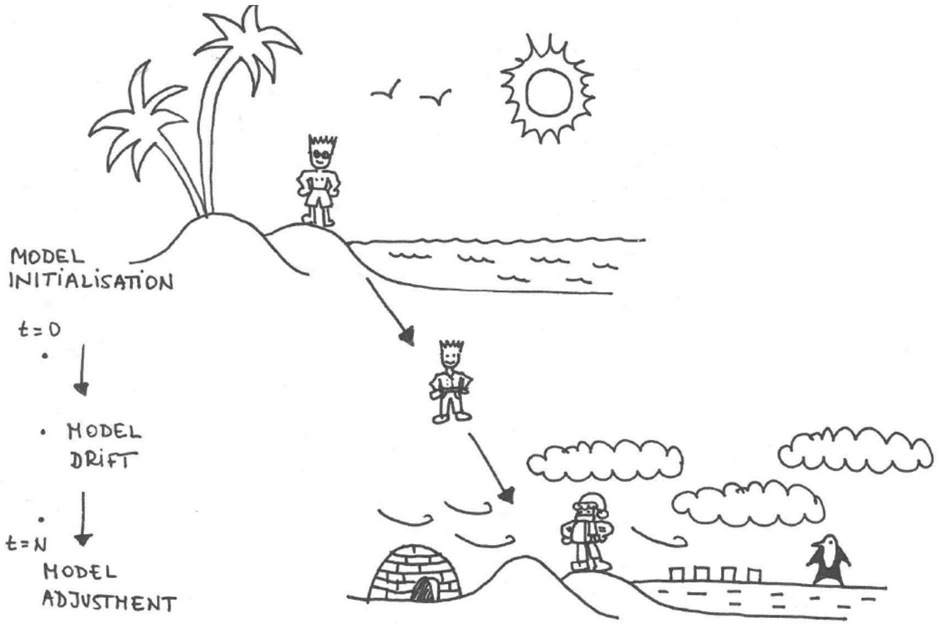


**Figure 4.4:** An illustration of the model drift in a climate prediction. The model (the guy) is initialised from an observed state, which is warmer than the model mean climate. The 'model guy' progressively adjusts (he wraps up) by to finally reach the equilibrium state.

In a recent paper, Sanchez-Gomez et al. 2015 provided a detailed physical and dynamical description of the drifts in the CNRM-CM5 coupled model using a set of decadal retrospective forecasts produced within CMIP5 (see also chapter 3). In this paper, we focused on two specific regions, namely the Tropical Pacific and the North Atlantic oceans, for which a detailed investigation of the relationship between the drift and some modes of variability such as El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) was documented. In the Equatorial Pacific, the model initial shock or fast adjustment was materialized by a quasi-systematic excitation of spurious ENSO warm events whatever the starting dates. This behavior and its dependence on the initial conditions has been described in Chapter 3 (section 3.2).

In the analysis described above, the drift in the North Atlantic region was estimated as the difference between the mean response of the initialised simulations, named as DEC (see chapter 3 for a more detailed description of these experiments) and the initial state. We observe a fast adjustment (up to ~5-years leadtime) leading to a rapid slackening of both the vertical (AMOC) and the horizontal ocean circulations, especially in the Subpolar Gyre (SPG) area. Slower adjustments of the entire water masses distribution in the North Atlantic then takes over involving several mechanisms, described in Sanchez-Gomez et al. 2015. Figure 4.4 (right) shows the differences in the AMOC between two prediction periods and the initial state, represented by the NOTROP_ICs. North of 30$^{o}$N, we observe a decrease of the deep-water formation together with the slowdown of the AMOC, leading to a reduction of the advection of warm and saline water from the subtropical gyre into the SPG. All these processes are occurring by the fact that the model is initialised from a state other than its mean state.

Figure 4.5 (left) shows the differences in SLP for the same prediction periods between DEC and NCEP/NCAR reanalysis. Here we use as reference NCEP/NCAR since the atmospheric adjustment is very fast, and the atmospheric model biases are already established in the initial conditions NOTROP_ICs (Fig. 4.5 left/top). Indeed, the NOTROP_IC coupled simulation can be considered for the atmosphere as an AMIP-type simulation since the SST is strongly restored to observation (see section 3.2, Chapter 3). From Figure 4.5 (left/top), the stand-alone atmospheric biases show positive (negative) SLP anomalies at high latitudes (in the subtropics). This anomalous atmospheric circulation strongly projects upon a negative NAO pattern. It is interesting to note that such an altered circulation is marginally reinforced in DEC, as a consequence of ocean-atmosphere coupling.

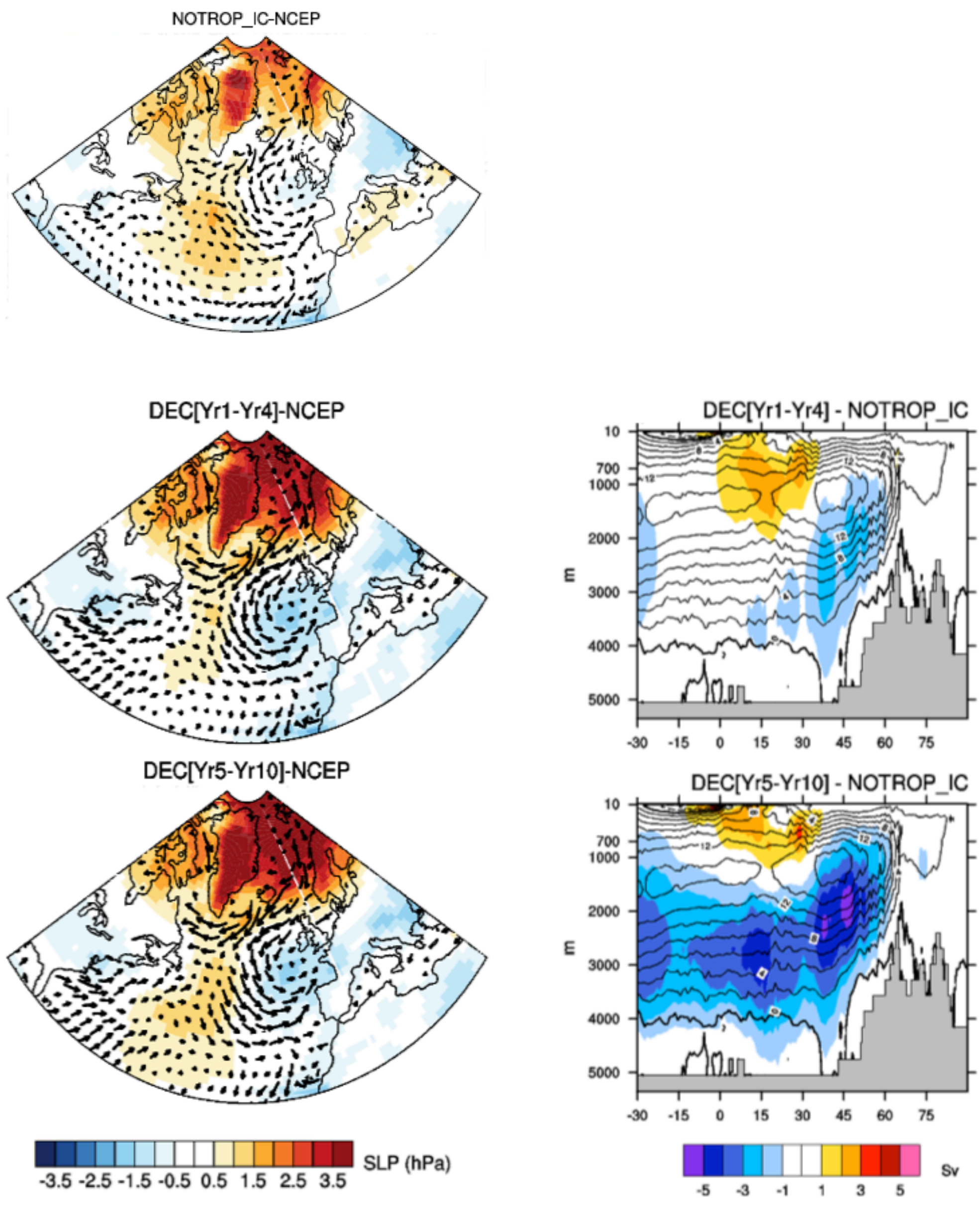


**Figure 4.5:**

(Left Panel) Differences in SLP (shading) and surface winds (vectors) between NOTROP_ICs and NCEP reanalysis (top), decadal forecasts and NCEP reanalysis for leadtimes averaged over Yr1-Yr4 (top) and Yr5-Yr10 (bottom). Color shading interval is every 0.5 hPa. Arrow units are 5 in $m.s^{-1}$.

