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Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the Consortium (including the Commission Services)	
CO	Confidential, only for members of the Consortium (including the Commission Services)	

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Contribution to project objectives – with this deliverable, the project has contributed to the achievement of the following objectives (from Annex I / DOW, Section B1.1.):

N.º	Objective	Yes	No
1	Reduce uncertainties in our knowledge of the functioning of Tropical Atlantic (TA) climate, particularly climate-related ocean processes (including stratification) and dynamics, coupled ocean, atmosphere, and land interactions; and internal and externally forced climate variability.	x	
2	Better understand the impact of model systematic error and its reduction on seasonal-to-decadal climate predictions and on climate change projections.	x	
3	Improve the simulation and prediction of TA climate on seasonal and longer time scales, and contribute to a better quantification of climate change impacts in the region.	x	
4	Improve understanding of the cumulative effects of the multiple stressors of climate variability, greenhouse-gas induced climate change (including warming and deoxygenation), and fisheries on marine ecosystems, functional diversity, and ecosystem services (e.g., fisheries) in the TA.		x
5	Assess the socio-economic vulnerabilities and evaluate the resilience of the welfare of West African fishing communities to climate-driven ecosystem shifts and global markets.		x

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Deviation from planned efforts for this deliverable: none to our best knowledge.

Executive Summary:

Work package 11 of the PREFACE project aimed to quantify the impact of both PREFACE model improvement and bias correction techniques on climate predictions and long-term projections; to assess the reliability of the latest climate information so as to provide the most reliable information to the PREFACE Core research Theme 5[1]; and to investigate the link between model error improvement and climate predictions of the West African monsoon.

This deliverable is a product of Task 11.1: "Impact of model improvement on climate predictions of the tropical Atlantic and neighbouring regions" and is a report on the impact of model improvements and inter-basin teleconnections on the forecast quality of a range of climate predictions.

Several PREFACE partners have assessed the prediction skill of sea surface temperature (SST), at seasonal timescales, in the best current operational seasonal climate prediction datasets (NMME and EUROSIP). One of the main outcomes is that prediction skill in eastern equatorial Atlantic (ATL3, 5°N–5°S, 20°W–0°), in terms of the anomaly correlation coefficient, drops quickly after initialization and is below standard skill benchmark (persistence) for most models the first few forecast months (Figures 1.5, 2.1, and 3.2). The month of initialization is important, with more models having better skill than persistence if they are initialized at the onset of the equatorial Atlantic cold tongue development, normally occurring in May-June, as compared to those initialized before the cold tongue (Figure 3.2). In addition, BSC and UiB found that there does not seem to be a relation between model mean state error and prediction skill of SST in ATL3 (Figure 2.1). BSC has assessed the latest EC-EARTH seasonal forecast system using the NMME seasonal forecast systems as a benchmark. The

[1] PREFACE CT5: Impacts of climate change on pelagic functional diversity in the tropical Atlantic with effects on western African fisheries economies.

new system does not show clear improvement in terms of anomaly correlation coefficient, but there is an improvement in terms of the root mean square error (RMSE, Figure 1.5).

The skill in predicting rainfall over regions of Africa has been also assessed in various seasonal climate prediction datasets (Figures 2.2 and 5.4). BSC and UiB have found that several systems have significant skill in predicting African rainfall in certain regions affected by the African monsoon, and that the rainfall skill is strongly associated with the SST skill in ATL3 (Figure 2.2). CERFACS and BSC analyses found that NMME predictions are not very skillful in the Sahel region at lead-times of 2-5 months for most models, whereas ECMWF and BSC prediction systems show a very similar behaviour with relatively high skill in June that decreases afterwards. The rainfall skill seems to be sensitive to the choice of the area box of averaging and other methodological choices, thus resulting in apparent discrepancies between the results of the two aforementioned partner groups, which should be explored further. At decadal timescales, the origins of skill in Sahel rainfall is found be dependent on how well we can predict the timing of the global warming (GW), the Atlantic multidecadal variability (AMV) and, to a lesser extent, the inter-decadal Pacific oscillation (IPO) signals (UCM, UiB and MPI, Section 6).

BSC has assessed the forecast quality of SST at decadal timescales over the Tropical North Atlantic (TNA) in retrospective CMIP5 decadal predictions, and compared it to the skill in historical simulations. They found that the initialization provides additional skill only the first two years, and from there on the skill comes exclusively from the external forcing (Figure 1.2). This skill is not sensitive to the drift correction method used (Figure 1.2). The initialization method, however, appears to have an impact on the skill, with the full field initialization method (FFI) giving the most skilful forecast in EC-Earthv2.3. This could be related to either (1) the correction of model mean biases during the full-field initialization process, or (2) a better estimation of the forecast drift in the FFI prediction.

BSC and UCM have examined the impact on the ENSO seasonal predictions from the skill in predicting Atlantic Niño events in the previous summer. Using the NMME and EUROSIP forecasts systems they find evidence that high prediction skill over the summer Tropical Atlantic is associated with a better reproduction of the teleconnection between the summer Tropical Atlantic SST and the winter Tropical Pacific SST, and with a better ENSO prediction skill (Figures 3.3 - 3.5).

Finally the impact on skill coming from bias reduction techniques is analysed in two different studies. UiB has compared simulations and predictions with a standard configuration to simulations with an anomaly coupled configuration, which significantly reduces the climatological errors. They find that the mechanisms for equatorial Atlantic variability are better represented, but the variability is reduced in amplitude (Section 7). CERFACS and BSC have analysed the WP6 coordinated experiments, where the wind-stress at the equator is corrected. The improvement of the mean state has led to an improvement of the skill, particularly over the ATL3 region and the coast of Angola, and hence to an increase of the level of predictability (Section 4). This important result highlights the need to improve the mean state of coupled models in the Tropical Atlantic in order to enhance the predictions over the region. The discrepancy between these results and the lack of relationship between mean state error and prediction skill in ATL3 requires further investigation, and is discussed in Section 2 from BSC and UiB.

1. Forecast quality assessment of operational climate prediction datasets

Yohan Ruprich-Robert (BSC), Valentina Sicardi (BSC), Eleftheria Exarchou (BSC), Pablo Ortega (BSC)

Variations in the tropical North Atlantic (TNA) sea surface temperature (SST) are linked to numerous climate impacts at both seasonal and decadal timescales. For example, by fueling the lower troposphere in warm and moist air, and also by reducing the wind shear, warm TNA anomalies can modulate the tropical cyclone activity over the Atlantic (e.g., Vimont and Kossin 2007, Zhang and Delworth 2006). By modifying the interhemispheric temperature gradient, TNA anomalies can also drive changes in the strength and in the location of the Inter-Tropical Convergence Zone, leading to rainfall anomalies over West Africa and over the Brazilian Northeast (e.g., Mohino et al. 2011, Folland et al. 2001). Recently, studies also suggest that TNA variations can impact the entire tropical belt by, for example, modulating the El Nino Southern Oscillation activity and the Western Pacific tropical cyclone activities (e.g., Kucharski et al. 2011, Ruprich-Robert et al. 2017, Zhang et al. 2018). Given the numerous climate impacts driven by the TNA, predicting its variations is a scientific challenge that has the potential to enhance our society resilience to such impacts.

A. CMIP5 decadal prediction skills: impacts of the forecast drift correction method on the forecast skill

The purpose of this section is (1) to investigate the SST TNA predictive skill from retrospective CMIP5 decadal predictions, (2) to assess the impacts on the predictive skill of different drift correction methods, and (3) to estimate the reliability of the predictions.

We use 6 decadal prediction datasets, all based on 9-year long predictions initialized from the observed climate state every year over the 1961-2006 period, and integrated with the observed external forcing variations. These retrospective decadal forecasts (hereafter hindcasts) allowed us to estimate the ability of the forecast systems to predict the real climate. To distinguish the forecast skill coming from the information introduced during the initialization process to the skill coming from the imposed external forcing, we compare the forecast skill of the hindcasts with the skill from the CMIP5 historical simulations. We focus here on the TNA index defined as the spatial SST averaged over the region 5°N-25°N / 55°W-18°W.

The left panel of Figure 1 shows the raw outputs of the predicted TNA index for the averaged lead-times 2 to 3 years after initialization. A large departure can be seen between the absolute TNA index values forecasted and observed, regardless of the initialization approach considered. This comes from the inevitable climate model drift toward its own system attractor, which is different from the one of the real climate system because of inherent model deficiencies and biases. In order to extract useful information from climate prediction, one have to correct this model drift.

The most basic and common method to remove the drift assumes that the drift is systematic and shared by all predictions, independently on the initial conditions (e.g. Garcia-Serrano 2012). For one given model, it is therefore estimated by averaging all the climate predictions together (across all the starting dates) for each lead-time (method Clim1; cf. right panel in Figure 1.1). Two alternative approaches assume that the forecast drift depends on the initial conditions. Kharin et al. (2012) argue that if models misrepresent the long-term trends (for example if they misrepresent the climate sensitivity), spurious signals can be introduced by the method Clim 1. To tackle this issue they propose a drift correction method that corrects for the difference in long-term trends between observations and forecasts (method Clim 2). The third method assumes that the model drift is sensitive to the initial conditions considered (e.g. warm vs cold observed anomalies). In this context, Fuckar et al. (2013) propose to build a linear regression model to estimate the drift as a function of the initial state (method Clim3).

Figure 1.2 shows the Anomaly Correlation Coefficient (ACC) and Root Mean Square Error (RMSE) skill score for these three drift correction methods. During the first year of the forecast, decadal predictions tend to show better prediction skill scores (especially in terms of RMSE). This indicates that the initialization provides additional skill to the one coming from the external forcing. However, from forecast lead-time 3-year and beyond, the skill scores of the decadal predictions and historical simulations become indistinguishable, implying that the forecast information is only coming from our knowledge of the external forcing. We do not find obvious improvement of the forecast skill from the drift correction method Clim 1 to the drift correction method Clim2, except for the mpi-esm-lr decadal prediction (light blue line), which is the only model exhibiting a negative long-term trend (cf. Figure 1.1).

The method Clim3 seems to improve the ACC and the RMSE scores of all prediction systems for the first year of the forecast. However, for this method the historical simulations' ACC scores are also improved and show comparable values. This suggests that such improvement may be an artefact of the method. It is indeed very likely that the linear regression model built to assess the forecast drift is over-calibrated given the limited number of starting date and therefore the limited degrees of freedom. In this context, it questions about the effective performance of the method for extracting useful information from future forecasts. In terms of reliability, all the forecast systems appear over-confident (not shown), and none of the drift correction methods can sufficiently correct for it (Figure 1.3), although method Clim3 seems to perform better than the two other methods.

B. Decadal prediction skills: impacts of the initialization method on the forecast skill

Another approach to limit the impact of the forecast drift on the prediction skill consists in minimizing the drift itself. This drift is indeed the dynamical adjustment of the model after being initialized with climate conditions that are not compatible with its own attractor. This happens inevitably when models are initialized directly with the full observational fields, as models are not perfect and exhibit biases. To minimize the incompatibility between the observed state and the model attractor, it has been proposed to use anomaly initialization (e.g., Smith et al. 2008). This consists in initializing the model to its own climatology (which therefore includes the mean model biases) plus anomalies coming from the observations.

In this section, we assess the impact of using different forecast initialization methods on the TNA SST forecast skill. For this we use different decadal prediction sets performed with the EC-Earthv2.3 model (e.g., Volpi et al. 2017). During the forecasts, external forcing evolved following the CMIP5 historical forcing. For all sets of experiments the initial conditions for atmosphere and land come from ERA-40 reanalysis (Uppala et al. 2005) before 1989 and from ERA-Interim (Dee et al. 2011) afterwards. The ocean initial conditions come from the ocean re-analysis NEMOVAR-ORAS4 (Mogensen et al. 2012). The different sets of decadal predictions differ exclusively in the initialization of the oceanic component:

- Full field initialization (FFI): the temperature and the salinity of the model are initialized with the full values of NEMOVAR-ORAS4,
- Anomaly initialization (AI): the model is initialized to its climatology plus anomalies taken from NEMOVAR-ORAS4,
- Weighed anomaly initialization (WAI): same as AI, but the anomalies are corrected by the ratio of standard deviation between the model and the reanalysis,
- Anomaly nudging (AN): the initial conditions come from a 3D ocean nudged simulation to NEMOVAR-ORAS4 anomalies,
- No initialized (Hist): in this simulation, no initialization has been performed, only the external forcing is in common with the other experiments. It corresponds to a CMIP5 historical simulation.

For all sets of decadal predictions, 5-year long predictions where performed starting from November the 1st every 2 years over the period 1960-2005. A minimum of 5-member ensembles were performed. 3 members were performed for the historical simulation.

Figure 1.4 shows the TNA SST forecast skill in terms of ACC and RMSE scores for the different datasets. Consistently with the previous section (cf. Figure 1.2), we found that the initialized decadal predictions exhibit more skill than the historical simulations only during the first 2 years of the predictions. We do not find significant skill improvement coming from the refined initialization technics (i.e. not FFI). Especially, after leadtime 1-year, the decadal predictions AI, WAI, and AN show less skill than the FFI one. This suggests that for the EC-Earthv3.1 model, the SST skill over the TNA region may partly be linked to correction of the mean model bias in the FFI prediction during the full-field initialization process. But it can also come from a better estimation of the forecast drift in the FFI than in the other decadal prediction sets. Indeed, this drift should not be considered *a priori* as systematic in anomaly initialization prediction, but it should rather be considered as dependent of the initial anomalies. However, as shown in Section 1-B, the drift correction method that estimates the drift as as function of the initial states (i.e. method Clim3) is not suitable for the TNA SST. This calls for further investigation and for the development of better techniques to estimate the forecast drift in the case of anomaly initialization prediction.

C. Assessment of the prediction skill in the new EC-Earth seasonal forecast system

In this section, we evaluate the forecast skill of the new EC-Earth seasonal system forecast EC-Eartv3.2 and compare it with the NMME forecasts and the previous version of the EC-Earth system (EC-Earthv3.1). We focus on the prediction of the May-June-July-August SST of the Atlantic 3 region (5°N–5°S, 20°W–0°) hereafter ATL3;), which has been shown to have numerous remote climate impacts (cf. Sections below). All seasonal predictions discussed in this section have been initialized on May the 1st of every year over the 1993-2009 period.

Figure 1.5 shows the time evolution of the ATL3 index along with the ACC and RMSE skill scores. The NMME model forecasts are used as benchmark to help located the performance of the EC-Earth forecast system. In terms of ACC, we see that the performance of the EC-Earth forecast systems are located in the first half of the NMME systems, and there is no amelioration from the previous to the actual system. However, in terms of RMSE we find a clear improvement of the EC-Earth forecast system, with the new system showing value lower than 0.4 °C even after 4 month of forecast.

