Initialization Techniques in Seasonal Forecasts

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1 Introduction

Seasonal forecasts predict variations in the atmospheric circulation in response to anomalous boundary forcing, changing significantly the probability of occurrence of weather patterns (Palmer and Anderson 1994). In order to extend the predictability horizon, these boundary conditions need to be either slow-varying or predictable given the initial conditions. Examples of boundary forcing are variations of sea surface temperature (SST), land conditions (snow depth, soil moisture), sea-ice and radiative gases.

Seasonal forecasting systems are based on coupled ocean-atmosphere general circulation models that predict both the surface boundary forcing and their impact on the atmospheric circulation. The chaotic nature of the atmosphere is taken into account by issuing probabilistic forecasts, obtained by performing an ensemble of coupled integrations. Because of the deficiencies in coupled models, the forecasts need calibration before the forecast is issued. The calibration is done by conducting a series of past seasonal hindcasts, which in turn requires initial conditions for a historical period (typically 15-25 years), usually obtained from reanalyses. The hindcasts are also needed for skill assessment. Operational seasonal forecasting also requires near-real time knowledge of the state of the climate.

This lecture deals in particular with the initialization of the ocean for successful predictions of SST at seasonal time scales. Of special importance are the variations of the tropical SST associated with El Niño Southern Oscillation (ENSO), which have the potential to alter the large-scale atmospheric circulation associated with tropical convective cells.

The most common approach for initializing seasonal forecasts is the so-called full uncoupled initialization (Stockdale et al. 1997, Balmaseda and Anderson 2009). This basically consists on producing a long ocean reanalysis (typically 20-years or longer) by assimilating ocean observations into an ocean model driven by atmospheric fluxes. More recently, with the advent of decadal forecast the so-called anomaly initialization (Smith et al. 2007) has become popular. In this approach, only the anomalous state is assimilated without any attempt of correcting the model mean state. The anomaly initialization is usually conducted in coupled mode, but coupled and anomaly initialization are not synonymous, and there are approaches where the initialization of the full state is done in coupled mode.

Section 2 provides a brief overview of the impact of SST variation sin climate. The different elements of ocean initialization (observing system, forcing fluxes, data assimilation methods, bias correction) are introduced in section 3 in the context of the full initialization approach. The impact on forecast skill is shown in section 4. Section 5 presents an assessment of initialization strategies.

2 Impact of SST on climate

The dominant climate fluctuations at interannual time scales are related to ENSO, a quasi-periodic warming of sea surface temperatures in the eastern and central equatorial Pacific affecting the patterns of temperature and rainfall in much of the world (Bjerkness, 1969). ENSO plays a dominant role in the climate anomalies over the land areas surrounding the entire Pacific basin. The effects of ENSO are also noticeable in other tropical and extra-tropical regions via the so-called atmospheric bridge (Lau et. al. 1996, Klein et. al. 1999), in, for example the Indian monsoon, Atlantic hurricanes and the climate of southern and eastern Africa. It has been shown that the most predictable variations in worldwide precipitation at interannual timescales are related to ENSO (Goddard and Delley, 2005).

The importance of ENSO in seasonal forecasts is further enhanced by its high potential predictability (Zebiak and Cane, 1987), which is largely based on the predictable equatorial wave dynamics. Figure 1 shows time-longitude diagrams illustrating cross-equatorial eastward the propagation of thermocline anomalies (left) preceding the