(Right Panel) AMOC differences between decadal forecasts and initial conditions for leadtimes averaged over Yr1-Yr4 (top) and Yr5-Yr10 (bottom). The black contour represents the AMOC long-term annual mean for initial conditions (NOTROP_IC). Contour interval is every 2 Sv.

Weaker winds over the northern North Atlantic lead to surface warming in the SPG region through reduced loss of heat from the ocean to the atmosphere and a reduction of formation of deep water masses, accompanied by shallower mixed layer and inhibited convection over the SPG, especially in the Labrador Sea. Reduced formation of intermediate to deep-water masses in the western SPG under NAO- like conditions also diminishes the AMOC, in agreement with previous modeling studies (Lohmann et al 2008; Barrier et al 2014). Note that the mechanisms for the AMOC reduction proposed here are different from the ones examined in Huang et al. 2015 using the CFSv2 decadal forecasts. In their case, the AMOC weakening is caused by a reduction of the upper ocean salinity in the SPG, likely due to an excessive freshwater transport from the Arctic due to rapid sea ice melting while in CNRM-CM5, drifts can be mostly interpreted as the integration by the ocean of intrinsic atmospheric biases.

In this study we show that a weak feedback is locally present between the atmospheric circulation and the ocean drift that controls the timescale of setting of the coupled model biases. In CNRM-CM5, this feedback is such that it is positive and progressively reinforces the intrinsic atmospheric model errors considered as the main seed for the fully coupled model biases. The study that I lead thus highlighted the important fact that the mean atmospheric model biases can be first attributed to the biases of the stand-alone atmospheric components, which strongly project upon a permanent negative NAO pattern. As pointed out in Vannière et al (2013) and Xie et al. (2015), the challenge for the climate community is to move beyond the routine evaluation of the climate model and to develop innovative techniques and approaches to trace climate model errors back to their physical origin. In other words, beyond simple comparison of measurable quantities, models evaluation should be process-based to identify model systematic errors and the timescale of their setting, with the ultimate goal to reduce them. Lessons might be drawn in light of our results for the implementation and use of drift correction schemes that are mandatory to apply in any forecast system. Our study ultimately contributes to the ongoing research effort to reduce the model errors or, in other words, to minimize their drifts when initialised.

# 5 Conclusions and future work

In this last chapter, I would like to conclude this research summary by a short resume of the main results presented in the previous chapters and by discussing some perspectives to my future research work. The perspectives might appear quite ambitious, but I believe they can be carried through, as the proposed work will be performed in a collaborative framework.

## 5.1 SUMMARY AND CONCLUSIONS

The main conclusions of the results that are presented in this manuscript are summarized below:

- A large body of my research relied on the use of weather regimes. We have shown that they are powerful tools to represent the large-scale dynamics of atmospheric internal variability. We show that they are linked to surface variables like temperature and precipitation and also to storm-tracks. It is interesting and useful to use straightforward decompositions to quantify the contribution of modifications in the residence frequency of weather regimes in changes in the mean state changes of a certain variable. In Chapter 2, this concept is illustrated using projected storm tracks in the North Atlantic. According to this, we have examined the projected response of the North Atlantic storm-tracks at the end of 21$^{st}$ century. The result showed no detectable response (signal emerging from the internal variability) at the end of the 21$^{st}$ century, which is likely due to the small ensemble size, indicating that to assess the role of internal versus external variability in the mid-latitudes, large ensembles size could be required.
- By using statistical analysis we can identify atmospheric oscillations in which the weather regimes constitute the phases. This "ondulatory" view of weather regimes may have important consequences on medium-range and intra-seasonal forecasts. Chapter 2 shows an example of intra-seasonal oscillation implying a certain number of weather regimes over the Mediterranean domain was presented. We also show that weather regimes are useful structures to study climate teleconnections. Along this line, a multi-model study shown in Chapter 2 indicates that tropical conditions in the ocean can affect the frequency of occurrence of North Atlantic weather regimes. In particular a warming over the Indian ocean leads to an excitation of the Zonal (NAO+) weather regime. Even if this response is quite robust amongst the models, the mechanism explaining this teleconnection is quite model-dependent. This highlights the important fact that, even if a teleconnection pattern is present in different models, the mechanism underneath to trigger may not be the same.
- During my PhD and in the latest years of my carrier (from 2009 on) I have conducted on climate predictability studies, whose summary is presented in Chapter3. In my earlier research, I investigated the empirical predictability of climate conditions at seasonal timescale on the North Atlantic region. Empirical forecast models are useful tools to

predict anomalous climate conditions from seasonal to decadal timescales. They complement the numerical predictions, since they allow for a complete forecast evaluation at a small computational cost. Besides, empirical forecast models do not need to consider the problem of the drift and they provide physical insight on the mechanisms at the origin of predictability. In the latter period, I focused on dynamical forecasts, and more specifically, on the model initialisation problem. In numerical forecasts (seasonal to decadal), the initialization method is a real challenge. We have designed here an initialisation method oriented toward decadal prediction. We showed how the initialisation affects the model initial shock at the beginning of the forecast period. In particular the model initial shock is characterised by a sequence of spurious ENSO events lasting 4 years, which could have strong implications outside the Pacific through teleconnections.

- To conclude, an important part of my work has been oriented to the evaluation of climate models (Chapter 4). Model evaluation is crucial to quantify and understand model errors. A hierarchy of diagnostic is necessary, starting from the biases in the mean state, to the representation of the variability and more sophisticated studies as the analysis of drifts in initialized simulations. In Chapter 4 I describe the physical analysis of the drift in a coupled model, by using decadal forecasts performed with the CNRM-CM5 model. In this work we conclude on the main role of the atmospheric stand-alone model in biases adjustment. Lessons might be drawn in light of our results for the implementation and use of drift correction schemes that are needed in any forecast system. Our study ultimately contributes to the ongoing research effort to reduce the model errors or, in other words, to minimize their drifts when initialized.

## 5.2 FURTHER UNDERSTANDING OF THE ROLE OF INTERNAL CLIMATE VARIABILITY IN OBSERVED CLIMATE TRENDS

The 5$^{th}$ IPCC report has confirmed the fact that anthropogenic activities since the industrial and technological development have induced the global warming trend and subsequent changes in the climate system. Indeed, the Earth's climate is responding to external forcings like GHGs and anthropogenic aerosols, and this response seems to be unequivocally robust among climate models. Nevertheless, in the recent years, and in particular at the beginning of 21$^{st}$ century, observational records showed that a near-zero warming trend in the globally averaged surface temperature. This phenomenon is known as the climate hiatus (Meehl et al. 2013 among others) and it has received considerable attention in the recent years. Understanding the reasons of this recent slow-down in the positive temperature trend is key, given that climate sceptics have taken the advantage of this "warming pause" to question the effect of human activities on observed climate changes, and to claim that the warming was mainly due to natural causes like solar forcing. Recent studies have pointed out that internal multi-decadal climate variability was part of the hiatus, specifically the variability related to a decadal cooling in the Pacific basin, associated to the negative phase of the PDV (Kosaka and Xie, 2013). This highlights the important fact that internal climate variability can modulate the global warming trend and can contribute to regional climate changes for periods of several decades or longer. Ensemble approaches techniques allows for an estimate of the internal and external contributions in a model's world. In this approach the forced response is obtained by averaging all the ensemble members, and the internal variability by subtracting the ensembles mean to each individual member. However, in general, climate output archives, like those contributing to CMIP3 and CMIP5, do not provide enough realizations or members, to estimate robustly the forced response (Deser et al. 2012). In particular, most of the models participating in CMIP5 data contain only 3 realizations, and a few provide up to 10 realizations. Screen et al. 2013 showed that signal-to-noise ratios differ considerably between variables and locations. The temperature and precipitation forced responses are significantly easier to detect (higher signal-to-noise ratio) than the sea level pressure or geopotential height responses. For the latter, more than 60 members are necessary to detect a robust signal in mid-latitudes atmospheric dynamics in response to Arctic Sea ice loss**.** In chapter 2, we show that the forced response of the North-Atlantic storm tracks cannot be detected from only 5 members, even in the latter 21$^{st}$ century, when the anthropogenic signal versus the internal variability is supposed to be stronger. Given the importance of extra-tropical cyclones in the mid-latitude climate, it is crucial to better understand how internal variability can modulate them, and how they will respond to global warming.

In the past years, the CESM modelling group has developed an interesting initiative: the creation of large ensembles from one climate model. The Large Ensemble Model Community project (https://www2.cesm.ucar.edu/models/experiments/LENS, Kay et al. 2015) has highlighted the importance of increasing the number of members to maximize the signal-to-noise, and to better interpret the observed climate trends in the past 50 years (Deser et al. 2016).