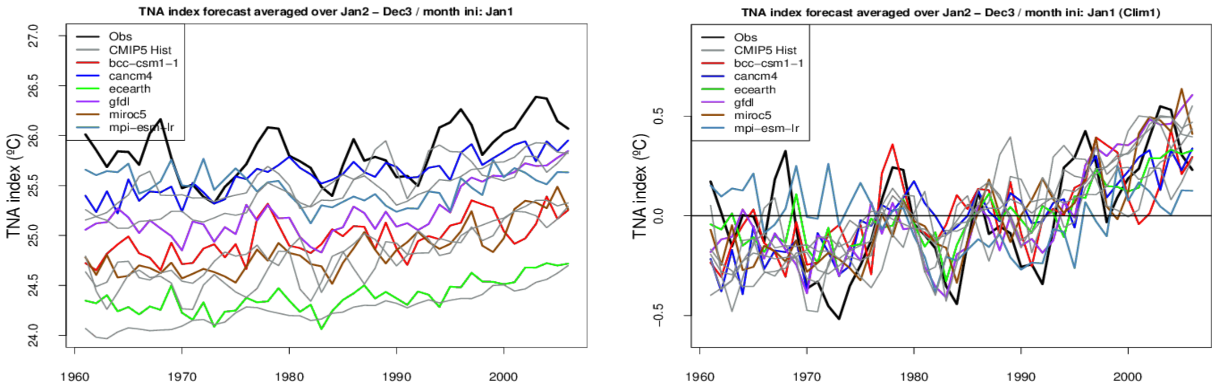

Figure 1.1: (left) 2-year averaged evolution of the TNA index from observation (black line; dataset: Hadisstv1.1), and from CMIP5 historical simulations (grey lines), along with the raw prediction values averaged over the leadtime forecast from 2 to 3 years (coloured lines). For the historical and decadal prediction, the ensemble mean average has been performed over all the members available for each model (this number may change from one model to another). (right) same as (left) but the prediction and historical values have been corrected of the mean climatological difference with observation for each leadtime (cf. drift correction method Clim1).

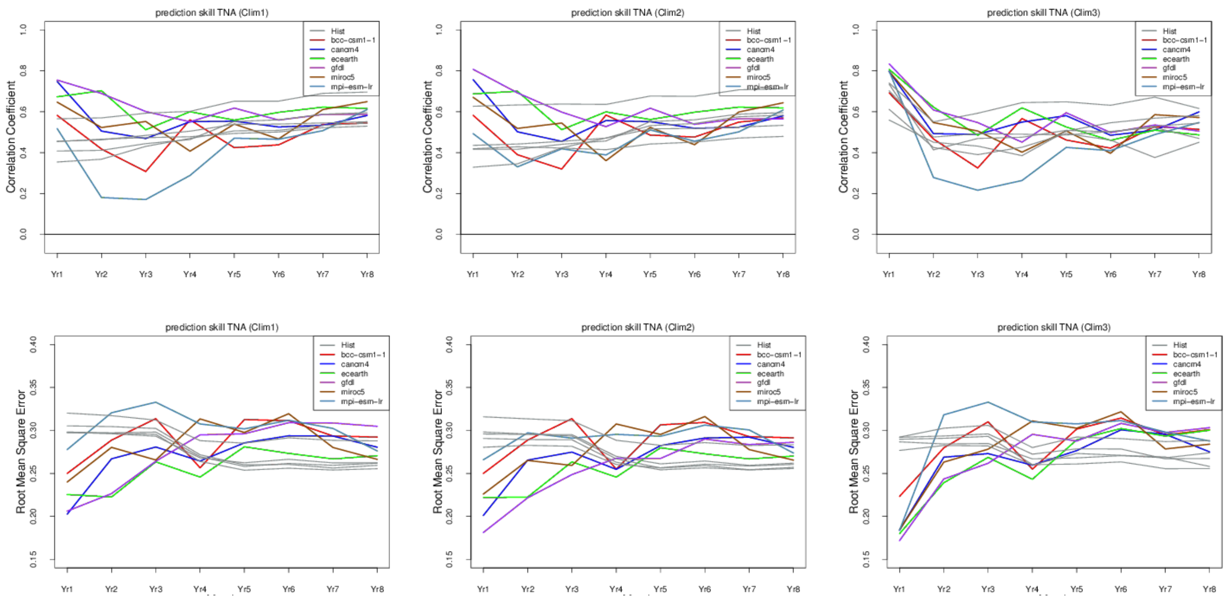

Figure 1.2: (top) ACC and (bottom) RMSE score in function of the forecast lead-time (in year) of the TNA SST index for the different CMIP5 decadal predictions (coloured lines) and for the historical simulation (grey lines). Scores computed after removing the forecast drift according to the (left) method Clim 1, (middle) method Clim 2, and (right) method Clim 3.

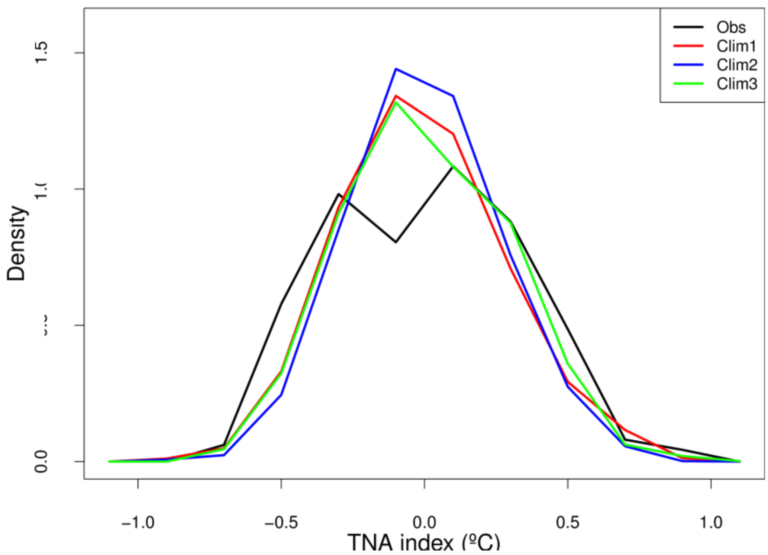

Figure 1.3: Probability Density Function (PDF) of the observed annual TNA SST (black line) and forecasted TNA SST over the first year lead-time as estimated after correcting the forecast drift according to method Clim 1 (red line), method Clim 2 (blue line), and method Clim 3 (green line). The PDFs were computed first for each forecast system then averaged all together.

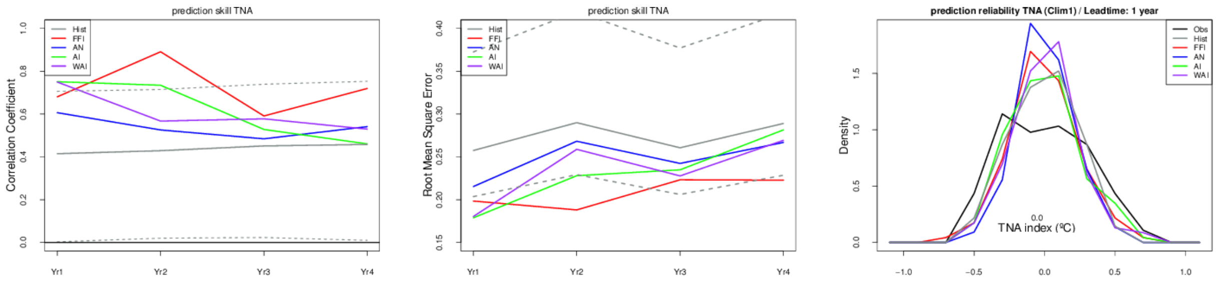

Figure 1.4: (left) ACC and (middle) RMSE score of the annual TNA SST for the EC-Earthv2.3 decadal forecasts FFI, AI, WAI, and AN, and the EC-Earthv2.3 historical simulations. (right) Probability density function of the observed (black) and forecasted (lead-time: 1year) TNA SST. The dashed line on the ACC and RMSE plots indicate the 90% confidence interval of the forecast skill of the historical simulation.

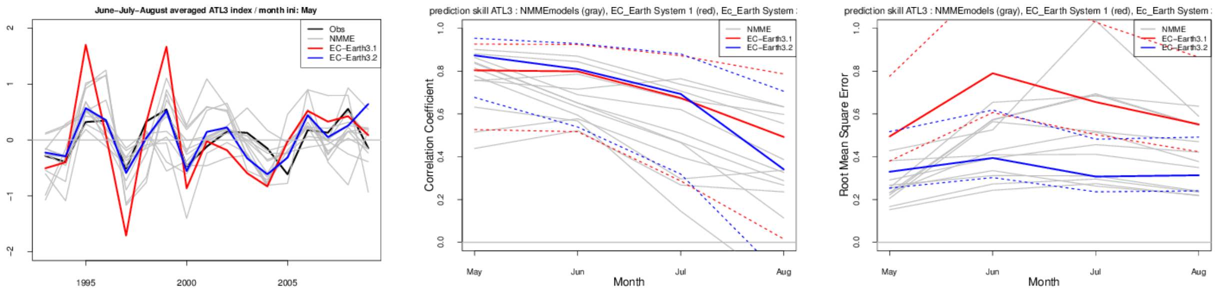

Figure 1.5: (left) June-July-August averaged ATL3 index from observation (black line; dataset: erasstv4), NMME forecasts (grey lines), EC-Eartv3.1 system (red line), and EC-Earthv3.2 system (blue line). ATL3 ACC (middle) and RMSE (right) score. The dashed line on the ACC and RMSE plots indicate the 90% confidence interval of EC-Earth systems.

2. Relation between forecast quality and mean state error

Chloé Prodhomme (BSC), Noel Keenlyside (UiB), Thomas Toniazzo (UiB)

Fisheries in the tropical Atlantic strongly depend on oceanic interannual variability and, therefore, the variability in this region strongly affects local surrounding populations [Zeeberg et al. 2008, Diankha et al. 2015, Bacha et al. 2016]. In addition, the Tropical Atlantic is an area of large impact due to the teleconnection with the rest of the tropics, such as El Niño-Southern Oscillation (ENSO) [Rodríguez-Fonseca et al. 2009], the West African Monsoon [Rodríguez-Fonseca et al. 2015], the Indian Monsoon [Kucharski et al. 2008] and the European climate [Cassou et al. 2005]. Despite, the importance of this region, SST biases are very strong (up to 6ºC) and widespread among all the CMIP5 models [Wang et al. 2014]. Therefore, it appears essential to better understand how these biases affect the predictability of the variability in the region.

To assess how biases could limit the predictability of interannual variability in the Atlantic, we use the North American Multi-Model Ensemble (NMME), jointly with the EUROSIP multi-model forecast system and with the EC-Earth and NorCPM seasonal forecast systems. As a result, we have available 18 seasonal forecast systems. We consider the period 1993-2009, which is the common period for all systems available.

Figure 2.1a shows the seasonal cycle in this multi-model in the forecast systems for the May start dates for the ATL3 box (20ºW0º-3ºS3ºN). This figure illustrates how all the coupled systems starts from very low biases at the beginning of the simulation due to the initialization, then the bias grows during the season in most of the systems. This process is called drift. Most of the systems fail to reproduce the large cooling occurring during spring in this region, consistently with the warm bias observed in the CMIP5 models, as mentioned earlier. Figure 2.1b shows the anomaly correlation coefficient (ACC) in the same region, it is interesting to note that most of the model have skill under persistence, however a few systems manage to have skill above and in some cases significantly above persistence. Figure 2.1c shows the relationship between the bias in JJA (June-July-August) and the JJA ACC for SST averaged in ATL3. This figure shows that there is absolutely no relationship between the ability of the model to forecast the ATL3 SST and the strength of the drift in this region. This result remains true when other starting months are considered (February, March and April; not shown). It might suggest that the quality of the initial condition as well as the quality of the model dynamics are more important than the mean state to achieve predictions in the ATL3 regions and therefore to predict the Atlantic Niño.

Although the skill in the ATL3 region is not related to the drift amplitude, Figure 2.2 shows that there is a very strong relationship between the SST skill in ATL3 and the skill of African rainfall precipitations. This result is consistent when considering three different African Monsoon indices, West African Monsoon (WAM), Guinean rainfall (GUI) and Sahelian precipitations (SAH). It is also interesting to note that several system have significant skill in predicting this range of monsoon indices, especially in the mature phase of the monsoon season. Among the models showing relatively high skills is the a007 forecast (EC-Earth 3.0.1). The possible mechanisms underlying the skill are planned to be analysed in the future.

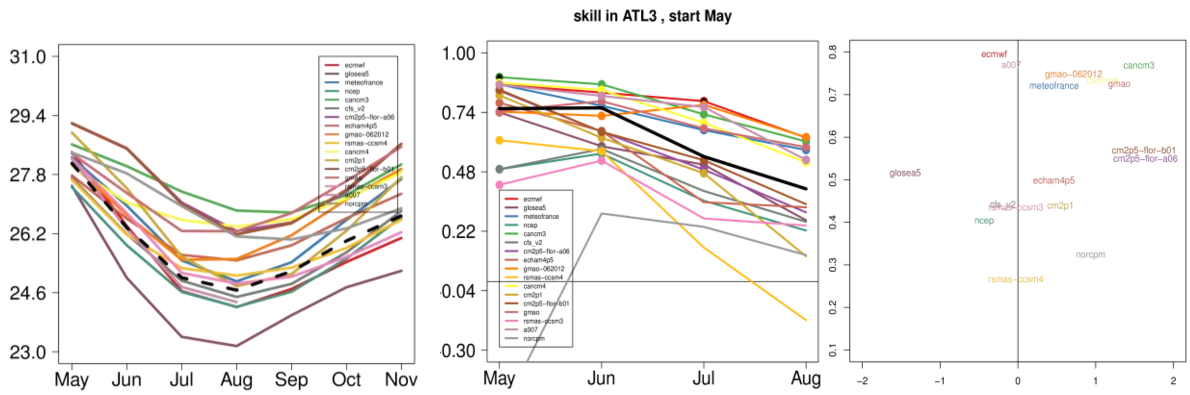

Figure 2.1: a) Climatology of the seasonal forecast systems considered for the May start date averaged in ATL3 (20ºW0º-3ºS3ºN) in Kelvin. Black dotted line shows observations (ERSST) b) ACC of the seasonal forecast considered for the May start date averaged in ATL3 (20ºW0º-3ºS3ºN). Dots show ACC values significant at 95% confidence level. The thick black line shows the skill of dumped persistence. Dark stars show correlation value significantly higher at 95% confidence level than the persistence. c) Scatter plot showing the SST bias averaged in JJA in ATL3 in each forecast system (x-axis in Kelvin) against the ACC of ATL3 SST in JJA (y-axis). a007 stands for EC-Earth 3.0.1.