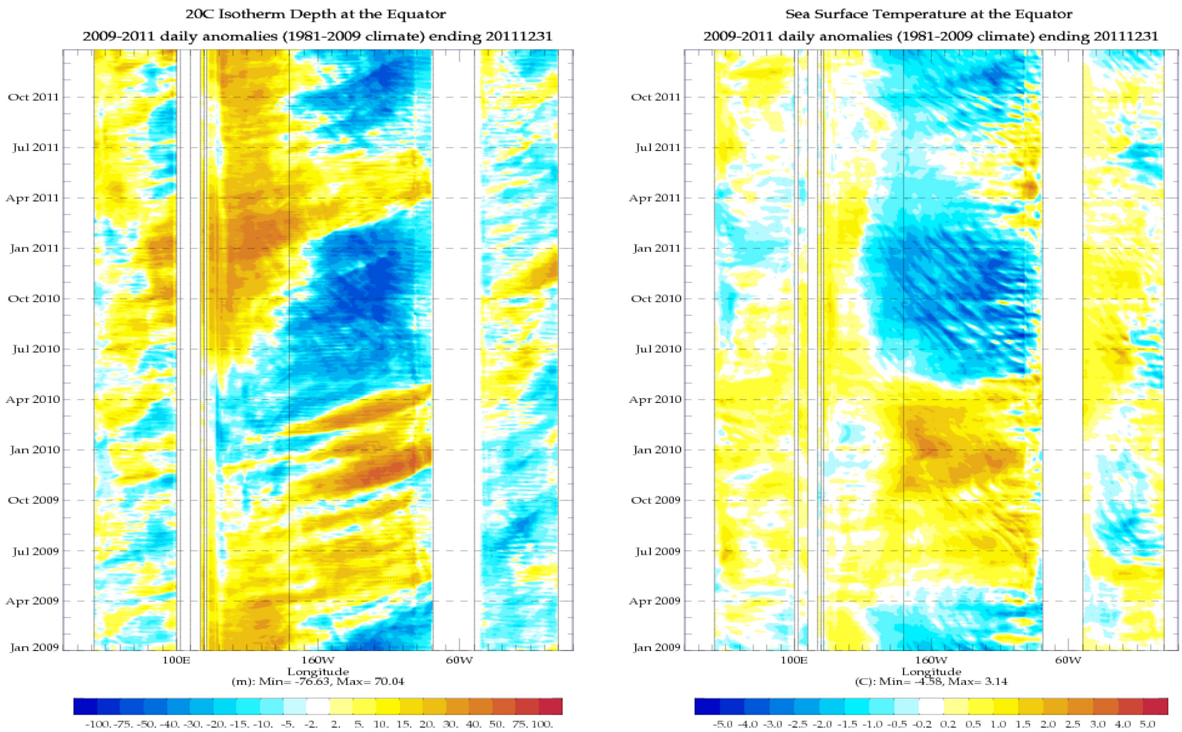

Figure 1: Longitude-time diagrams of equatorial thermocline depth (left) and SST (right) anomalies. The thermocline depth is represented by the depth of the 20 degree Isotherm (D20). The anomalies are computed respect the 1989-2008 climatology. The eastward propagation of equatorial Kelvin waves is visible in D20 usually preceding the appearance of SST anomalies in the Eastern Pacific. (From the ORAS4 ocean reanalysis (Balmaseda et al 2013)).

onset of the ENSO-related SST anomalies (right) in the eastern Pacific. The figure also shows that a thermocline anomaly associated with an individual Kelvin wave does not always translate into a large scale SST anomaly, as it happened in the “failed” El Niño of 2011, when in spite of a substantial propagation of the thermocline anomalies the warm SST anomaly was very short lived, and the El Niño did not materialized.

Anomalies in SST other than ENSO can also drive temperature and precipitation anomalies on seasonal time-scales. Examples include the connection of the tropical Atlantic with north-east Brazil rainfall (Folland et al. 2001) and the rainfall in west Africa and Sahel (Giannini et al. 2003), the impact of the extratropical Atlantic (e.g. Rodwell et al. 2003) on European climate, and the tropical Indian Ocean (in particular the mode of variability known as the Indian Ocean Dipole (Saji et al. 1999) impact on east African rainfall and the Indian monsoon (Goddard and Graham 1999).

3 Initialization Requirements

The quality of seasonal forecasts is determined by the various components of the system (the ocean initialization, the coupled model, the ensemble generation and the calibration strategy), which are closely interrelated. The interdependence of the different components becomes clear when considering the calibration procedure. The a-posteriori calibration of model output requires an estimate of the model climatology, which is obtained by performing a series of coupled hindcasts during some historical period, which ideally should cover a several El Niño events. A historical record of hindcasts is also needed for skill assessment. Ocean initial conditions spanning the chosen calibration period are then required, which is equivalent to a historical ocean “reanalysis”. The interannual variability represented by ocean reanalysis will have an impact on both the calibration and on the assessment of the skill. Because of the large impact on the forecast, the uncertainty in the ocean initial conditions should be considered in the ensemble generation.

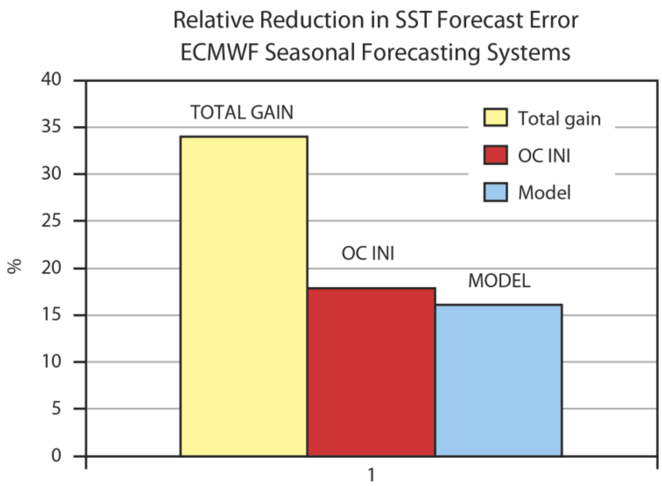

Figure 2. Progress in the seasonal forecast skill of the ECMWF operational system during the last decade. The yellow bar shows the relative reduction in mean absolute error of forecast of SST in the eastern Pacific (NINO3). The red bar shows the contribution from the ocean initialization, and the blue bar is the contribution from model improvement. From Balmaseda et al 2010a.

The consolidation of seasonal forecasting as a routine operational activity during the last decades has been possible thanks to the improvement in coupled models, data assimilation methods, availability of forcing fluxes from atmospheric reanalysis, and the development of the ocean observing system. Fig. 2 shows that the improvements in ENSO forecasts at the ECMWF over the past decade. The improvements can be attributed equally to better initialization of the ocean and improved coupled models (Balmaseda et al 2010a).