I consider that the large ensemble approach are crucial improving our understanding and interpret the physical mechanisms underlying internal and forced climate variability. For this reason, one of my research perspectives will consist of generating and analysing a large ensemble approach to study the role of the multi-decadal internal variability, in particular the AMV and PDV, on shifts in the mid-latitudes atmospheric dynamics and associated synoptic variability in last decades. This ensemble will also allow for studying the tropical influences of the mid-latitudes storm tracks. We will be able to investigate the origin of changes in the position of the storm tracks, but also in the winds and precipitation distribution. For this purpose, the use of a coarse resolution model (~T127 (1.4$^{o}$) for the atmosphere, and 1$^{o}$ for the ocean) would be more suitable. In a first stage, only the atmosphere can be perturbed to generate the members of the ensemble, as done by the CESM1 community. In a second stage, it would be also pertinent to perturb the ocean, in order to estimate the contribution of the ocean intrinsic variability (Serazin et al. 2014), which is also a question of interest for the CERFACS team. Finally, this large ensemble could be useful for many applications within the CNRM-CERFACS research teams.

## 5.3 IMPROVING CLIMATE MODELING: ADDED VALUE OF THE HIGH RESOLUTION

Recently, the development of new supercomputers and storage systems has allowed the possibility to increase horizontal and vertical resolutions in climate models. High-resolution has been identified as one essential element of the development of GCMs to reproduce key climate processes with higher fidelity than coarser resolution GCMs, thus potentially enabling detailed process understanding.

There are some processes in which we can expect a positive impact of increasing the resolution in climate models, in particular the air-sea interactions in the frontal regions of SSTs in mid-latitudes (Gulf Stream, Kuroshio, Agulhas). In these areas, strong horizontal SSTs gradients lead to intense air-sea exchanges and to a strong baroclinicity, leading to the development of extra-tropical storms. Recent studies have shown encouraging results concerning the high-resolution modeling of SST fronts and extra-tropical storm tracks (Taguchi et al. 2009; Woollings et al. 2010; Small et al. 2014; Piazza et al. 2015). The consequences in terms of variability of atmospheric circulation and large-scale hydrological impacts remain however unproven.

Most of modelling centres have developed high resolution versions of their climate models and first studies emerging point to a positive added value of increasing resolution in both, the ocean and atmosphere components (Woollings et al. 2010; Huang et al. 2015; Griffies et al. 2015; Saba et al. 2016). Nevertheless, these studies have been sometimes conducted with different model versions (disabling a proper low-resolution versus high resolution comparison), or typically by individual modelling centres on an ad-hoc basis. Hence, the profit of increasing model resolution is not fully proven today. For example, it does improve the simulated eddy kinetic energy on the SST fronts and the position of storm track (Woolings et al., 2010). Nevertheless, it is still not fully proven that increasing model resolution reduces large biases that have been persisting for generations of models, like in the upwelling zones or western boundary currents (Goubanova et al. in preparation).

In order to assess the role of the model resolution in the representation of the climate system and its variability and change, CMIP community has proposed the HighResMIP[23], that will be a component of CMIP6. It will provide a multi-model assessment of the benefits of increased vertical and horizontal resolution in CGCMs and their respective components.

One of my next research interests aims at studying the impact of oceanic and atmospheric resolution on the representation of ocean-atmosphere interactions over frontal SSTs zones, including the synoptic variability. I plan to focus on three midlatitude regions : the Gulf stream in the North Atlantic , the Kuroshio in the North Pacific and the Agulhas current in the southern hemisphere. This work will be conducted in the international context of the EU H2020 PRIMAVERA[24] project.

[23] High-Resolution Model Inter-comparison Project

[24] PRocess-based climate sIMulation: AdVances in high-resolution modelling and European climate Risk Assessment (https://www.primavera-h2020.eu/)

## 5.4 EXPLORING THE IMPACT OF NEW MODEL PARAMETERISATIONS

As a complementary work to the assessment on the added value of the high-resolution climate models on the representation of some physical mechanisms, it is necessary to conduct studies oriented on testing and evaluating the impact of new parameterisations. I am interested in contributing to this research line, and in particular on working on parameterisations of unresolved ocean processes related to mesoscale temperature and salinity fluctuations. In a recent work, Brankart (2013) developed a new parameterisation aimed at simulating the uncertainties in the computation of the large-scale horizontal density gradient from the large-scale temperature and salinity. For this purpose, a stochastic term was added to the seawater equation of state to mimic the sub-grid random fluctuations of temperature and salinity fields. The stochastic parameterisation was implemented in a low-resolution configuration of the NEMO ocean model (ORCA2, ~2$^{o}$). Brankart 2013 showed that this parameterisation can considerably impact the ocean large-scale circulation, especially in the regions of intense mesoscale activity like western boundary currents regions. One main improvement is the much more realistic Gulf Stream pathway in, the stochastic version of the low-resolution NEMO model compared to observations.

Following this idea, I plan to go further in understanding the work by Brankart 2013, by studying the impact of the stochastic parameterisation in a low-resolution coupled model (~T127 (1.4$^{o}$) for the atmosphere, and 1$^{o}$ for the ocean). In particular I will focus on frontal regions of SSTs (Kuroshio/Gulf Stream/Agulhas) and on the storm-tracks location and intensity. Given the uncertainties related to this parameterisation, an ensemble approach is necessary to avoid misleading interpretations (please note that Brankart 2013 only performed one realisation of the NEMO model). The effect of the stochastic ocean on the mean state of the model would be analysed in a first stage. In a second stage, and to complement my research on the mid-latitudes storm-tracks, the impact of this parameterisation on the representation of the storm-track in the Pacific and the Atlantic will be investigated. These are open questions that I consider relevant in our way towards improving climate models.

## 5.5 EVALUATING AND UNDERSTANDING THE REPRESENTATION OF OCEAN PROCESSESS IN CLIMATE MODELS

Over the last year, two publications that appeared had a high impact in our scientific community. These are the works by Clement et al. 2015, published in Science, and by Nnamchi et al. 2015 published in Nature Communications. Both studies assess the role of the ocean dynamics in generating Atlantic SST variability in different regions and on different timescales. Clement et al. 2015 analyse the contribution of ocean circulation, and more specifically the AMOC, to the Atlantic multi-decadal variability represented by the AMV. On the other hand; Nnamchi et al. 2015 assess the role of the ocean dynamics on the SST equatorial variability, related to the Equatorial Mode or Atlantic Niño, at inter-annual timescales. Both studies compared fully-coupled models versus slab-ocean models coupled to the same atmosphere. The models considered in both studies were used in CMIP3/5 exercises. The slab-ocean models do not allow, by definition, ocean processes implying a horizontal or vertical transport (e.g. ocean advection, mixing and entrainment). Their results show that the main features of the observed SST variability (AMV or equatorial Atlantic) are practically reproduced in slab-ocean models, i.e. models without any ocean dynamics can reproduce patterns that are thought to result from ocean transport. Clement et al. 2015 conclude that the AMV is the response to mid-latitudes atmospheric stochastic forcing, with the thermodynamic coupling playing a role in the tropics. Nnamchi et al. 2015 point that the thermodynamic feedbacks, which can be excited by stochastic atmospheric forcing, can generate equatorial SST variability and the Atlantic Niño mode.

The above-mentioned studies have opened a door towards a very interesting question: What is the role of ocean dynamics in generating SSTs variability from interannual to multi-decadal timescales *in coupled models and hence in the real world*? The limited role of ocean dynamics in generating the AMV of the Atlantic Niño, as suggested by Clement et al. and Nnamchi et al. may be also two other interpretations: i) the fact of obtained similar patterns as the observed ones does not necessarily imply that they are generated from identical mechanisms, the challenge is to elucidate if the different elements of the ocean circulation are well simulated by models. ii) In coupled models, the role of the ocean dynamics versus thermodynamics processes can be misrepresented, particularly in the tropical Atlantic, which can be considered as a model bias.

This is one of the questions that motivated the EU-FP7 PREFACE project, which was designed to assess the representation of Tropical Atlantic variability by state-of-the-art coupled models. Ding et al. 2015 conclude, from a stand-alone model analysis, that the role of thermodynamic processes may be overestimated when such biased models are used in assessing the origin of equatorial Atlantic SST variability and its predictability. More recently, Planton et al. 2016 and Martin del Rey et al. 2016 have used a non eddy-permitting and a eddy permitting ocean stand-alone simulation respectively to perform an exhaustive heat budget analysis over the equatorial Atlantic region. They both showed that the vertical advection terms could contribute substantially to create SST variability in the equatorial Atlantic.