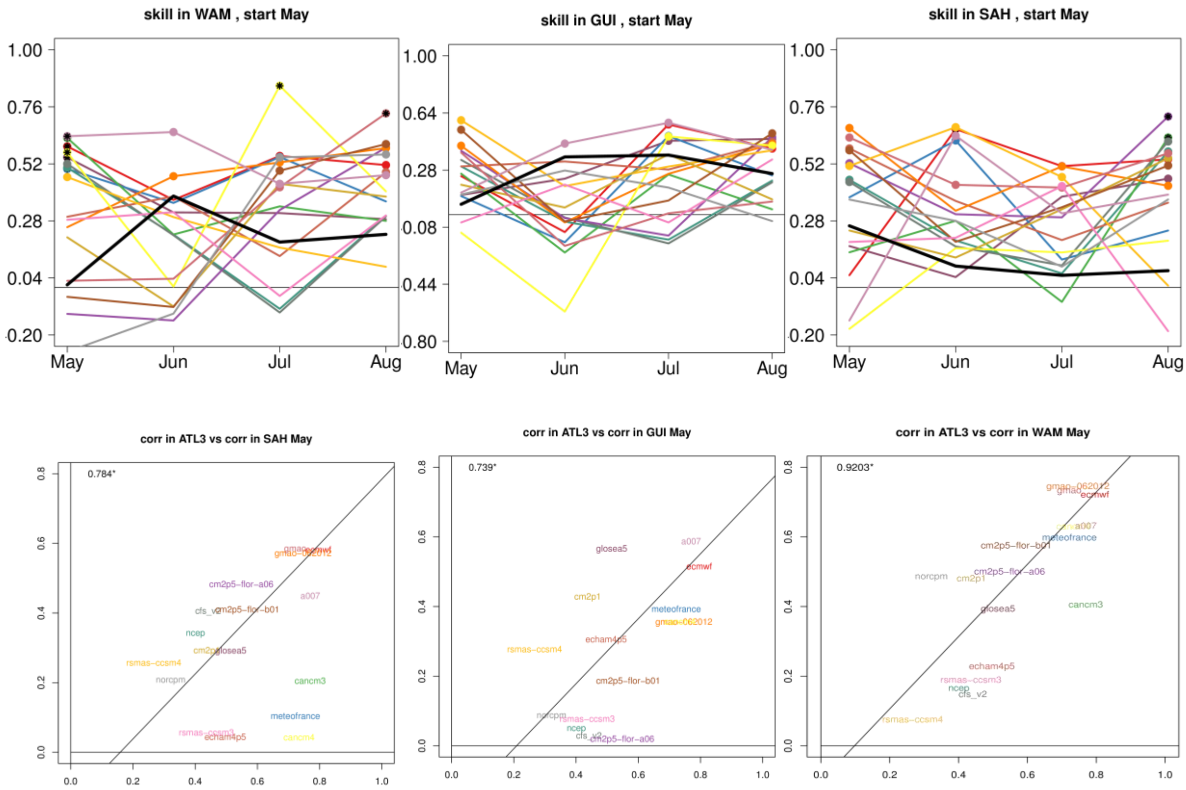

Figure 2.2: a) ACC of the seasonal forecast considered for precipitations averaged in the West African Monsoon region (WAM: 10ºW0º-0º22ºN). Dots show ACC values significant at 95% confidence level. Thick black line shows the skill of dumped persistence. Dark stars show correlation value significantly higher at 95% confidence level than the persistence. b) Same as a) but for the Guinean rainfall (GUI: 10ºW10ºE-5ºN10ºN). c) Same as a) but for the Sahelian rainfall (SAH: 15ºW15ºE-10ºN18ºN). d) Scatter plot showing the ACC of SST averaged over JJA in ATL3 in each forecast system (x-axis) against the ACC of precipitation averaged in the WAM region (y-axis). e) Same as d) but for GUI. f) Same as d) but for the SAH.

3. Impact of Tropical Atlantic variability on Tropical Pacific predictability

Eleftheria Exarchou (BSC), Maria-Belen Rodriguez De Fonseca (UCM), Teresa Losada (UCM), Irene Polo (UCM), Yohan Ruprich-Robert (BSC), Pablo Ortega (BSC)

Rodriguez-Fonseca et al (2009) shows that, during certain years, boreal summer equatorial Atlantic SSTs are highly anticorrelated with the equatorial Pacific SST of the following winter months (cf. Figure 3.1). This driving influence of the tropical Atlantic on the tropical Pacific is explained by a modification of the Walker circulation. For positive summertime tropical Atlantic SST anomalies (hereafter Atlantic Niño conditions), the anomalous surface warming drives an anomalous atmospheric ascending motion over the Atlantic and modifies the entire tropical atmospheric circulation within a month. In particular, the anomalous ascending motion over the Atlantic is compensated by an anomalous descending motion over the central tropical Pacific, which drives an anomalous wind surface divergence there and reinforces the easterly winds over western Pacific at the end of the summer. The anomalous easterlies create preconditioning for the development of Pacific La Niña conditions in the following winter through thermocline / Bjerkness / WES feedbacks (Losada et al., 2010; Polo et al., 2015).

Motivated by the aforementioned studies, we investigate here the impact of Tropical Atlantic variability on the predictability of ENSO in several seasonal forecast systems. We use the North American Multi-Model Ensemble (NMME, 12 models) and 3 models of the EUROSIP seasonal prediction systems for the period of 1981-2014. A first set of forecasts is initialized in February, just before the onset of the cold tongue development and preceding by a few months the peak of variability in Eastern Tropical Atlantic, normally occurring in June. In addition, a complementary set of forecasts is initialized in June, thus chosen to better capture the Tropical Atlantic variability.

The prediction skill of the forecasts, evaluated by the anomaly correlation coefficient, is shown in Figure 3.2, for the eastern Tropical Atlantic (ATL3: 20°W-0°W and 3°S-3°N) and the eastern Tropical Pacific (Niño3: 90°W-150°W and 5°S- 5°N). In ATL3 almost no model has skill above persistence in the February initialized forecasts the first two months, but some of them beat persistence from June onwards. For the June-initialized forecasts, about half of the models have better skill than persistence after 3 months. The generally poor skill in ATL3 is indicative of the systematic problem in predicting Tropical Atlantic variability in climate models (i.e. Stockdale et al., 2006). Focusing on the time-average skill in JJAS, the February initialized forecasts skill scores range between 0.1-0.5, whereas the June initialized skill scores are significantly higher (between 0.4-0.7), due to the shorter lead time.

The overall prediction skill in Niño3 is much higher than in ATL3, and remains high and statistically significant until the end of the forecast (Figure 3.2, bottom row). The June-initialized forecasts have better skill than the ones initialized in February at lead times longer than 5 months. The multi-model mean skill for winter (September-October-November) is 0.76 for the June initialized forecasts, much higher than the skill of 0.5 for the February initialized ones. The better skill in the former is not entirely due to the shorter lead time (months 4 to 6), since the February initialized forecasts have lower skill score (equal to 0.65) for the same lead time of 4-6 months. Therefore, there is an additional source of ENSO predictability in the initialization of June.

We assess the relation between the predictability of summer ATL3 and winter Niño3 in Figure 3.3. Better skill in summer ATL3 implies better skill in the following winter Niño3 in the June initialized forecasts. This suggests two major possible interpretations: 1) That improved skill in the ATL3 region in the summer leads to improved skill in the winter NINO3 (via the teleconnection in Rodriguez-Fonseca et al 2009), or 2) that the best performing models are simply better in the two regions, with no real impact from the Atlantic to the Pacific. The causality, however, can be proven in additional tailored-made simulations to isolate the role of the Atlantic, which we planned to perform in the near future. The February initialized forecasts have considerably lower skill in the summer, and the subsequent winter, and there is no clear linear relationship between them.

Figure 3.4 assess how realistically the models reproduce the teleconnection between Tropical Atlantic and Tropical Pacific, by comparing the simulated (coloured dots) and observed (black dots) correlations between the ATL3 JJAS and Niño3 at different lead times (JJAS, first row; SON, second row; and DJF, third row, this one only in the right hand side panel).. The June initialized forecasts are better able to represent the teleconnection than the February initialized forecasts. We further find that models with high skill in summer ATL3 are more consistent with the observed teleconnection (Figure 3.5, left panel), something that also happens for the models showing better skill in winter Nino3 (Figure 3.5, right panel). Further work is planned to explore the dynamics in the forecast systems and whether those are consistent with the Walker circulation mechanism suggested in previous literature.

Overall, we find evidence that high prediction skill over the summer Tropical Atlantic is associated with a better reproduction of the teleconnection between the summer Tropical Atlantic SST and the winter Tropical Pacific SST. We also find that better prediction of Tropical Atlantic is associated with better ENSO prediction. Given that the Tropical Atlantic is an area of large and systematic biases and poor prediction skill (Stockdale et al., 2006; Richter et al., 2017) this study emphasizes the importance of correctly representing the Tropical Atlantic mean state and variability in order to improve Tropical Pacific predictability.

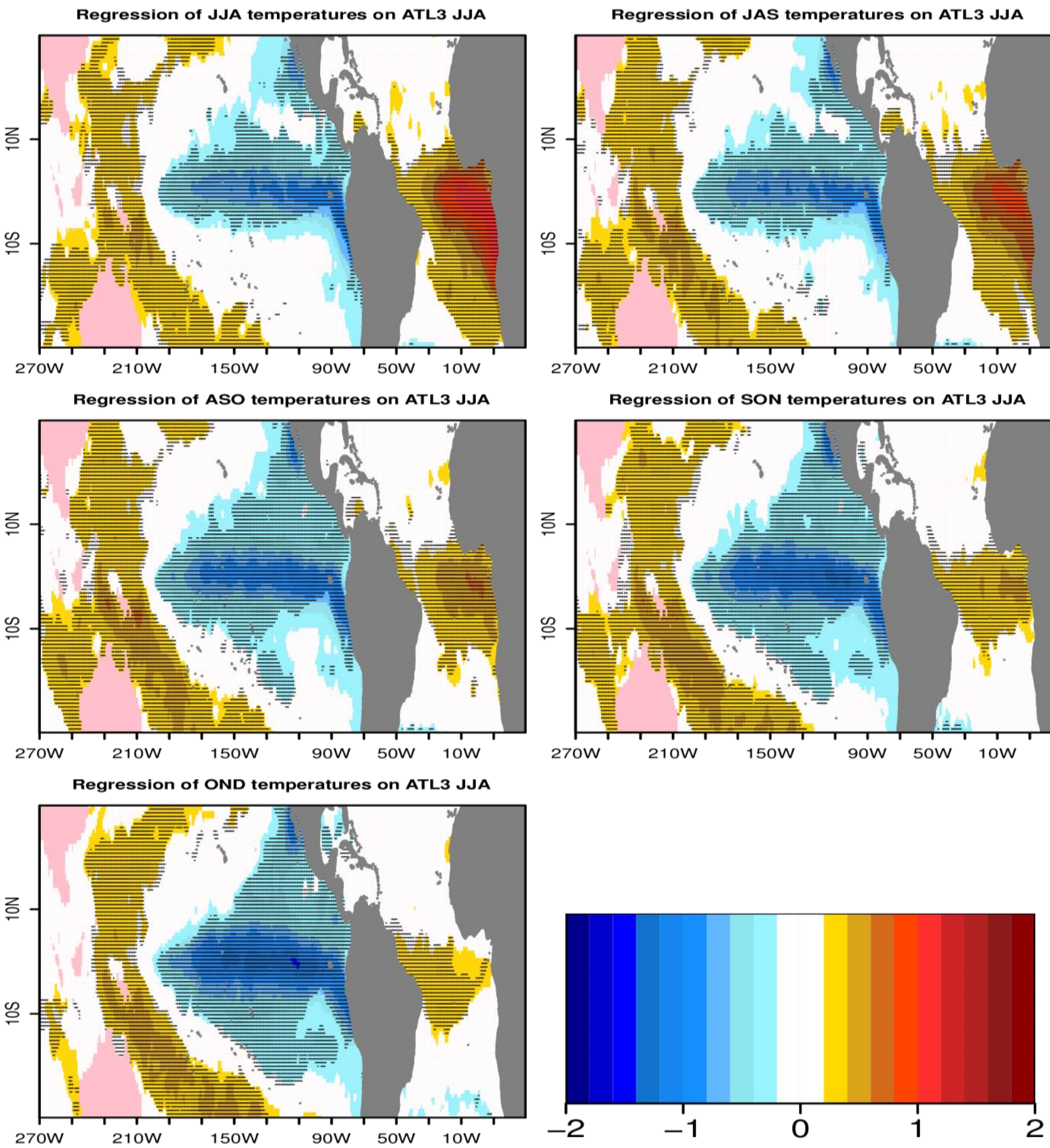

Figure 3.1: Regression of SST, at different time lags, on the ATL3 SST in JJA (ATL3 is 20°W-0, 3°S-3°N) for the period 1981-2014, using HadISST data (Rayner et al., 2003). Dashed areas indicate statistically significant correlations (at a 90% confidence interval).

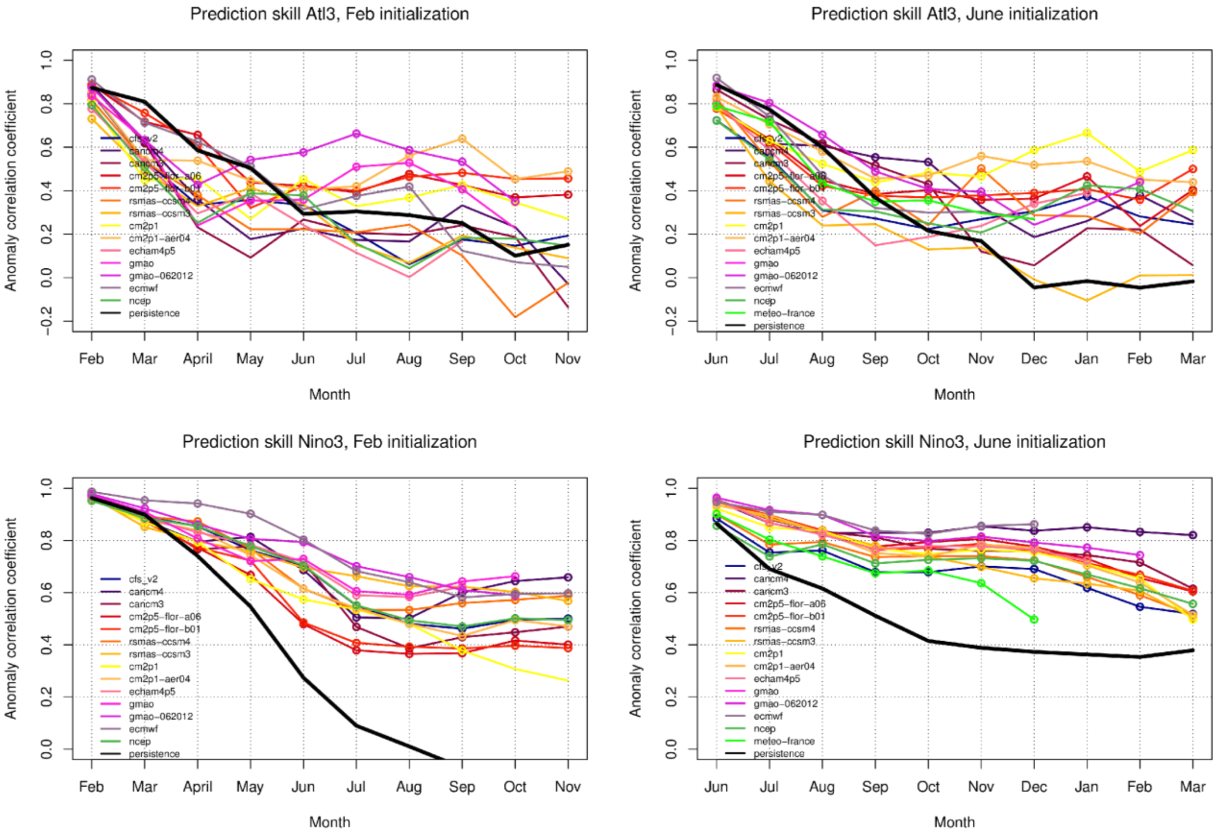

Figure 3.2: Prediction skill (anomaly correlation coefficient) of the NMME and EUROSIP forecast systems in the ATL3 region (20°W-0°W and 3°S-3°N) and Niño3 region (90°W-150°W and 5°S- 5°N), for February and June-initialized forecasts between 1981-2014. The reference dataset is HadISST. Dotted values denote statistically significant values at a 90% confidence interval. The black line denotes the skill of the persistence. Notice the different y-axis in the top row.