This is an interesting issue that deserves further investigation in order to improve our understanding of our climate models and hence of the real world. From my point of view, to derive a complete picture of the contribution of ocean dynamics in state-of-the-art models a comprehensive heat budget analysis is required for both coupled models and stand-alone ocean models in order to assess the impact of air-sea coupling. A multi-model approach should be undertaken to address this issue. I am aware that the ocean diagnostics involved in the heat budget analysis constitutes a large storage cost, since they are 3D variables and are required at high time frequency. Other alternatives could be explored, in order to estimate the role of ocean dynamics. For example, Ding et al. 2015 used an interesting metric: the correlation between the SSTs and Sea Surface Height (SSH) for each grid point.

# EPILOGUE

Here I conclude this summary on some of my research activities performed from my PhD (April 2002) until now. Unfortunately I was not able to include everything in this manuscript. The choice for the selection of published papers presented here is not based on the paper's relevance (from my point of view), but more to tell you a coherent history amongst the different chapters. I have also wanted to present some new material, not necessarily published yet, as North Atlantic weather regimes and storm-tracks links in Chapter 2; and the evaluation of the AMM simulated by CMIP5 models in Chapter 4.

The last chapter also includes some of the directions in which I would like my future work to be oriented. These perspectives have emerging as a result of my previous research and with other interactions avec other colleagues during these years. Concerning this aspect, I consider the communication amongst researchers essential to achieve progress in science. I have really appreciated these scientific discussions, often occurring in an improvised way.

During almost the half part of my "life as a researcher" I have had a post-doctoral fellow status (from 2003-2010). This means (in France) that we can marginally participate to the supervision of master and PhD students. Nevertheless I had the opportunity to collaborate with some of these students when I was a "post-doc" at CNRM and CERFACS, which was very motivating. At the end of 2010 I finally obtained my permanent position at CERFACS, within the GLOBC team. During the 2009-2011 period I was concentrated in the realisation of the CMIP5 decadal experiment for the CNRM-CERFACS group. This consisted of the model development; model tuning, test of initialisation and performance of the decadal experiments. This activity practically monopolized my work during these two years, in which I combined both research and engineering activities. After my almost one year of maternity leave (end 2012), I started to supervise PhD students with at different degree of implication. Today I am officially the co-supervisor of Thomas Oudar, on the topic: "Low frequency variability of large scale atmospheric circulation and associated synoptic variability, role of external versus external forcings". For me this experience on "science transmission" has been very stimulating. I have also learnt a lot on the exchanges with the students and I definitely want to contribute to the training of future researchers.

During these years I have also feed my research network by the participation to different outstanding European projects. This has also allowed me to collaborate and interact not only with the French community, but also to others European colleagues, and in particular the Spanish researchers, which I greatly admire, since they are authentic warriors, given the precarious situation of the research in my native country. One of my objectives is to expand my research network to other countries outside Europe.

I conclude here, I hope that you have enjoyed this manuscript and thank you for your reading.

# 6 Annexe A

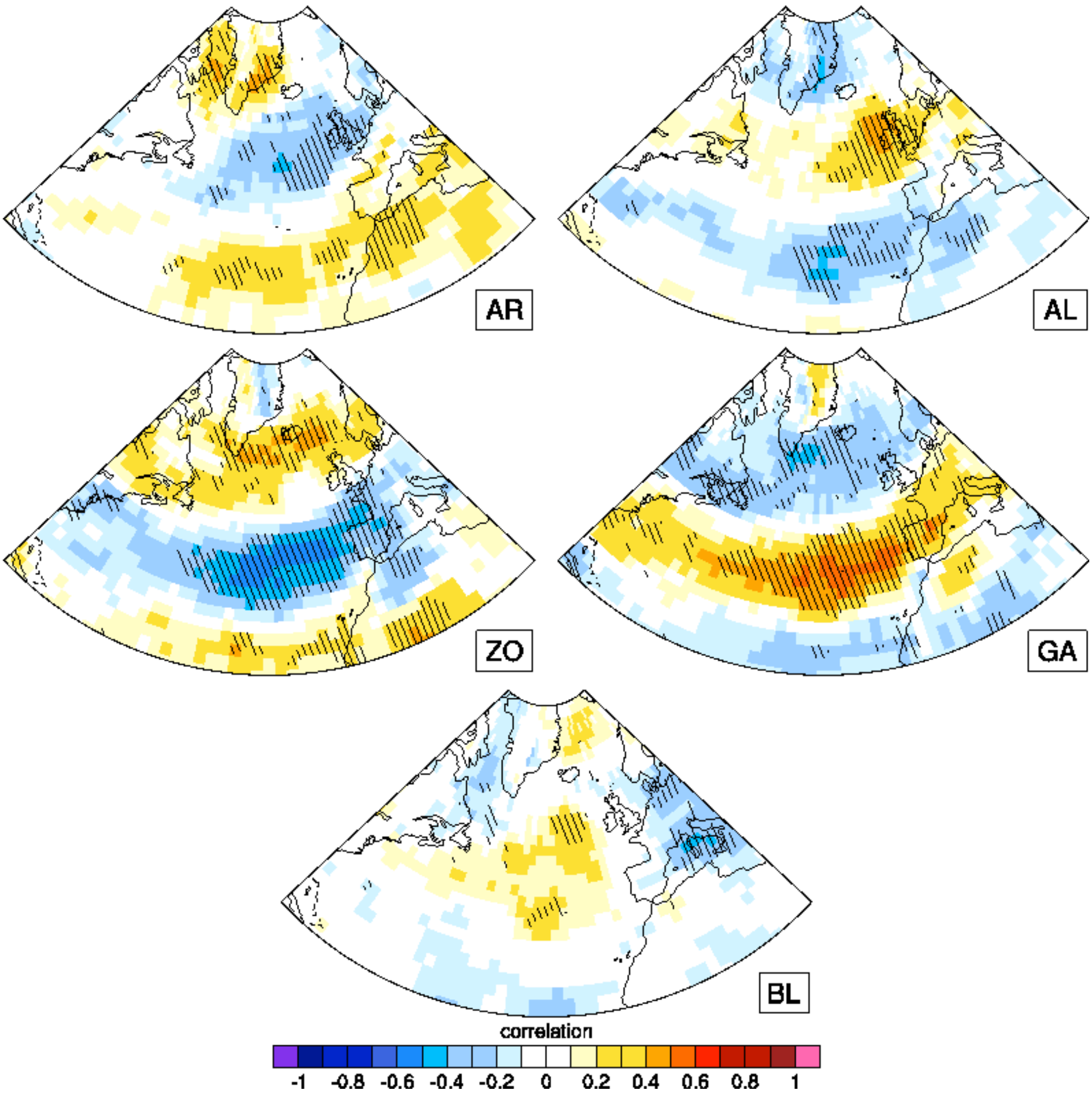


**Figure A1:** Correlations between the frequency of occurrence of North Atlantic weather regimes and the density of tracks for DJFM for the historical simulation (1961-1990) performed with CNRM-CM5 model. In this figure the ensembles mean is shown. Black hatching indicates those grids points where the signal-to-noise ratio, estimates as the ensembles mean divided by the confidence interval $t_\alpha * std/\sqrt{n}$, is greater than 1.

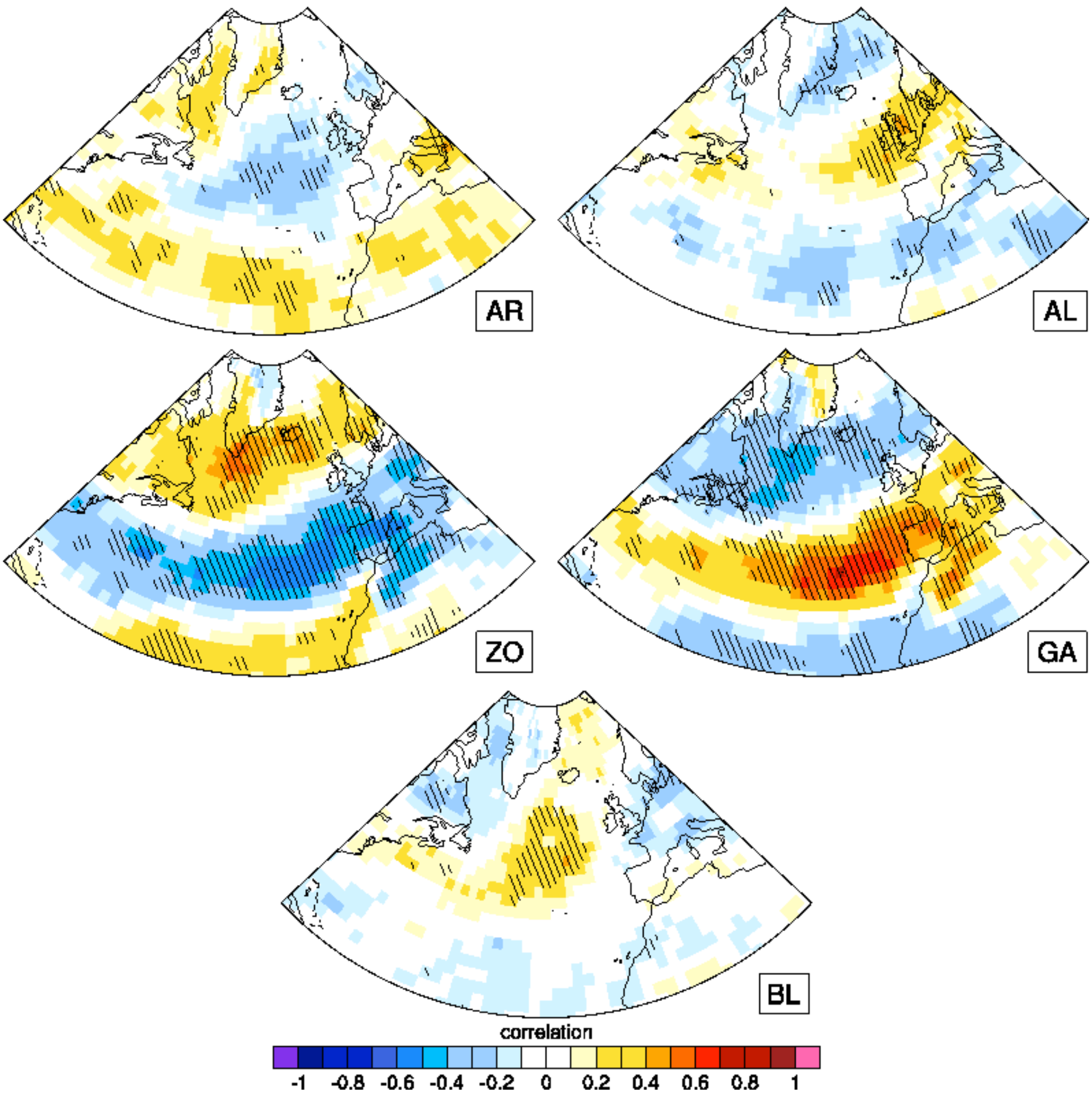


**Figure A2:** Correlations between the frequency of occurrence of North Atlantic weather regimes and the density of tracks for DJFM for the RCP85 simulation (1971-2100) performed with CNRM-CM5 model. In this figure the ensembles mean is shown. Black hatching indicates those grids points where the signal-to-noise ratio, estimates as the ensembles mean divided by the confidence interval $t_\alpha * std/\sqrt{n}$, is greater than 1.

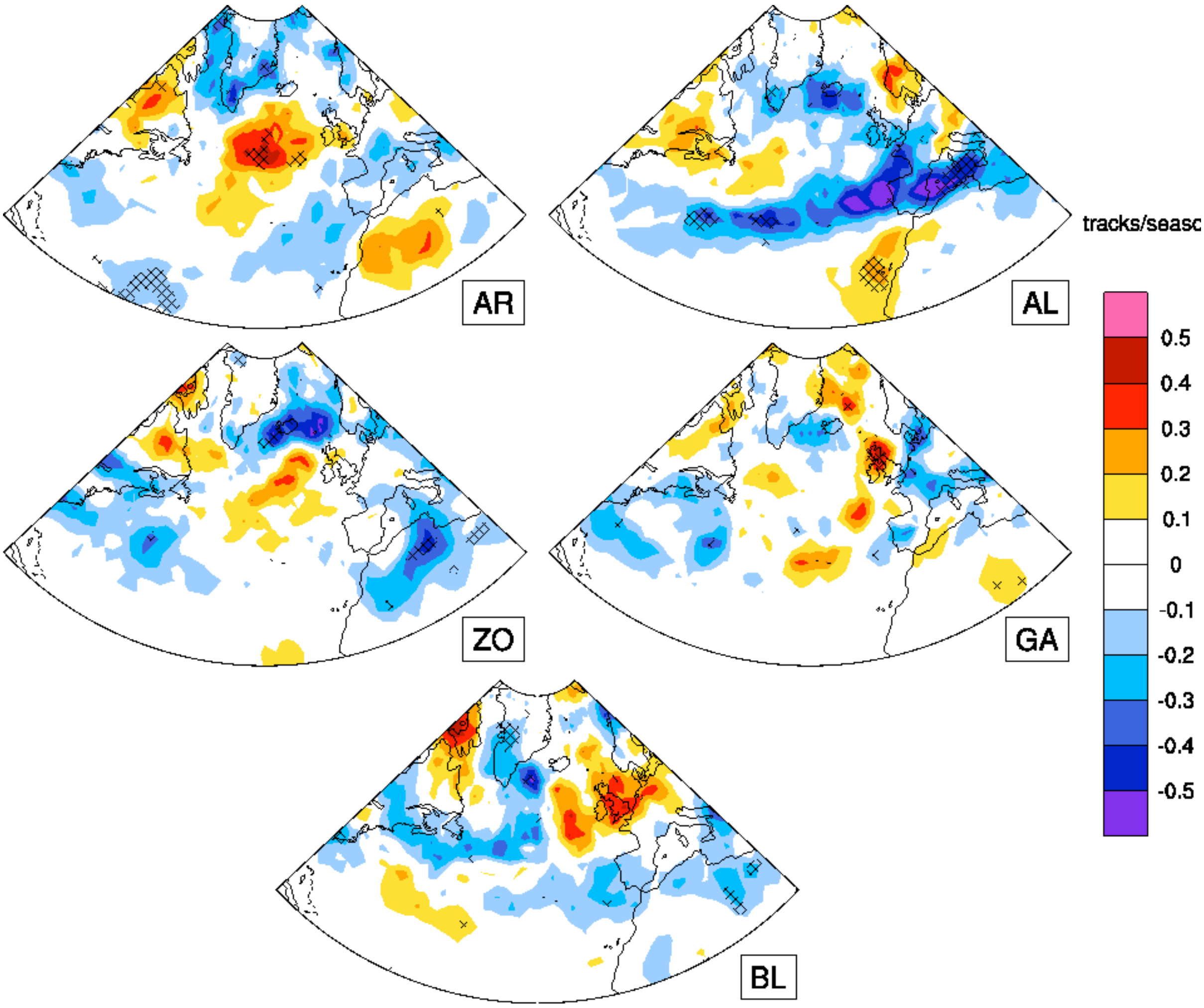


**Figure A3:** Decomposition of the CMC term (Figure 2.6, equation 2.3 in Chapter 2) into the different North Atlantic weather regimes. Changes are concerning the difference between a future time-slice period (2071-2100) minus a present period (1961-1990). Units are in tracks per winter season, considering here DJFM. In this figure the ensembles mean is shown. Black hatching indicates those grids points where the signal-to-noise ratio, estimates as the ensembles mean divided by the confidence interval $t_{\alpha} * std/\sqrt{n}$, is greater than 1.

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Zappa G., Shaffrey L., Hodges K., Sansom P. G. and Stephenson D. B., 2013, A multimodel asssessment of guture projections of North Atlantic and European extratropical cyclones in the CMIP5 climate models, J. Climate, 26, 5846–5862.

Zhang R and Delworth T. L., 2006, Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. Geophys. Res. Lett., 33, L17712, doi:10.1029/ 2006GL026267.

# Curriculum Vitae

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**Personal information:**
Nationality: Spanish
Place and date of birth: Madrid, 19/05/1974
Age: 41
Status: Married, 3 children

## Employment

- **Since 2010:** Senior Scientist (Permanent staff) at CERFACS with the climate Modelling and Global Change Team (GLOBC)
- **2009-2010:** Post-doctoral fellow (CERFACS/CNRS, Toulouse, France)
- **2007-2009:** Post-doctoral fellow (Météo-France/CNRM, Toulouse, France)
- **2005-2007:** Post-doctoral fellow (CERFACS/CNRS, Toulouse, France)
- **2002-2003:** Post-doctoral fellow (Collecte Localisation Sateline, CLS, Toulouse, France)

## Education

- **1998-2002:** Doctor on Sciences (Physics of climate), Universidad de Alcala de Henares, Spain. Mention: Sobresaliente Cum Laudem.
- **1997-1998:** Post-graduate fellow, Universidad de Granada, Spain.
- **1992-1998:** Degree in Physics, Universidad de Granada, Spain. Mention: Notable

## Participation to research projects

National (French) projects - European or international projects

1. **EU-H2020 PRIMAVERA (2015-2019):** Model Metrics, high resolution climate modelling over North Atlantic and Europe.
2. **HyMeX programme (2010-2020):** Science Team on Mediterranean cyclones. Member of the HyMeX executive team in France.
3. **ANR[1]-MORDICUS (2014-2018):** Understanding mechanism of decadal climate variability.
4. **EU-FP7 PREFACE (2013-2017):** Understanding model biases in Tropical Atlantic

[1] Agence Nationale de Recherche

variability and predictability.