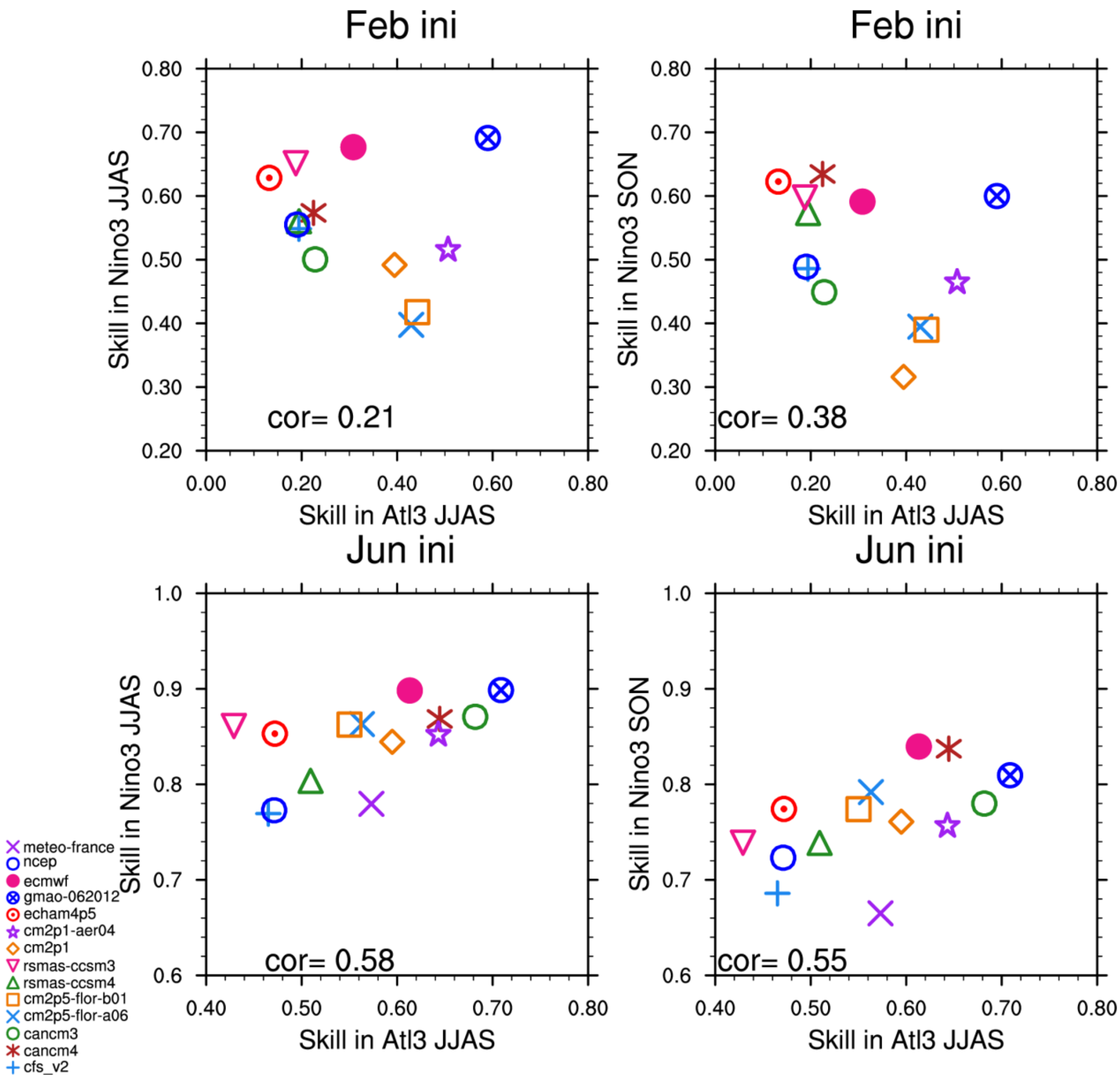

Figure 3.3: Scatter plots, where the x-axis represents the prediction skill (anomaly correlation coefficient) in ATL3 (20°W-0°W and 3°S-3°N) in JJAS and the y-axis represents the prediction kill in Niño3 (90°W-150°W and 5°S- 5°N), in JJAS, SON, for February and June initialized forecasts.

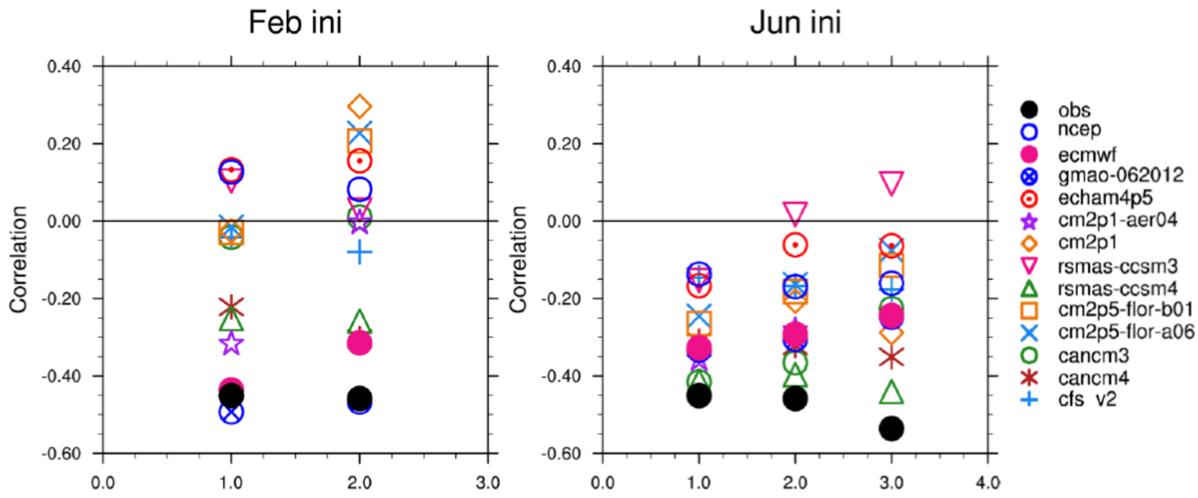

Figure 3.4: Each point represents the correlation between the model ATL3 JJAS and (i) model Niño3 JJAS (first row), (ii) model Niño3 SON (second row) and, (iii) model Niño3 DJF (third row in the right hand side panel), for the February (left panel) and June (right panel) initialized forecasts. Observations are represented by the black dot (HadISST).

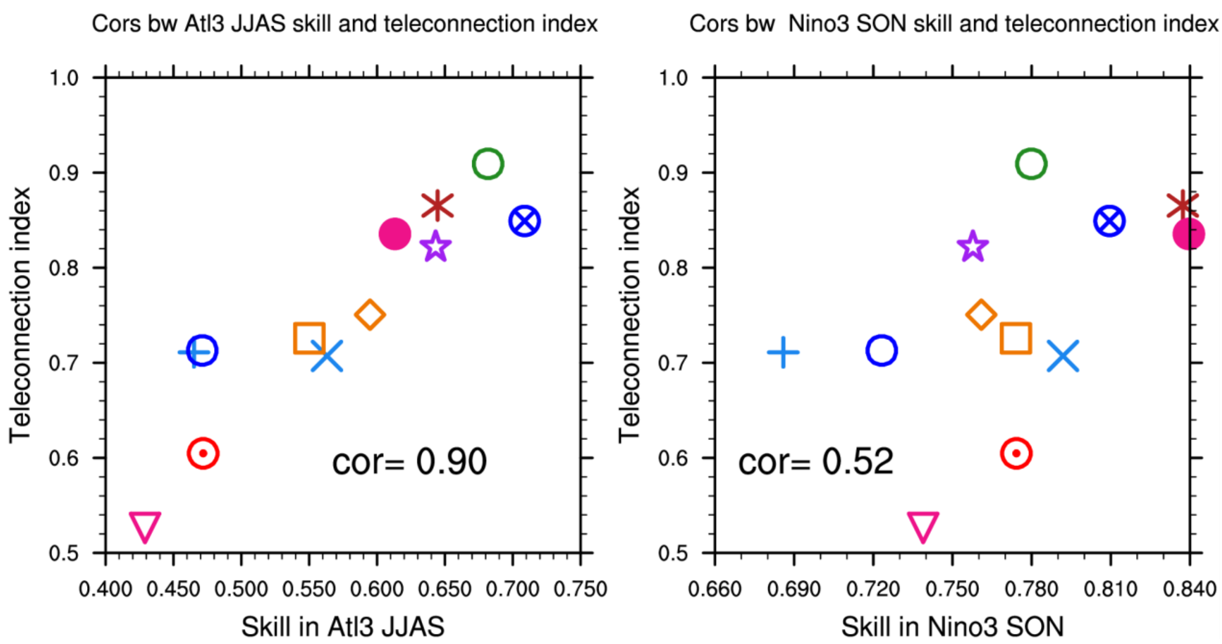

Figure 3.5: Scatter plots, where the x-axis represents the prediction skill in ATL3 JJAS (left panel) and in Niño3 SON (right panel) and the y-axis is the "teleconnection index", defined here as: index = 1-abs (r_model - r_obs), with r indicating the correlations between ATL3 JJAS and Niño3 SON (shown in Figure 4, second row of each panel), so as when the index is 1 the model perfectly reproduces the teleconnection, and when the index is 0 the model is not able to reproduce the teleconnection. The legend is shown in Figures 4&5. Here we have excluded rsmas-ccsm4 as an outlier.

4. Forecast verification on seasonal predictions performed with improved model climatologies in the Tropical Atlantic

Emilia Sanchez-Gomez (CERFACS), Eleftheria Exarchou (BSC), Aurore Voldoire (MF-CNRM)

In this study we provide a skill assessment of the coordinated seasonal forecasts experiments performed in WP6. The aim, rationale and description of these experiments were presented in previous deliverables (D6.1-D6.3), but a short summary is given here.

Results based on multi-model studies, mainly from CMIP (Coupled Model Intercomparison-Phase) database, have shown that the SST warm bias over the SETA (South-East Tropical Atlantic) can be related to the well-documented westerly wind biases at the equator simulated by CGCMs in spring (Toniazzo and Woolnough, 2014). The equatorial westerly wind bias leads to an erroneous thermocline east–west tilt. A deeper thermocline in the eastern equatorial Atlantic prevents the development of the cold tongue in boreal summer and results in a strong regional warm SST error along the equator. To confirm this hypothesis of remote equatorial wind-stress forcing on setting the SST SETA bias, a set of coordinated sensitivity experiments have been performed in WP6 by using different coupled models. In a first stage, seasonal hindcasts over the period 2000-2009 and initialised on 1st February and 1st May were performed with the different coupled models (see Table 1) in a seasonal prediction system (SPS) framework. The initialisation method has not been imposed but all the seasonal hindcasts have been initialised at least at the ocean surface. The idea was to use simple coordinated protocols in order to ease the experimental set up for all the groups, including those who are not running seasonal forecasts routinely.

Model	Ocean model	Atmospheric model	Ocean initialisation product
ECMWFS4	NEMO ORCA1° L42	IFS T255 L91	ORA-S4
EC-Earth	NEMO ORCA1° L46	IFS T255 L91	ORA-S4
CNRM	NEMO ORCA1° L42	ARPEGE-Climat T127 L31	ORA-S4
Cerfacs	NEMO ORCA0.25° L75	ARPEGE-Climat T359 L31	Glorys2v3
IPSL	NEMO ORCA1° L75	LMDZ 2.5°x1.2° L79	ORA-S4
NorESM	MICOM 1° L53	CAM4 2° L26	EnKF with HadISST

Table 1: List of models involved their ocean and atmospheric components name and resolution as well as the ocean initialisation product. From Voldoire et al., manuscript in preparation.

In a second stage, the same seasonal forecast are performed, but in this case the wind stress is replaced over key regions in the Tropical Atlantic following a common protocol, very similar to the one implemented in Voldoire et al. 2014. Practically speaking, the wind stress computed from the atmospheric model and applied to the ocean model is replaced by those issued from ERA-Interim reanalysis (ERAI, Dee et al., 2011). All others coupling fluxes are not modified. According to this, to disentangle the role of the local wind-stress biases in setting the large scale SST bias, three sensitivity experiments were performed and described in Voldoire et al. (in preparation). The main characteristics of these experiments are summarised in Table 2.

Results from the latter experiments show an important reduction of the model bias (not only SST but other variables) when the wind-stress at the equator is corrected in the coupled model. However, the magnitude of the impact of correcting the equatorial wind-stress greatly differs amongst the different models. Moreover, over the equator, improvement in mean state leads to improvement of the Bjerknes feedback, which could have important implications for the predictability at seasonal scale. On the contrary, along the coast over the SETA region, the wind correction has only a local impact on the SST bias.

Experiment Name	Description
CTRL	Initialised experiments: 6 months seasonal hindcasts for the 2000-2009 period with 3 members
Sensitivity experiments to CTRL : same as CTRL with ERAI wind stress replacement over a specific domain	
TAU30	30S-30N only over the Atlantic basin
TAUEQ	5S-5N only over the Atlantic basin
TAUBE	30S-10S from 0E to the African Coast

Table 2 : Summary of seasonal forecasts experiments performed in the coordinated exercise. From Voldoire et al., manuscript in preparation.

Following these results, we have performed the skill assessment of the CTRL and TAUXX experiments for 4 different regions in the Tropical Atlantic basin (ATL3 (3S-3N 20W-0E); ANGOLA (15S-3S 10E-20E); BENGUELA (32S-20S 12E-20E); SEFO (20S-5S 0E-10E)). These are also the regions largely studied in Voldoire et al. in preparation. The goal is to assess if improved mean state models lead to an improvement of the model performances in terms of skill. The measure of the skill is the ACC (anomaly correlation coefficient) and the observational data set used is HadISST (Rayner et al. 2003). We are aware that the sample size (3 members and 10 years for the forecast period) is not optimal for a robust forecast verification procedure. Nevertheless, given the amplitude of the reduction of the SST bias in the Tropical Atlantic reported in the WP6 sensitivity experiments (Voldoire et al. in preparation), we can argue that the signal is strong in the seasonal predictions to attribute the skill improvement/degradation to the changes in the models mean state.