5. **ANR-CONVERGENCE (2013-2017):** Working on common climate model assessment framework amongst French climate laboratories.
6. **EU-FP7 COMBINE (2009-2012):** Decadal predictability. Initialisation of climate models for climate predictions.
7. **CMIP5 (2009-2012):** Preparation and realisation of the decadal forecast exercise CNRM-CERFACS group.
8. **GMMC-RETCLIF (2012-2013):** Real time decadal forecast using analysis products from Mercator-Ocean.
9. **GICC[2]-EPIDOM (2011-2013):** Decadal predictability. Initialisation of climate models for climate predictions.
10. **GMMC-RETCLIF (2012-2013):** Real time decadal forecast using analysis products from Mercator-Ocean.
11. **ANR-SCAMPEI (2009-2012):** Evaluating regional climate change on mountains regions in France.
12. **EU-FP6 ENSEMBLES (2003-2008):** Regional Climate modelling
13. **EU-FP6 DYNAMITE (2005-2008):** Understanding the dynamics of the coupled climate system
14. **AIC-CYPRIM (2005-2007):** Intense precipitation events on the Mediterranean region
15. **GICC-IMFREX (2003-2004):** Global warming impact of extreme events over France: precipitation episodes and severe storms
16. **EU FP4 PROVOST (1996-1999):** Empirical predictability at seasonal timescales

## Teaching

- Statistics (Discriminant analysis) from 2008 : ENM (Ecole Nationale de la Météorologie) 6 hours every year
- CERFACS formation: Statistical downscaling methods
- Several PhD courses at the Universidad de Alcala (2009, 2010)

## Supervising

- **Master Degree students supervisions**: 10 students

- **Co-Supervision of PhD fellows**:

1. Thomas Oudar (PhD title: Low frequency variability of atmospheric annular modes and the associated synoptic activity)
2. Marie Piazza (PhD title: Influence of the mesoscale ocean processes over the Gulf Stream region of the large-scale atmospheric circulation in the North Atlantic) \
3. Antoine Colmet-Daage (PhD title: Climate change impact on extreme precipitation events and flash floods over some French river catchments)

**- Collaboration with PhD fellows**:

[2] Gestion et Impacts du Changement Climatique

4. Fatima Driouech (PhD title: Dynamical downscaling of the winter Moroccan precipitation: climate change and uncertainties)
5. Virginie Guemas PhD title Role of the ocean surface on the intra-seasonal atmospheric variability in the North Atlantic)

- **Post-doctoral fellows:**

Paul-Arthur Monerie (SPECS/PREFACE projects), Katerina Goubanova (PREFACE project)

## Peer reviewed Publications

### Published:

1. **Sanchez-Gomez, E**. , F. Alvarez Garcıa et M.J. Ortiz Bevia, 2001 : Empirica seasonal forecast of 850 hPa air temperature anomalies on the North Atlantic, Quaterly Journal of the Royal Meteorological Society, 127, 2761-2786.

2. **Sanchez-Gomez, E**. , W. Cabos Narvaez et M.J. Ortiz Bevia , 2002 : Sea ice concentration anomalies as long range predictors of anomalous conditions in the North Atlantic, TellusA , 54, 245-259.

3. **Sanchez-Gomez, E**. et M.J. Ortiz Bevia, 2003 : Seasonal forecast of anomalous conditions in the North Atlantic basin, Monthly Weather Review, 131, 3061-3068.

4. **Sanchez-Gomez, E**. et L.Terray, 2005 : Large scale atmospheric dynamics and local intense precipitation episodes , Geophysical Research Letters, 32, L24711, doi :10.1029/2005 GL023990.

5. **Sanchez-Gomez, E.** , L. Terray et B. Joly, 2008 : Weather regimes and intra-seasonal atmospheric oscillations on the Mediterranean basin, Geophysical Research Let- ters,35, L15708, doi :10.1029/2008GL034515.

6. **Sanchez-Gomez, E**. ,C. Cassou, L. Terray, N. Keenlyside and D. Hodson, 2008 : Weather regimes and intra-seasonal atmospheric oscillations on the Mediterranean basin, Geophysical Research Letters,35, L15706, doi :10.1029/2008GL034345.

7. **Sanchez-Gomez, E**. ,S. Somot et M. Déqué, 2008 : Ability of an ensemble of regional climate models to reproduce weather regimes over Europe-Atlantic during the period 1961- 2000, Climate Dynamics, 35, L15706, doi :10.1007/s00382-008-0502-7.

8. T. Zhou, R. Yu, J. Zhang, H. Drange, C. Cassou, C. Deser, D.L.R. Hodson, **E. Sanchez-Gomez** , J. Li, N. Keenlyside, X. Xin, Y. Okumura, 2008 : Why the Western Pacific Subtropical High has Extended Westward since the Late 1970s ?, Journal of Climate ,DOI : 10.1175/2008JCLI2527.1

9. V. Guemas, D. Salas-Melia, M. Kageyama, H. Giordani, A. Voldoire et **E. Sanchez-Gomez** , 2009 : Summer interactions between weather regimes and surface ocean in the North-Atlantic region, Climate Dynamics,DOI 10.1007/s00382-008-0491-6.

10. V. Guemas, D. Salas-Melia, M. Kageyama, H. Giordani, A. Voldoire et **E. Sanchez-Gomez ,** 2009 : Winter interactions between weather regimes and surface ocean in the North-Atlantic region, Geophysical Research Letters,36, 9, doi :10.1029/2009GL037551.

11. **Sanchez-Gomez, E.** ,S. Somot et A. Mariotti, 2009 : Future changes in the Mediterranean water budget projected by an ensemble of Regional Climate Models, Geophysical Research Letters, 35, L15706, doi :10.1007/s00382-008-0502-7.

12. Driouech F., M. Déqué et **E. Sanchez-Gomez** , 2010 : Weather regimes-Moroccan precipitation link in a regional climate change simulation, Global and Planetary Change, doi :10.1016/j.gloplacha.2010.03.004.

13. **Sanchez-Gomez, E**. , Somot S., Josey S.A., Dubois C., Elguindi N. and Déqué M. 2011 : Evaluation of Mediterranean Sea water and heat budgets simulated by an ensemble de high resolution regional climate models, Clim. Dyn., doi : 10.1007/s00382-011-1012-6.

14. Déqué M., Somot S. **E. Sanchez-Gomez** , Goodess C.M., Jacob D., Lenderink G. and Christensen O.B., 2011 : The spread amongst ENSEMBLES regional scenarios : regional climate models, driving general circulation models and interannual variability, Clim. Dyn., doi : 10.1007/s00382-011-1053-x.

15. Voldoire A., **E. Sanchez-Gomez** , Salas y Melia D., Decharme B., Cassou C., Senesi S., Valcke S., Beau I., Alias A., Chevallier M., Deque M., Deshayes J., Douville H., Fernandez E., MadecG., Maisonnave E., Moine M.-P., Planton S., Saint-Martin D., Szopa S., Tyteca S. Alkama R., Belamari S., Braun A., Coquart L., Chauvin F., 2011 : The CNRM-CM5.1 global climate model : Description and basic evaluation. Clim. Dyn. Special Issue, doi :10.1007/s00382-011-1259-y.

16. Ortiz-Bevia M.J., **E. Sanchez-Gomez** and Alvarez-Garcia F.J., 2011 : North At- lantic atmospheric regimes and winter extremes in the Iberian Peninsula, Nat. Hazards Earth Syst. Sci., 11, pp. 971-980.

17. Tramblay Y., L. Neppel, J. Carreau and **E. Sanchez-Gomez** , 2012 : Extreme value modelling of daily areal rainfall over Mediterranean catchments in a changing climate, Hydrologial Processess, DOI : 10.1002/hyp.8417.

18. Piazza M., Boe J., Terray L., Page C., **E. Sanchez-Gomez** and M. Deque, 2014 : Projected 21st century snowfall changes over the French Alps and related uncertainties, Climatic Change, Volume 122, Issue 4, pp 583-594.