A. Skill assessment of the CTRL experiments

In the first step, we compared the different SPSs performances by considering only the CTRL experiment. Figures 4.1 and 4.2 show the ACC values for the CTRL seasonal hindcasts initialised at 1st February and 1st May respectively, over the 4 regions defined in the study.

In general all SPS initialised on February show very low skill values for the spring season, whatever the region considered. ACC is not significant from leadtimes greater than 1 month. In particular ECMWFS4 is the best performing SPS. For forecast initialised in May, the skill value is greater and significant for leadtimes lower than 3 months (May, June, July) and then it drops drastically. In particular the skill is high for the ATL3 and SEFO regions, which is encouraging and indicates than in these key regions some predictability is captured by several of the SPS. The best performing SPS are ECMWFS4, EC-Earth and CNRM. CNRM and CERFACS have practically used the same model CNRM-CM but different versions : low resolution for CNRM and high resolution for CERFACS. The impact of the model resolution of the skill is not significant here (except for BENGUELA region). This question will be more discussed in the next sections. Note that NorESM model shows several deficiencies at lag=1 for several regions. The reason of that probably resides in the initialisation procedure, and this is being investigated in the study by Voldoire et al. in preparation.

B. Skill assessment of the wind stress sensitivity experiments

The ACC scores for the different PREFACE SPS and wind stress replacement coordinated experiments are depicted in Figures 4.3-4.6. Note that for ECMWFS4 only the CTRL simulation was available, since the ECMWF did not participate in PREFACE-WP6 and hence did not perform the coordinated sensitivity experiments.

In general there is a significant skill improvement for TAU30/TAUEQ experiments for both seasons, though the greatest impact is observed in February runs. Note that TAU30 and TAUEQ lead to very similar results, suggesting the primary role of the wind stress at the equator to correct SST biases in the Tropical Atlantic basin. This fact has also been documented in D6.3 and in the incoming paper (Voldoire et al.). TAUBE experiment has a marginal but not significant impact over the BENGUELA region. The regions most affected by the skill improvement are ATL3 and ANGO, and this behaviour is quite consistent amongst the SPSs.

To finish this part, even if the sample size of the seasonal experiments analysed here is not pertinent for a robust skill assessment, we can conclude that the improvement of the mean state in the coupled model (achieved here through wind stress correction over key regions in the basin), has led to a improvement of the skill, and hence to an increase of the levels of predictability. We have documented skill improvements in two specific regions: ATL3 and the ANGOLA region. This important result highlights the need to improve the mean state of coupled models in the Tropical Atlantic in order to enhance the predictions over the region.

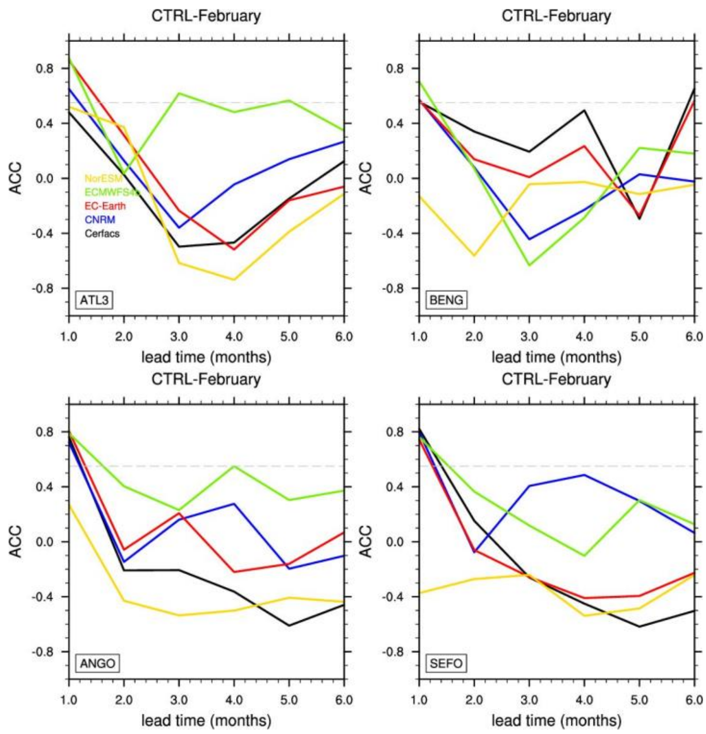

Figure 4.1: ACC values for the seasonal hindcasts initialised on 1st February for the period 2000-2009 for the four regions defined in the text. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance.

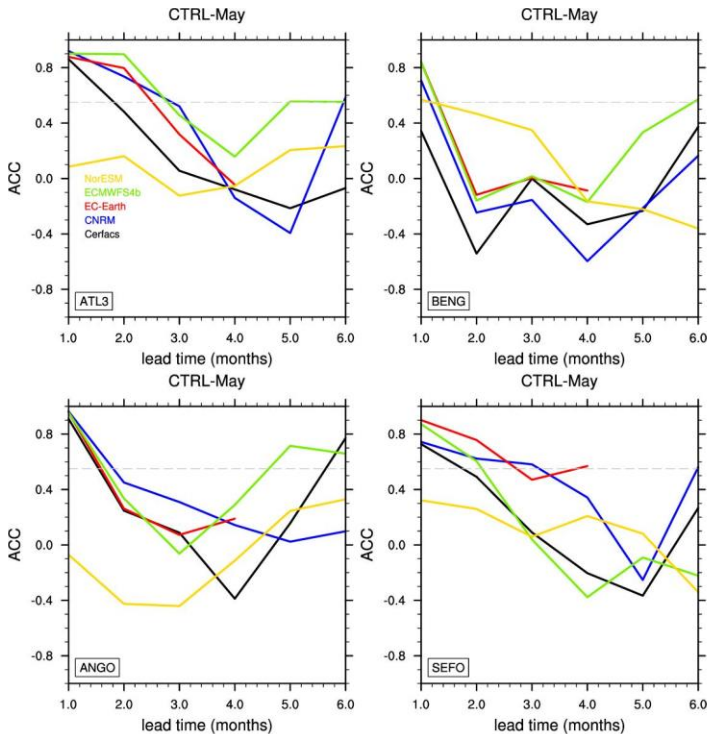

Figure 4.2: ACC values for the seasonal hindcasts initialised on 1st May for the period 2000-2009 for the four regions defined in the text. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance.

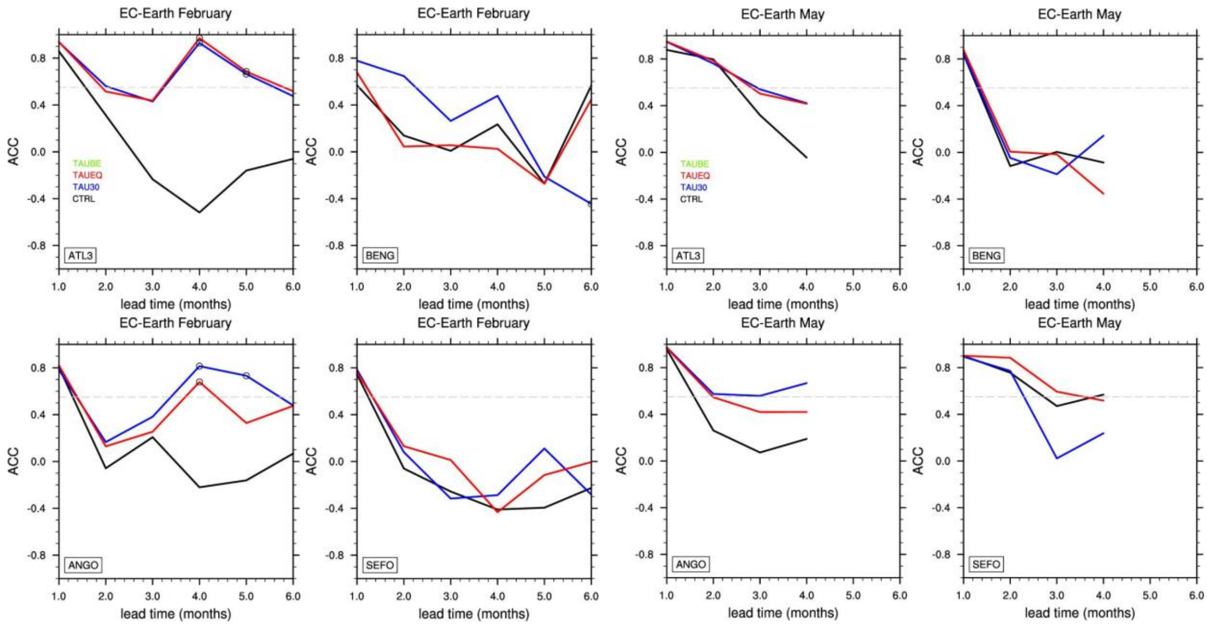

Figure 4.3: ACC values for the seasonal hindcasts performed with EC-EARTH initialised on 1st February (left) and May (right) for the period 2000-2009 for the four regions defined in the text and for the four sensitivity experiments of wind-stress correction. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance. White markers indicate where the skill from the sensitivity experiment is significantly greater than in CTRL. Note that TAUBE was not available for EC-EARTH, and May hindcasts are of 4 months length.

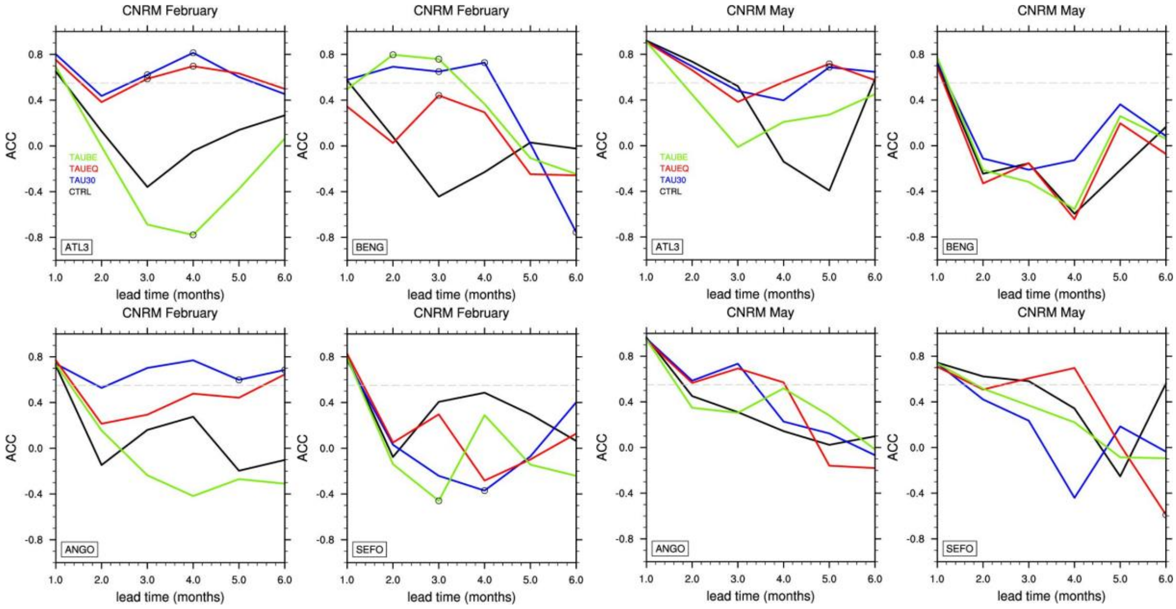

Figure 4.4: ACC values for the seasonal hindcasts performed with CNRM initialised on 1st February (left) and May (right) for the period 2000-2009 for the four regions defined in the text and for the four sensitivity experiments of wind-stress correction. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance. White markers indicate where the skill from the sensitivity experiment is significantly greater than in CTRL.

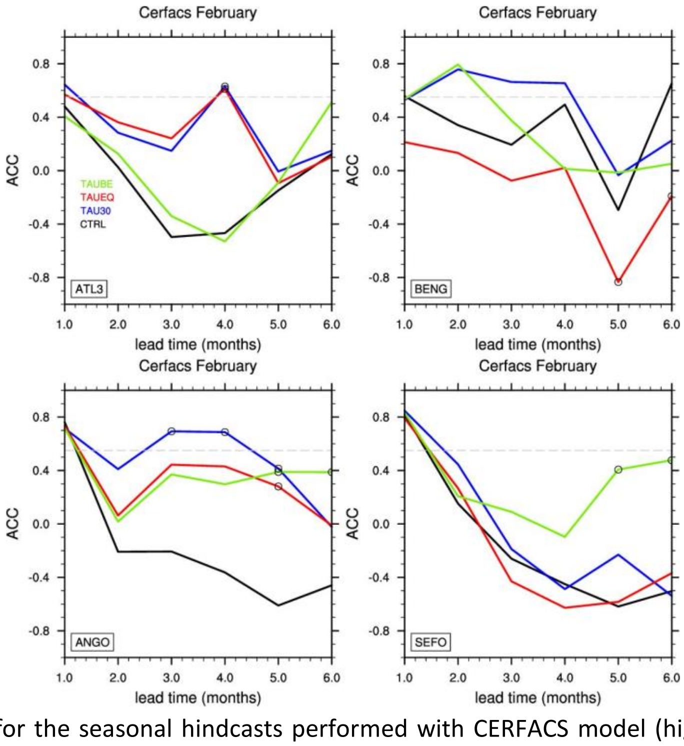

Figure 4.5: ACC values for the seasonal hindcasts performed with CERFACS model (high resolution version of CNRM-CM, Figure 4) initialised on 1st February for the period 2000-2009 for the four regions defined in the text and for the four sensitivity experiments of wind-stress correction. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance. White markers indicate where the skill from the sensitivity experiment is significantly greater than in CTRL. Note than for this model, the May sensitivity experiments were not available.

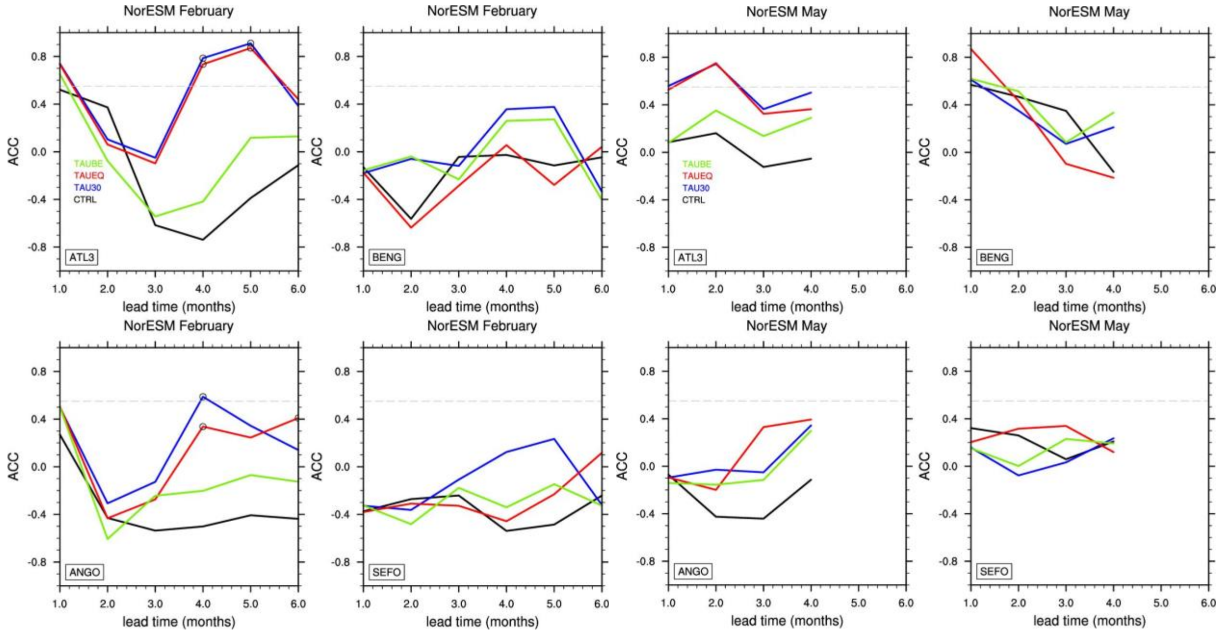

Figure 4.6: ACC values for the seasonal hindcasts performed with NorESM initialised on 1st February (left) and May (right) for the period 2000-2009 for the four regions defined in the text and for the four sensitivity experiments of wind-stress correction. The reference dataset is HadISST. Horizontal grey dashed line corresponds to the limits of the 95% level of significance. White markers indicate where the skill from the sensitivity experiment is significantly greater than in CTRL.

5. Quantification of the skill in the Sahel in state-of-the-art seasonal predictions systems

Emilia Sanchez-Gomez (CERFACS) and Eleftheria Exarchou (BSC)

In this study, a skill assessment of state-of-the-art seasonal predictions initialised at 1st May over the Sahelian region for June-July-August has been performed. The ensemble Seasonal Predictions Systems (SPS) are NMME (North American Multi-Model ENSEMBLE), EUROSIP (European Multi-Model Seasonal Predictions Systems) and BSC seasonal forecasts performed with different versions of the EC-Earth coupled model. The common period of study is 1993-2009. Even if some of seasonal predictions are available for a longer period, we have decided to include in this study as many models as possible and to shorten the validation period. Different initialisations have been applied on the different SPSs, except for BSC for which the initialisation is the same, and only the model version and resolution changes.

In general, coupled models exhibit strong biases in the Tropical Atlantic ITCZ (Richter and Xie, 2008; Richter et al. 2014), that affect the simulation, variability and predictability of the Sahelian precipitation. Over the Sahel, climate predictions and projections are still quite uncertain (Monerie et al. 2016). A quick analysis of precipitation biases in summer (JJA) in the Tropical Atlantic has been made in the different coupled models from NMME, EUROSIP and BSC (Figs. 5.1-5.3).

Biases of tropical precipitation are quite large, they can reach more than 8mm/day in several models. In general, as documented in previous studies, models fail in simulating the right position of the ITCZ, which is located southward in models respect to observations. Precipitation biases are large in the maritime ITCZ, northwestern Brazil and Sahelian region. Note that ECMWF and EC-EARTH exhibit the lower biases in precipitation. These coupled models are sharing the atmospheric component (IFS model), which was originally developed for numerical weather prediction.

Skill analysis has been made by computing the ACC (anomaly correlation coefficient) in June-July-August over the Sahelian box, defined here as 0N-10N, 10W-10E. The number of members available for each model varies between 3 and 52. The skill scores for the 3 SPSs ensembles are depicted in Figure 5.4. In general NMME predictions are not skilful in the Sahel at 2-5 leadtimes, except for the rsmas-ccsm4 coupled model, whose levels of skill are larger comparing with other models in the ensemble. ECMWF and BSC ensembles show a very similar behaviour with the largest ACC values peaking at leadtime=3 (July) and decreasing afterwards. BSC ensemble, which includes different versions and resolutions of the EC-EARTH model (ocean and atmosphere) is quite homogeneous at there is not impact of the model resolution on the skill.

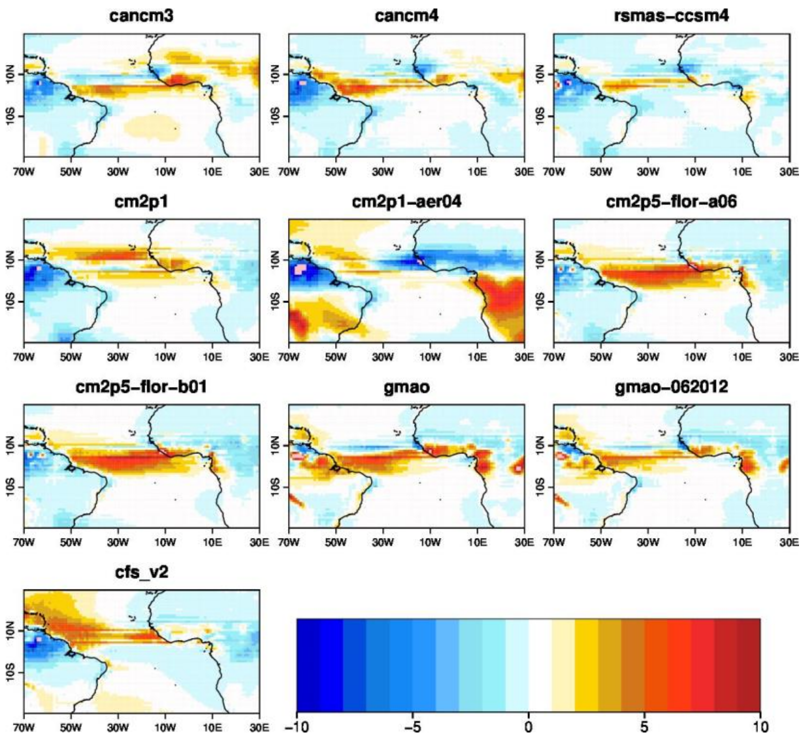

Figure 5.1: Precipitation biases in JJA (reference GPCPv2) for the different coupled models in the NMME ensemble. Units in mm/day.

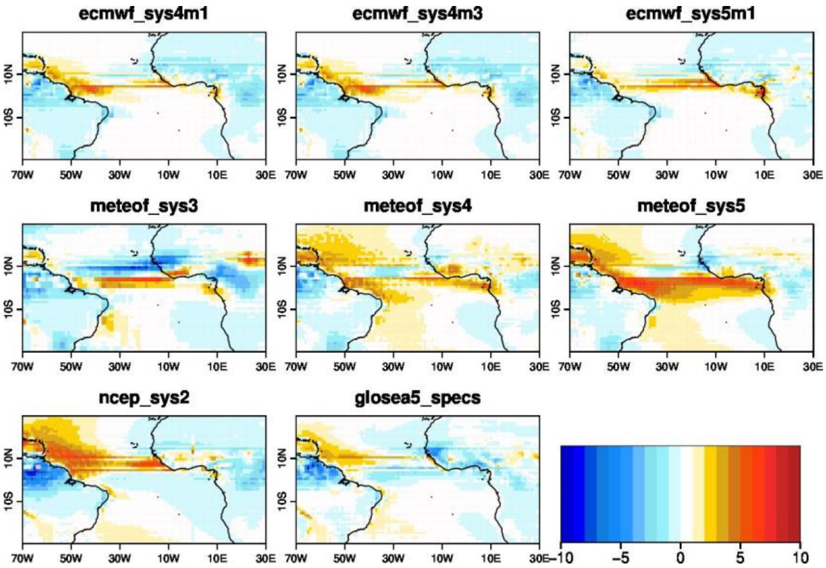

Figure 5.2: Precipitation biases in JJA (reference GPCPv2) for the different coupled models in the EUROSIP ensemble. Units in mm/day.

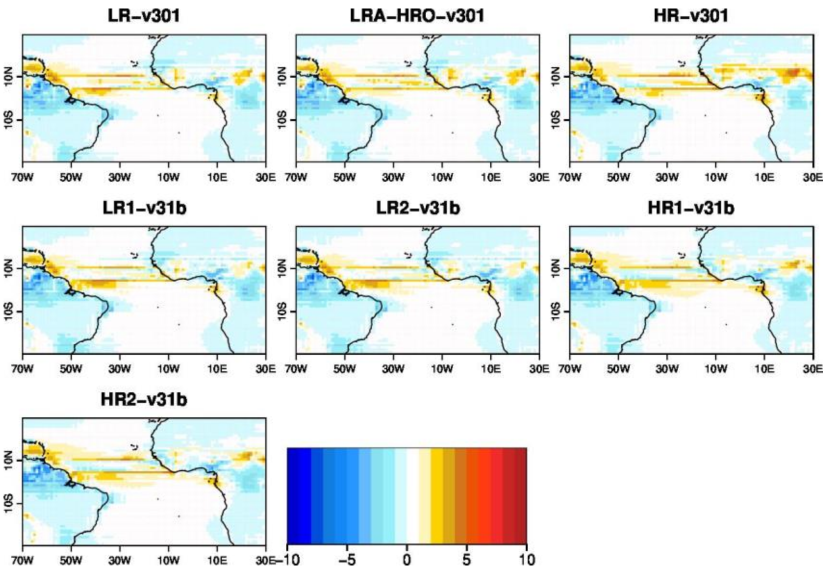

Figure 5.3: Precipitation biases in JJA (reference GPCPv2) for the different coupled models in the BSC ensemble. Units in mm/day.

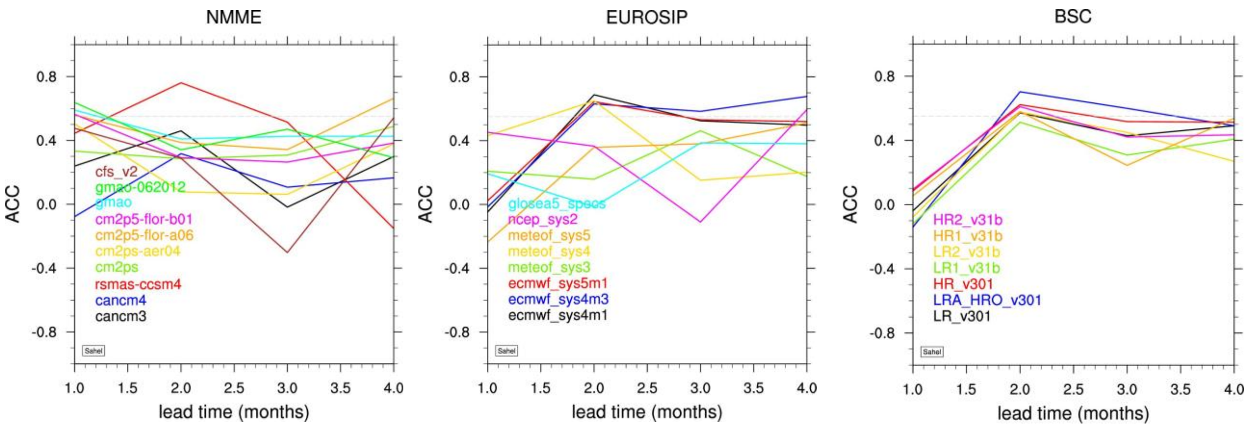

Figure 5.4: ACC values over the Sahel in JJA for the seasonal hindcasts from NMME, EUSOSIP and BSC ensembles for the period 1993-2009. The reference dataset is GPCPv2. Horizontal grey dashed line corresponds to the limits of the 95% level of significance.

6. Decadal prediction of Sahel rainfall: where does the skill (or lack thereof) come from?

Elsa Mohino (UCM), Noel Keenlyside (UiB), Holger Pohlmann (MPI)
(these results are published in Mohino et al. 2016)

The Sahel is an African semiarid region located between the Sahara desert to the north and the Savanna to the south. Rainfall over the Sahel shows high variability at decadal time scales. Mohino et al. (2011) suggested that the evolution of Sahel rainfall at decadal timescales could be explained by the competing effects of the Atlantic Multidecadal Variability (AMV), the Interdecadal Pacific Oscillation (IPO) and the global warming trend (GW), especially in the tropics. Predicting the trends in Sahel rainfall several years ahead would be highly beneficial for decision making and planning in the region.

Previous works suggest decadal predictions of Sahel rainfall could be skilful. However, the sources of such skill are still under debate (Gaetani and Mohino 2013; Martin and Thorncroft 2014; García-Serrano et al. 2015). In addition, previous results are based on short validation periods (i.e. less than 50 years). In this work we evaluate the skill scores in predicting Sahel rainfall by an extended decadal hindcast performed with the MPI-ESM-LR model that span from 1901 to 2010 with one year sampling interval.

The decadal hindcasts of Sahel rainfall show statistically significant ACC for all lead times, although less skilful than persistence; the ACC skill of historical runs is not significant (Figure 6.1). In accordance with previous works (Gaetani and Mohino 2013; Bellucci et al. 2015; Martin and Thorncroft 2014; García-Serrano et al. 2013; Otero et al. 2015) the skill in predicting Sahel rainfall changes with lead time: the biggest ACC scores are obtained at lead times 2-5 and 3-4 years. ACC scores are subsequently reduced until lead time 7-10 years, when they increase. Roughly the opposite can be observed for RMSE scores. There are several possible reasons for such changes in skill: initial shock and non-linear drifts could be responsible for lower skill values at short lead times, while long-term trends could enhance skill at long lead times, as Bellucci et al. (2015) found. However, when the ACC scores are recomputed using the same time series with the trend previously removed (labelled as “detrended” in Figure 6.1), they are not reduced at middle lead times and are even enhanced at long leads (7-9 years), which suggests that the skill at these time scales is not coming from the long-term trend.

To further investigate the sources for this skill (or lack thereof) we propose a framework based on multi-linear regression analysis to study the potential sources of skill for predicting Sahel trends several years ahead (Figure 6.2).

Our results show that the skill mainly depends on how well we can predict the timing of the global warming (GW), the Atlantic multidecadal variability (AMV) and, to a lesser extent, the inter-decadal Pacific oscillation (IPO) signals, and on how well the system simulates the associated SST and West African rainfall response patterns. In the case of the MPI-ESM-LR decadal extended hindcast, the observed timing is well reproduced only for the GW and AMV signals (not shown). However, only the West African rainfall response to the AMV is correctly reproduced (not shown). Thus, for most of the lead times the main source of skill in the decadal hindcast of West African rainfall is from the AMV (Figure 6.2). The GW signal degrades skill at some lead times (Figure 6.2) because the response of West African rainfall to GW is incorrectly captured (not shown). Our results also suggest that initialized decadal predictions of West African rainfall can be further improved by better simulating the response of global SST to GW and AMV. Furthermore, our approach may be applied to understand and attribute prediction skill for other variables and regions.