19. Bellucci A., R. Haarsma, S. Gualdi, P. Athanasiadis, M. Caian, C. Cassou, E. Fernandez, A. Germe, J. Jungclaus, J. Kroeger; D. Matei, W. Mueller, H. Pohlmann, D. Salas y Melia, **E. Sanchez-Gomez** , D.M. Smith, L. Terray, K. Wyser, S. Yang, 2014 : An assessment of a multi-model ensemble of decadal climate predictions Clim. Dyn., DOI :10.1007/s00382-014-2164-y.

20. A. Germe, M. Chevallier, D. Salas y Melia, **E. Sanchez-Gomez** and C. Cassou, 2014 : Interannual predictability of Arctic sea ice in a global climate model : regional contrasts and temporal evolution, Clim. dyn., Volume 43, Issue 9-10, pp 2519-2538.

21. Piazza M., Terray L., Boe J., Maisonnave E. and **E. Sanchez-Gomez** , 2015 : Influence of small-scale North Atlantic sea surface temperature patterns on the marine boundary layer and free troposphere : a study using the atmospheric ARPEGE model, Clim. Dyn., DOI : 10.1007/s00382-015-2669-z.

22. **Sanchez-Gomez, E**. , Cassou C., Ruprich-Robert Y., Fernandez E. and L. Terray, 2015 : Drift dynamics in a coupled model initialized for decadal forecasts, Clim. Dyn., DOI : 10.1007/s00382-015-2678-y.

## Accepted, under revision:

1. Monerie PA**, Sanchez-Gomez E.** and Boe J.**,** On the range of future Sahel precipitation projections and the selection of a subsample of CMIP5 models, Clim. Dyn.

2. Flaounas E, Kelemen FD, Wernli H, Gaertner MA, Reale M, **Sanchez-Gomez E,** Lionello P, Calmanti S, Podrascanin Z, Somot S, Akhtar N, Romera R, Conte D, Assessment of an ensemble of ocean-atmosphere coupled and uncoupled regional climate models to reproduce Mediterranean cyclones climatology, Clim. Dyn.

3. **E. Sanchez-Gomez** and S. Somot, Internal variability in a Mediterranean regional climate model: from climate to synoptic scales, Clim, Dyn.

4. Somot S, Houpert L, Sevault F, Testor P, Bosse A, Taupier-Letage I, Bouin MN, Waldman R, Cassou C, **Sanchez-Gomez E,** Durrieu de Madron X, Adloff F, Nabat P, Herrmann M, Characterizing, modelling and understanding the climate variability of the deep water formation in the North-Western Mediterranean Sea, Clim. Dyn.

## Submitted:

1. J. García-Serrano, C. Frankignoul, M. P. King, A. Arribas, Y. Gao, V. Guemas, D. Matei, R. Msadek, W. Park, **E. Sanchez-Gomez**, Multi-model assessment of linkages between Arctic sea-ice variability and the Euro-Atlantic atmospheric circulation in CMIP5 present climate, submitted to Clim. Dyn.

2. Oudar T., **Sanchez-Gomez E**., Chauvin F., Cattiaux J and Terray L., Impact of Arctic sea ice loss and increasing GHGs on large-scale atmospheric circulation based on fully-coupled sensitivity experiments, submitted to Clim Dyn.

## In preparation:

1. Oudar T., Chauvin F., and **E. Sanchez-Gomez** : Low-Frequency changes of the North Atlantic Storm-Track, impacts of external forcing versus internal variability.

2. **E Sanchez-Gomez** and K. Goubanova, The Atlantic Meridional Mode and WES feedback on CMIP5 models.

3. Goubanova K., **Sanchez-Gomez E**., Frauen C. and Voldoire A., SST bias development in the South-Eastern Tropical Atlantic in a high resolution version of CNRM-CM CGCM

## National publications (French/ Spanish)

### French

1. **Sanchez-Gomez, E.** et S. Somot, 2010 : Study of the Mediterranean sea water and heat budgets simulated by an ensemble of high resolution regional climate models, Note Interne M´et´eo-France, n. 112.

2. B. Boudevillain, S. Argence, C. Claud, V. Ducrocq, B. Joly, A. Joly, D. Lambert, O. Nuissier, M. Plu, D. Ricard, P. Arbogast, A. Berne, JP Chaboureau, B. Chapon, F. Crepin, G. Delrieu, E. Doerflinger, B. Funatsu, PE Kirstetter, F. Masson, K. Maynard, E. Richard, **E. Sanchez-Gomez** , L. Terray and A. Walpersdorf, 2009 : Projet Cyprim, Partie II. Cyclogenèses et précipitations intenses en région méditerranéenne : origines et caractéristiques, La Météorologie, 66, pp. 18-28.

3. A. Doerenbecher, S. Argence, C. Cassou, O. Caumont, L. Descamps, V. Ducrocq, N. Fourri´e, V. Guidard, G. Jaubert, A. Joly, D. Lambert, C. Lebeaupin-Brossier, T. Pangaud, **E. Sanchez-Gomez** , O. Talagrand, L. Terray and B. Vincendon, 2010 : Projet Cyprim, Partie III. Cyclogenèses et précipitations intenses :´el´ements de pr´evisibilit´e, besoins en observations, La Météorologie, 68, pp. 23-34.

4. Piazza M., Deque M., Page C., **E. Sanchez-Gomez** et Laurent Terray, 2013 : Comparaison de deux méthodes de désagrégation pour l'étude du climat et du changement climatique sur les zones de montagne en France, La Houille Blanche, 5, 2013, p. 22-29.

### Spanish

1. Montavez J.P., **E. Sanchez-Gomez** et J.I. Jimenez, 1998 : Some Applications of Montecarlo Methods to Urban Climate, Applied Sciences and the Environment, WIT Press/Computational Mechanics Publications, Southampton, UK, 113-121.

2**. Sanchez-Gomez, E.** , J.P Monta´vez et J.I. Jimenez, 1998 : Statistical Methods in Climatology. A case study, Applied Sciences and the Environment, WIT Press/Computational Mechanics Publications, Southampton, UK, 133-146.

3. **Sanchez-Gomez, E.** et M.J. Ortiz Bevia, 2002 : Aplicación de los patrones principales de acoplamiento al estudio de la predictibilidad en el Atlántico Norte, El Tiempo del Clima, Publicaciones de la Asociación Española de Climatología, Serie A no2, 207-218.

4. **Sanchez-Gomez, E.** et M.J. Ortiz Bevia, 2002 : Estimación de la evolución pluviométrica de la España seca atendiendo a diversos pronósticos empíricos de la NAO, El Agua y el Clima, Publicaciones de la Asociación Española de Climatología, 63-72.

5. Cabos Narváez W., F. Alvarez García, **E. Sanchez-Gomez** et J. Ortiz Bevia, 2002 : Influencia de las Temperaturas superficiales del mar sobre las precipitaciones en el Atlántico Tropical, El Agua y el Clima, Publicaciones de la Asociación Española de Climatología, 3-12.

6. **Sanchez-Gomez, E.** et M.J. Ortiz Bevia, 2002 : Predicción empírica en el Atlántico Norte : Invierno de 1976 y verano de 1994, El Agua y el Clima, Publicaciones de la 9 Asociación Española de Climatología, 73-82.

7. **Sanchez-Gomez, E**. et M.J. Ortiz Bevia, 2002 : Predicción estacional de condiciones anómalas en el Atlántico Norte, El Agua y el Clima, Publicaciones de la Asociación Española de Climatología, 83-92.

## Other publications

1. Piazza M., M. D´equ´e, C. Page, **E. Sanchez-Gomez** and L. Terray : Comparaison de deux méthodes de désagrégation pour l'étude du climat et du changement climatique sur les zones de montagne en France, La Houille Blanche, Proceedings : Eau en montagne/Water in mountain areas, 16-17 April 2011, Lyon, France.

2. Bellucci A., R. Haarsma, S. Gualdi, P. Athanasiadis, M. Caian, C. Cassou, A. Germe, J. Jungclaus, J. Kruger, D. Matei, W. Mu¿ller, H. Pohlmann, D. Salas y Melia, **E. Sanchez-Gomez** , D. Smith, L. Terray, K. Wyser, 2012 : An assessment of a multi- model ensemble of decadal climate predictions performed within the framework of the COMBINE project, COMBINE Technical Report No. 2, July 2012.

3. Haarsma R. , A. Bellucci, S. Gualdi, C. Cassou, J. Junclaus, W. Mueller, H. Pohlmann, **E. Sanchez-Gomez** , D. Smith, L. Terray, K. Wyser : The COMBINE Stream 1 Deca- dal Prediction Experiments, Quarterly Newsletter 4, April 2011, http ://www.combineproject.eu/Newsletters.1556+M54a708de802.0.html.

## Conferences

1. Montavez JP , A.J. Rodríguez , **E. Sanchez-Gomez** and J.I. Jiménez, Modificación de las series climatológicas debido al proceso de urbanización, I Reunión Científica Hispano- Sudamericana para el Análisis y la Predicción de la Variabilidad Climática, Salamanca,1997.

2. **Sanchez-Gomez, E**. , J.P. Montavez, A.J. Rodríguez and J.I. Jiménez, Contribución al estudio de la variabilidad climática mediante el estudio de series urbanas. Descripción del clima urbano, 1a Asamblea Hispano-Portuguesa de Geodesia y Geofísica, Almería, 1998.

3. **Sanchez-Gomez,E**.,J.P.Montavez, A.J. Rodríguez and J.I. Jiménez, Estudio metodológico de patrones de variabilidad climática en el sur de la Península Ibérica, 1aAsamblea Hispano-Portuguesa de Geodesia y Geofísica, Almería, 1998.

4. Montavez JP, A.J. Rodríguez, **E. Sanchez-Gomez** and J.I. Jiménez, La isla de calor en Granada, IV Reunión Nacional de Climatología Madrid. 1998.

5. **Sanchez-Gomez, E**. , J.P. Montavez, A.J. Rodrıguez and J.I. Jimenez, On the use of Multivariate Analysis in Climate Variability. A case study, International Geographical Union, Commission on Climatology : Climate y Environmental Change, Evora (Portugal), 1998.

6. Montavez JP , A.J. Rodrıguez , **E. Sanchez-Gomez** and J.I. Jimenez, An Analysis of urban and rural temperature records for some cities of Andalucia, International Geographical Union, Commission on Climatology : Climate y Environmental Change, Evora (Portugal), 1998.

7. Montavez JP, **E. Sanchez-Gomez** and J.I. Jimenez, A Montecarlo Simulation of the Long-Wave radiation in Urban Structures, Conference in Computational Physics, (CCP), Granada, 1998.

8. **Sanchez-Gomez, E.** , J.P. Montavez and J.I. Jimenez, Statistical Methods in Climatology. A case study, ASE 98, Cadiz, 1998.

9. Montavez JP, **E. Sanchez-Gomez** and J.I. Jimenez, Some applications of Montecarlo Methods in Urban Climate, ASE 98, Cadiz, 1998.

10**. Sanchez-Gomez, E**. , J.P. Monta´vez and J.I. Jim´enez, Multivariate study of the Variability of Climatological Time Series, ECAC 98, Viene, 1998.

11. Montavez JP, **E. Sanchez-Gomez** and J.I. Jimenez, A simple Model of Long-Wave radiation in Urban Canyons, ECAC 98, Viene, 1998.

12. **Sanchez-Gomez, E**. , C. Gutierrez and M.J. OrtizBevia, Empirical seasonal forecast of North Atlantic atmospheric anomalies, IUGG99, Birmingham, 1999.

13. **Sanchez-Gomez, E.** , M. Seisdedos and M.J. OrtizBevia, Position of the North Atlantic jet stream, global climatic signals and other signals of regional interest, Second International Conference on Reanalysis, Reading 1999.

14**. Sanchez-Gomez, E.** , M. Seisdedos and M.J. OrtizBevia, Relationships between the forecast skill of some empirical forecasts of the North Atlantic atmospheric anomalies and the ENSO and NAO phases, 4th International Conference on Modelling of Global Climatic Change and Variability, Hambourg, 1999.

15. **Sanchez-Gomez, E**. and M.J. OrtizBevia, Dependence of the location of the North Atlantic Jet Stream on global climatic signals, 4th International Conference on Modelling of Global Climatic Change and Variability, Hambourg, 1999.

16. **Sanchez-Gomez, E**. and M.J. OrtizBevia , Prediccion empırica de anomalıas atmosfericas en el Atlantico Norte, Reunion Bienal de Fısica, Valencia, 1999.

17. **Sanchez-Gomez, E**. , W. Cabos and M.J. OrtizBevia , Empirical predictability of the North Atlantic Oscillation, Chapman AGU Conference on the North Atlantic Oscillation, Orense, 2000.

18. **Sanchez-Gomez, E.** , W. Cabos and M.J. OrtizBevia´, Assessing the predictability of the North Atlantic Oscillation with soma empirical forecast experiments, Chapman AGU Conference on the North Atlantic Oscillation, Orense, 2000.

19. **Sanchez-Gomez, E.** and M.J. OrtizBevia´, Aplicacio´n de los patrones de acoplamiento al estudio de la predecibilidad en el Atlantico Norte, II CONGRES de la Asociacion espaniola de Climatologıa, Valencia, 2000.

20. **Sanchez-Gomez, E. ,** W. Cabos and M.J. OrtizBevia´, North Atlantic decadal variability connected to sea ice, Climate Conference, Utrecht, 2001.

21**. Sanchez-Gomez, E.** and M.J. OrtizBevia, Pronósticos empíricos estacionales de la variabilidad atmosférica en el Atla´ntico Norte, XXVII Reunión Bienal de la Real Sociedad Española de Física, Sevilla, 2001.

22. **Sanchez-Gomez, E.** and M.J. Ortiz Bevia, Estimación de la evolución pluviométrica de la España Seca atendiendo a diversos pronósticos de la NAO, III Congreso de la Asociación

española de Climatología, Palma de Mallorca, 2002.

23. **Sanchez-Gomez, E.** and M.J. Ortiz Bevia , Predicción Empírica en el Atlántico Norte : Invierno de 1976 y verano de 1994, III Congreso de la Asociación española de Climatología, Palma de Mallorca, 2002.

24. **Sanchez-Gomez, E.** and M.J. OrtizBevia, Predicción estacional de condiciones anómalas en el Atlántico Norte, III Congreso de la Asociación´n española de Climatología, Palma de Mallorca, 2002.

25. Cabos W, F. Álvarez**, E. Sanchez-Gomez** and M.J. OrtizBevia, Influencia de las temperaturas superficiales del mar sobre las precipitaciones en el Atlántico Tropical, III Congreso de la Asociación´n española de Climatología, Palma de Mallorca, 2002.

26. **Sanchez-Gomez, E**. and M.J. OrtizBevia, Empirical seasonal forecast of the NAO, EGU, Nice, 2003.

27. **Sanchez-Gomez, E**. , G. Larnicol y Pierre Yves LeTraon, Combinaison et comparation des données de satellite et données in-situ pour estimer la circulation termohaline de l'océan, Rencontres de Marie-Curie Fellowships, Paris, 2003.

28**. Sanchez-Gomez, E.** , F. Alvarez and M.J. OrtizBevia, Análisis de las predicciones retroactivas de la NAO formuladas en tiempo real con un modelo estadístico basado en la Descomposición en Valores Singulares, XXVIII Reunión Bienal de la Real Sociedad Española de Física, Madrid, 2003.

29. **Sanchez-Gomez, E**. Terray L. and A. Joly, Weather regimes in the Arpege-Climat Model simulations, EGU, Nice, 2004. 30. Sanchez-Gomez, E. Terray L. and A. Joly, Large-scale atmospheric dynamics related to local precipitation extreme events, EGU, Viene, 2005.

31. Joly B, **E. Sanchez-Gomez** , A. Joly and P. Raynaud, Large-scale environments for high impact weather in the Mediterranean, 7th Plinius Conference in Mediterranean Storms, Crete, 2005.

32. **Sanchez-Gomez, E**. , Joly A. and L. Terray, Estimation du risque d'évènement extrêmes dans un scenario climatique, AMA2006, Toulouse, 2006.

33. **Sanchez-Gomez, E.** , S. Somot, L. Terray and M. Déqué, Weather regimes and local climate over the Mediterranean basin, MEDCLIVAR workshop, Toulon, 2007.

34. **Sanchez-Gomez, E.** , S. Somot and M. Déqué, Analysis of European weather regimes from an ensemble of several regional climate model experiments, GA ENSEMBLES, Prague, 2007.

35. **Sanchez-Gomez, E. ,** S. Somot, N. Elguindi, M. Déqué, Climate Change Projections of the water budget over the Mediterranean sea from an ensemble of regional climate models, MedClivar workshop, Rodes, 2008.

36. **Sanchez-Gomez, E.** , S. Somot, M. Déqué, Present-climate evaluation and climate change projections for the water and heat budgets of the Mediterranean Sea using ENSEMBLES RCM, GA ENSEMBLES, Santander, 2008.

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