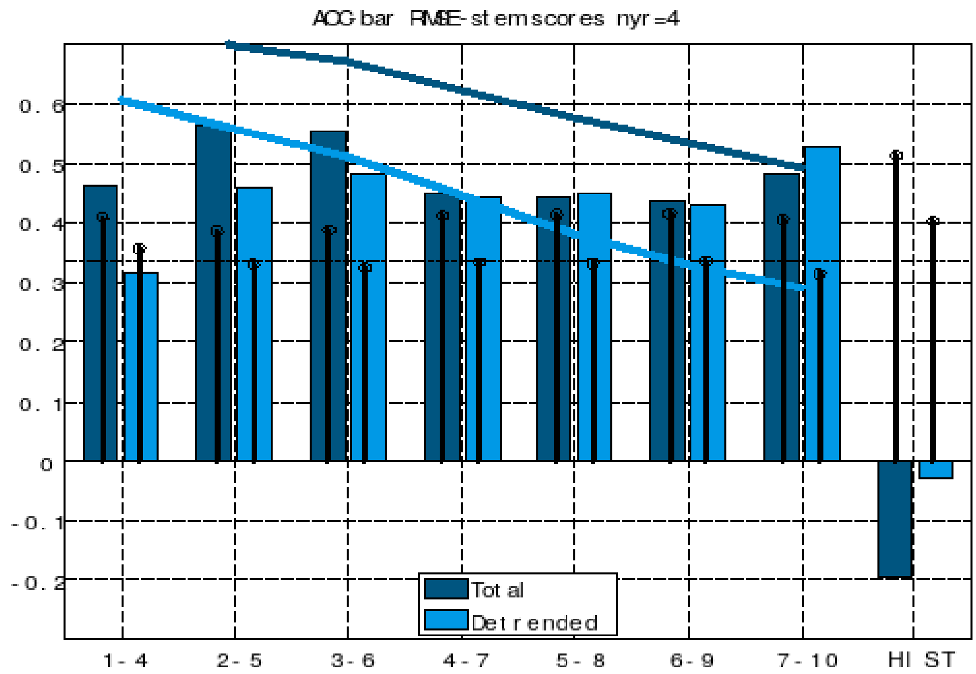

Figure 6.1: Prediction skill: Anomaly correlation coefficients (ACC, adimensional, bars) and root mean square errors (RMSE in mm/day, stems) scores for Sahel rainfall at different lead times (1 to 4, 2 to 5, 3 to 6, 4 to 7, 5 to 9, 6 to 9 and 7 to 10: seven first columns, respectively) in the decadal hindcast and in the historical uninitialized simulation (last column) for raw (dark blue) and de-trended data (light blue) in the 1914-2004 period. The detrended scores are calculated over the same time series as the raw ones except that the linear trends are previously removed. Note that the detrended time series cannot be calculated in real-time prediction. Solid lines indicate the ACC skill of persistence for raw (dark blue) and detrended data (light blue). Persistence is calculated as the average over the 4 years preceding the model initialization. The dot-dashed line show the threshold to reject the null hypothesis that the correlations come from chance (at the 5% level) for 4-year running mean filtered data. Reference data for both metrics is CRUTS3.1 rainfall estimates.

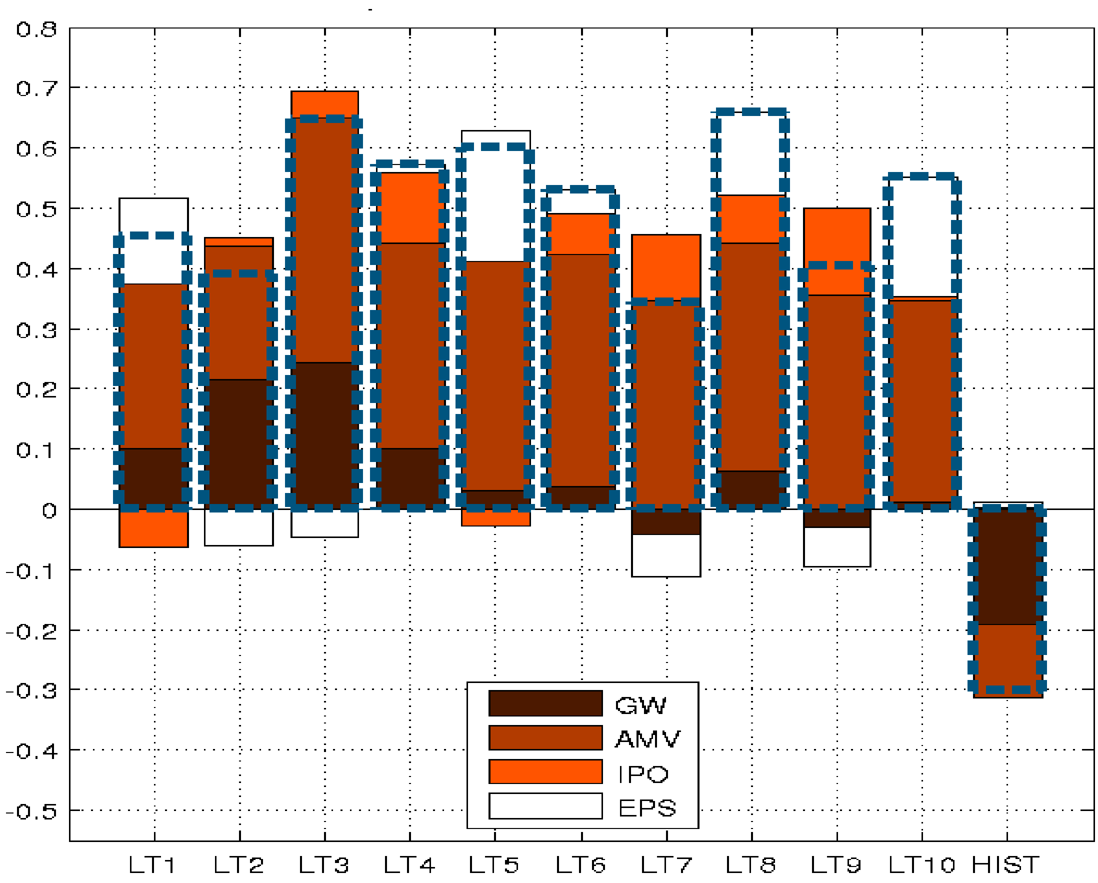

Figure 6.2: Explained SRI ACC scores: Anomaly correlation coefficient (ACC) of the simulated decadal-SRI for each of the 10 lead times in the decadal hindcast and the historical experiment (blue dashed bars) and its decomposition into four terms following the multi-linear regression analysis, which are due to: GW, AMV, IPO and the residual of the fit (labelled as EPS). Positive and negative contributions are shown separately as stacked bars. The subtraction of the total stack positive bar minus the stack negative bar provides the ACC scores.

7. Seasonal prediction with an anomaly coupling

Francois Counillon (NERSC), Noel Keenlyside (UiB), Shunya Koseki (UiB), Yiguo Wang (NERSC), Lea Svendsen (UiB), Ingo Bethke (UiB), Teferi Dejene Demissie (UiB)

Current state-of-the-art models exhibit large climatological errors in the tropical Atlantic. To what extent this contributes to the poor seasonal prediction of these models in the tropical Atlantic remains unclear. Here we investigate this issue by comparing simulations and predictions with a standard and an anomaly coupled configurations of the Norwegian Climate Prediction Model (NorCPM). The standard model has climatological biases typical of other models. Correcting momentum and SST fields exchanged between oceanic and atmospheric models significantly reduces the climatological errors in the anomaly-coupled version. The mechanisms for equatorial Atlantic variability are thus better represented, but the variability is reduced in strength. This enhances the ability of the model to assimilate ocean observations in this region. A set of seasonal predictions with both standard and anomaly-coupled models indicates that reducing mean state errors leads to a significant improvement in the skill in predicting the Atlantic Niño mode. This has implications for seasonal predictions in the region, but also potentially for the Indo-Pacific sector.

A- An alternative anomaly coupling

Uni Research and UiB have developed an alternative anomaly coupling methodology (Toniazzo and Koseki, in prep). In this methodology, a modelled monthly climatology of momentum flux and sea surface temperature (SST) is replaced by an observed climatology. The method was successfully implemented in the Norwegian Earth System Model (NorESM), and it reduces SST and associated precipitation biases, in particular, in the tropical oceans with this anomaly coupling (Figure 7.1).

B- Reanalysis with NorCPM

We have developed the Norwegian Climate Prediction Model that is based on NorESM and the ensemble Kalman Filter (EnKF) assimilation of observed SST, 3 dimensional profile of ocean temperature and salinity, and sea ice concentration (e.g., Counillon et al., 2016; Wang et al., in prep; Kimmritz et al., under revision). With the NorCPM we have objectives of (1) long climate reconstruction and (2) skillful and reliable climate prediction. As the NorCPM is assimilated with monthly anomalies of SST, the climatic biases of the system remain (e.g., Koseki et al., 2017). To suppress these systematic biases, the anomaly coupling method is implemented in to the NorCPM.

Figure 7.2 shows the correlation skill of upper ocean heat content for ocean reanalysis performed with NorCPM without and with the anomaly coupling in the tropical Atlantic Ocean with respect to EN4 objective analysis. In both cases, anomalies of SST, ocean temperature and salinity profiles are assimilated on 15th every month. The anomaly coupling is at every time step of calculation of atmosphere-ocean fluxes. For the anomaly coupling, we employ the monthly climatology (1980-2000) of HadISST and ERA-Interim for SST and wind stress. We see that the anomaly coupling improves the ocean reanalysis in the equatorial Atlantic zone, as the region of high correlation becomes relatively wider. In particular, the reconstruction of the Gulf of Guinea and the south of the equator, where the NorESM exhibits a warm SST bias (e.g., Mechoso et al., 2016; Koseki et al., 2017), is largely improved with the anomaly coupling. Additionally, the southern subtropical Atlantic is also reconstructed well.

C- Improvements in seasonal hindcasts with the NorCPM by anomaly coupling

As shown in Figure 7.3, seasonal hindcast experiments of NorCPM without/with the anomaly coupling are performed initialized four times (15tn of February, May, August, and November) each year between 1980 and 2010. Each prediction has 10 ensemble members.

Figure 7.4 presents the horizontal map of prediction skill of 1-3 lead months averaged SST for the two hindcast experiments. NorCPM shows already a good prediction skill over the tropical Pacific Ocean. In particular, NorCPM is one of the best model for predicting the warm pool of the tropical western Pacific Ocean among the North American Multi-Model Ensemble (Wang et al., in prep). The tropical Atlantic is also well predicted, but only in the western part. Anomaly coupling has little impact on prediction skill in the Indo-Pacific sector, but there is a remarkable improvement in the skill in the south of the equatorial Atlantic, the NorCPM without anomaly coupling does not have skill.

Figure 7.5 gives a time series of Atlantic3 Index (defined as averaged SST over 3S-3N and 20W-0) for 1, 3, and 5 lead months in two hindcasts. The prediction skill is quite low (only 0.26) even at 1 month lead without the anomaly coupling; this coincides with the white spot in Figure 7.4. At 3 months lead, the skill becomes a bit improved (0.32), but it drops down to 0.07 at 5 months lead, indicating that the initialization impact does not survive anymore in the system. On the other hand, with the anomaly coupling, the prediction skill is enhanced to large extent. At 1 month lead, the skill is enhanced up to 0.62. The relatively high skill remains until 5 months lead (0.32). As concluded by Ding et al. (2015), the tropical Atlantic variability is affected largely by the climatological mean-state. It is considered that with the anomaly coupling, the climatic biases are constrained and consequently, the prediction skill is improved. Koseki et al. (in prep-a) shows that anomaly coupling improves the representation of ocean-atmosphere interaction in the tropical Atlantic.

On the other hand, the amplitude of the SST variability seems to be reduced in NorCPM with the anomaly coupling as seen in Figure 7.5. The other experiments of NorESM also show that the amplitude of the inter-annual variability of the tropical Atlantic SST is reduced by anomaly coupling (Koseki et al., in prep-a). The observation shows that the cold anomaly develops gradually for 4-5 months in the equatorial Atlantic Ocean (e.g., Lübbecke et al., 2014; Lübbecke and McPhaden, 2017). Interestingly, the cold SST anomalies are detected in the South Atlantic in February to March in advance. This anomaly is weakened in June when the Atlantic Niña is matur as shown in Figure 7.6. In NorESM free run, the equatorial SST anomaly already exists in February and it decays until April. The anomaly is enhanced modestly from April to May and radically from May to June. The sudden reinforcement of the anomalies from May to June is likely linked to the thermodynamical amplification in the NorESM free run. The observation shows that the heat flux acts to damping the variability (e.g., Lübbecke and McPhaden, 2017; Koseki et al., in prep-a), but in the NorESM free run, the heat flux acts to amplifying the variability, in particular in May (Koseki et al., in prep-a). With the anomaly coupling, the evolution of the cold anomaly appears to be more realistic although the amplitude of the matured cold anomaly is relatively small in Figure 7.6. In NorESM with the anomaly coupling, the turbulent heat flux acts to damp variability, and this is more realistic (not shown, Koseki et al., in prep-a).

As concluded by Lübbecke et al. (2014), the JJA Atlantic Niño is related to the variability in the South Atlantic Anticyclone (SAA) in February and March. As seen in Figure 7.7, the SAA is reinforced in February and March, corresponding to the cold SST in the South Atlantic before the Atlantic Niña occurs in Figure 7.6. This high-pressure anomaly induces the easterly anomaly of the trade winds (not shown). The easterly anomaly can be a trigger of the equatorial SST anomaly and consequently, the cold anomaly develops via the Bjerknes Feedback in the tropics. In both NorESM runs, the SAA anomaly in February and March does not form. Rather, the SAA is to some extent weakened in February and March indicating that the triggering by the SAA does not excite tropical Atlantic variability as observed. Our other study with a regionally-coupled model also suggests that the SAA is responsible for the tropical Atlantic variability (Koseki et al., in prep-b). While the anomaly coupling improves the processes responsible for the tropical Atlantic Niño (the Bjerknes Feedback and the thermodynamical damping), the connection between the subtropics and tropics is still poorly represented. The presence of thermal damping in the absence of SAA forcing may explain why the variability is too weak in the anomaly coupled version of NorCPM.

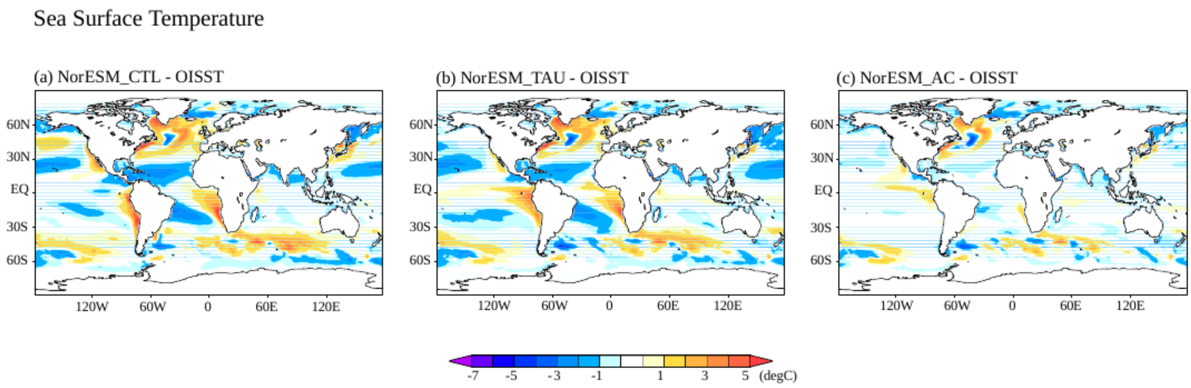

Figure 7.1: Annual-mean climatological bias of SST for (a) free run, (b) experiment of wind stress replacement, and (c) experiment of wind stress and SST replacement (anomaly coupling).

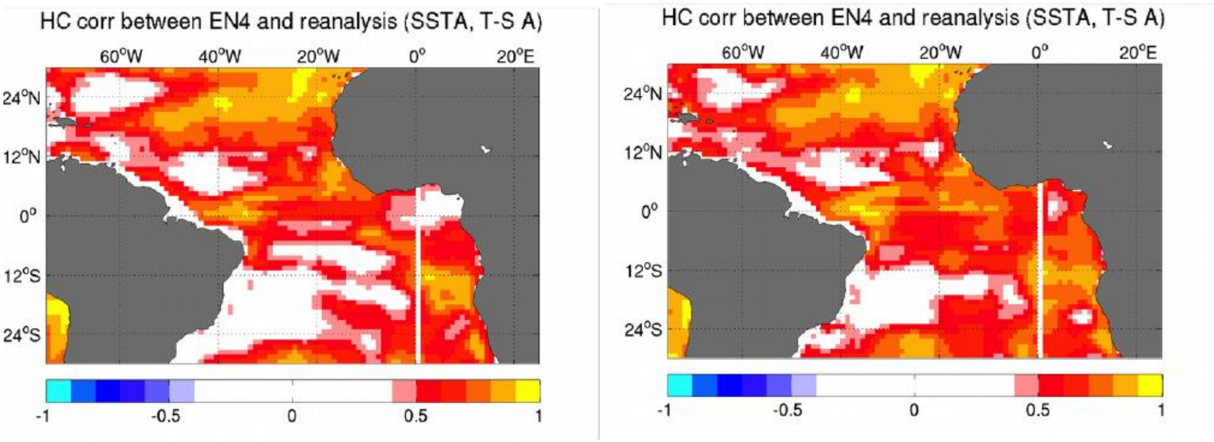

Figure 7.2: Correlation map of ocean heat content for (left) the NorCPM without the anomaly coupling and (right) the NorCPM with the anomaly coupling for 1950-2010 with respect to EN4 objective analysis.

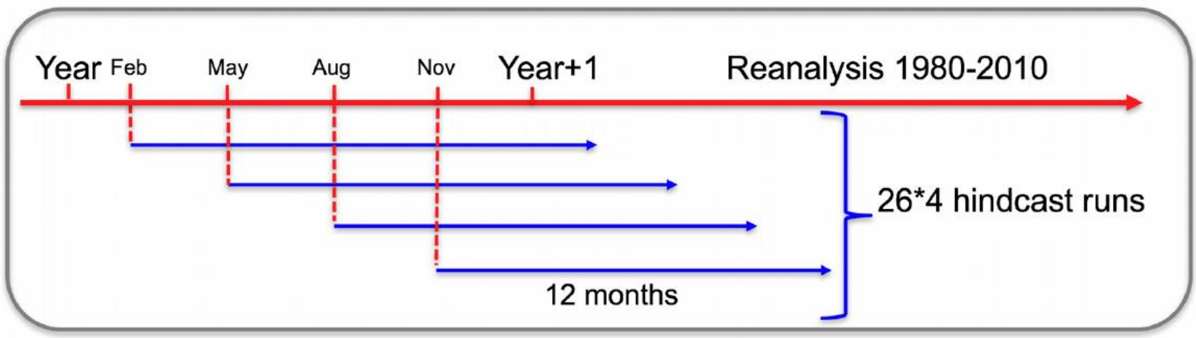

Figure 7.3. Experimental design of seasonal prediction of NorCPM.

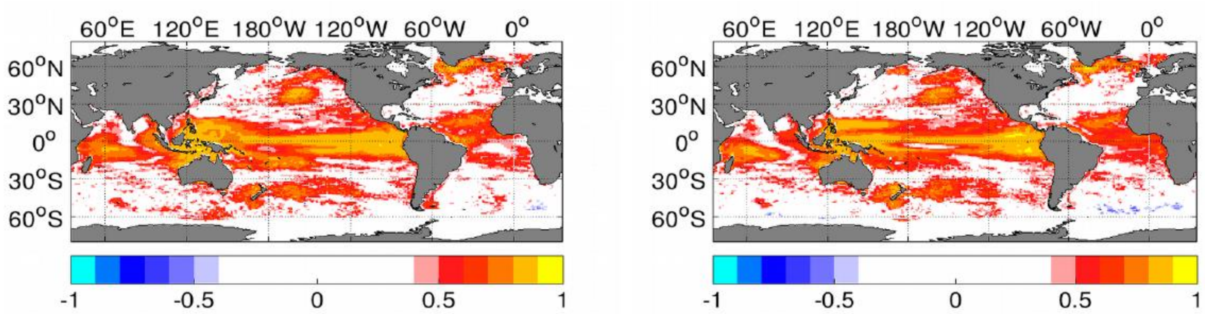

Figure 7.4: Prediction skill of 1-3 lead months averaged SST for (left) the NorCPM and (right) the NorCPM with the anomaly coupling.

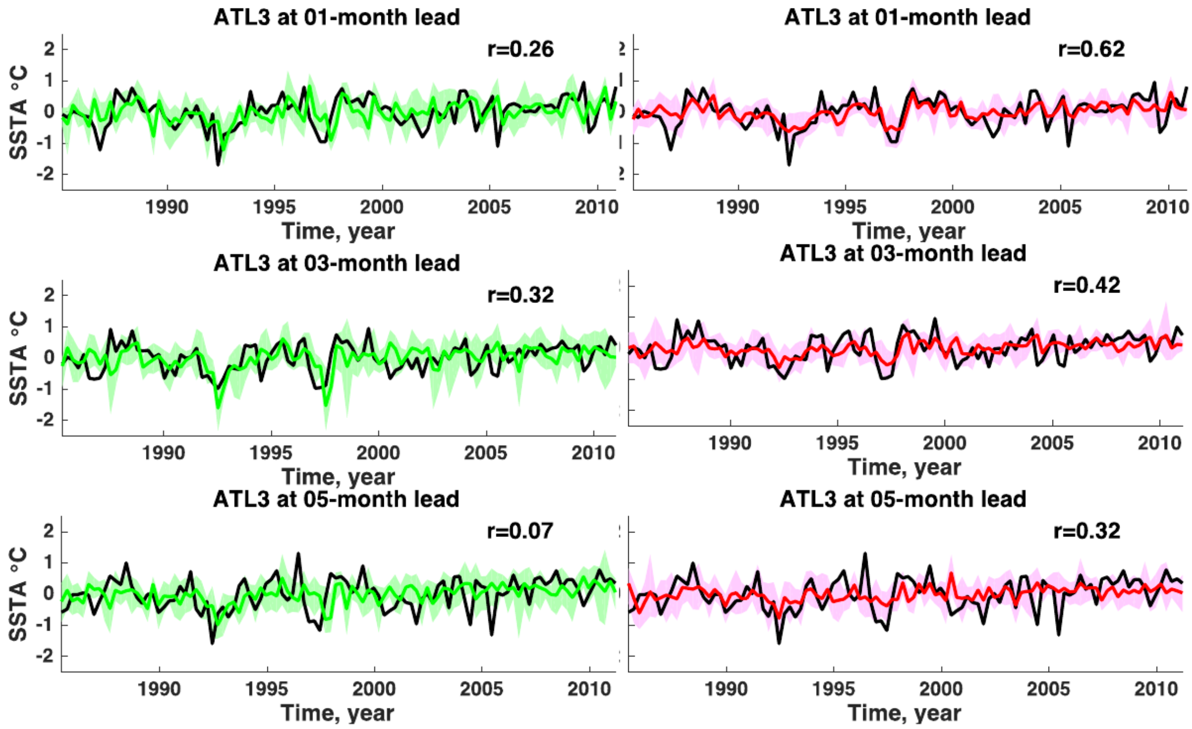

Figure 7.5: Prediction skill of Atlantic3 Index (averaged SST over 3S-3N and 20W-0) at 01, 03, and 05 lead months for (left) the NorCPM and (right) the NorCPM with the anomaly coupling. The black line denotes the observation.

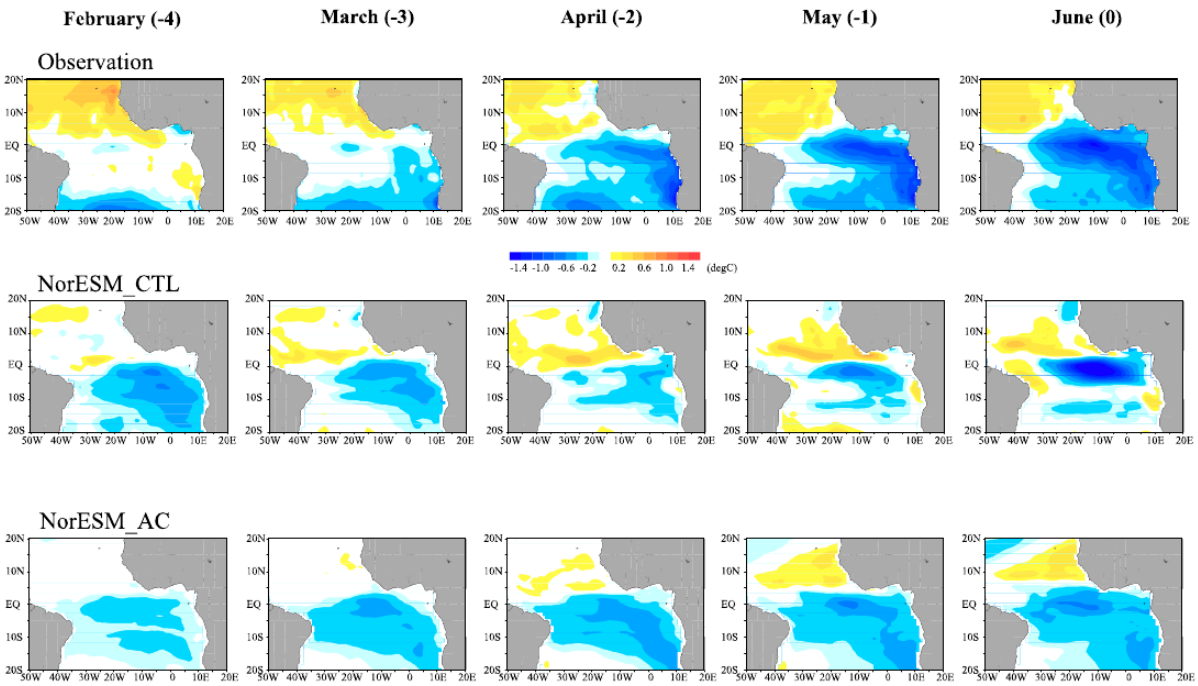

Figure 7.6: Lag-composite of SST anomalies in cold events for (top) observations, (middle) NorESM free run and (c) NorESM with the anomaly coupling. The cold events are defined as Atlantic 3 Index that is lower by one standard deviation than the climatology of Atlantic 3 Index in June. The anomalies are difference between the composites and each monthly climatology of SST.

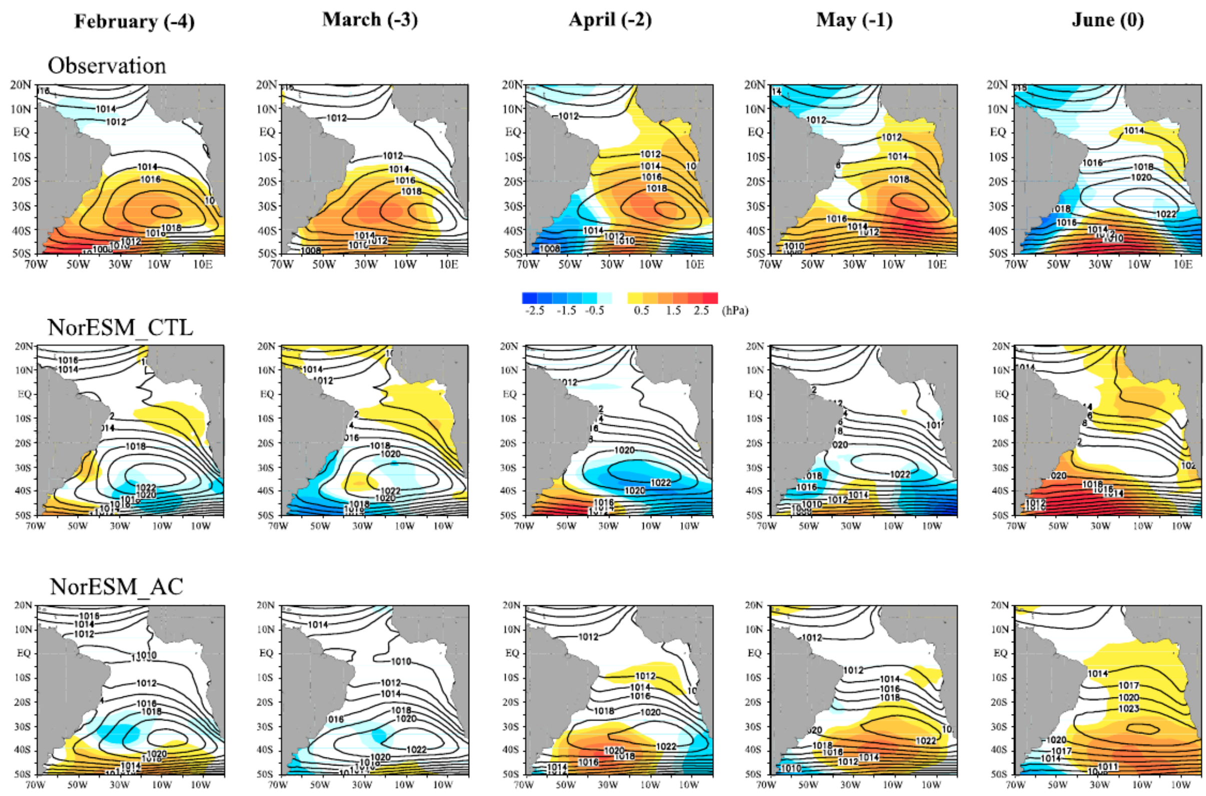

Figure 7.7: Same as Figure 7.6, but for sea level pressure.

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