Assimilation of observations into an ocean model forced by prescribed atmospheric fluxes is the most common practice for initialization of the ocean component of a coupled model (Balmaseda et al 2010b). The assimilation should improve the estimation of the ocean state (reducing uncertainty and improving the mean an interannual variability), but ultimately it should improve the skill of the seasonal forecasts. These objectives are challenged by the paucity of ocean observations and the abrupt changes in the ocean observing system, and by presence of model error (i.e. it is not guaranteed that a good estimation of the real world can project in the model attractor and thus evolve successfully into the forecasts). In what follows we discuss why the initialization of seasonal forecasts needs data assimilation. We will describe the ocean observing system, the impact of data assimilation in correcting model error, and the need to apply bias corrections for reliable representation of the interannual variability. The section ends with a description of the ocean initialization system used in the ECMWF System4 (S4) operational seasonal forecasting system.

3.1 Why do we need to assimilate subsurface ocean data?

In seasonal forecasts the emphasis is on the initialization of the upper ocean thermal structure, particularly in the tropics, where SST anomalies have a strong influence on the atmospheric circulation.

A simple way of providing initial conditions would be to run an ocean model forced with winds and fresh water fluxes from atmospheric reanalyses and with a strong relaxation of observations of SST.

But the quality of the models and surface fluxes is usually not sufficient to provide an accurate estimation of the ocean state. The uncertainty induced in the upper ocean by using different wind products can be as large as the interannual variability. Figure 3(top) shows the evolution of upper-300m averaged temperature in the Equatorial Atlantic from two ocean-only simulations forced by different atmospheric fluxes. The magnitude of the differences is comparable with the interannual variability. By assimilating ocean observations it is possible to reduce the uncertainty in the ocean estimate. Figure 3(bottom) shows the equivalent quantity in two equivalent ocean reanalysis, where the first guess is given by an ocean model forced by the different surface fluxes, but this time subsurface ocean observations are assimilated.

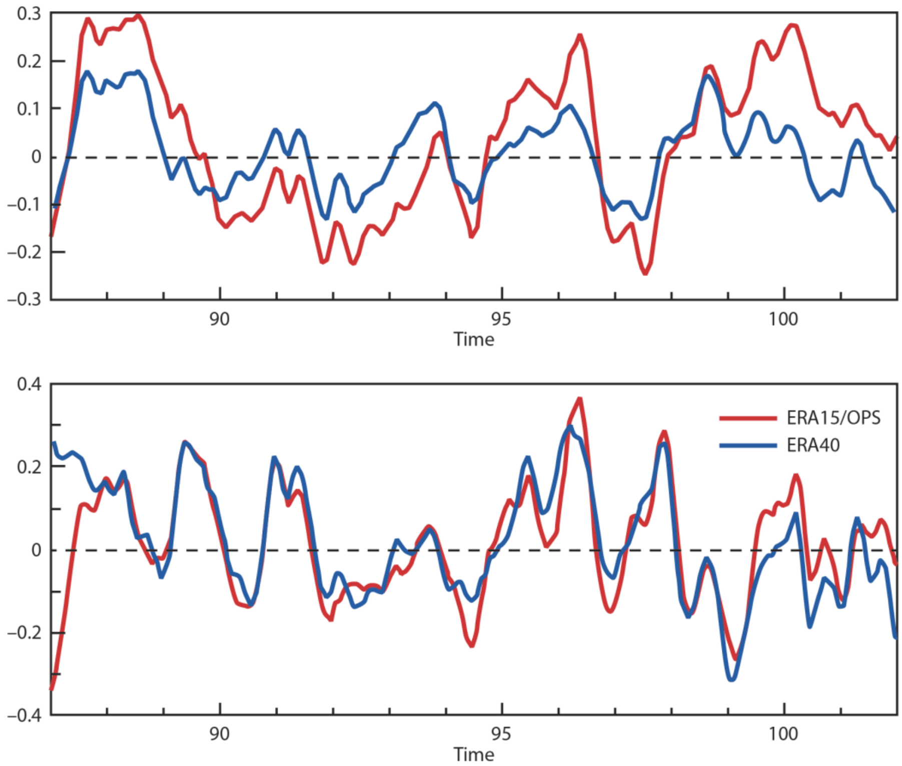

Figure 3. top) Evolution of the upper-300m averaged temperature in Equatorial Atlantic from two ocean-only simulations forced by different atmospheric fluxes. The magnitude of the differences is comparable with the interannual variability. Bottom) As above but assimilating subsurface observations. The assimilation of ocean observations is efficient in reducing the uncertainty in the ocean estimate resulting from uncertainty in surface fluxes.

3.2 Ocean Observing System

Figure 4a shows schematically the different components of the ocean observing system and their availability in time. Sea surface temperature observations are essential for seasonal forecasts. Most of the initialization systems also use subsurface temperature from XBT's (Expendable bathythermograph, Goni et al. 2010), CTDs (Conductivity, Temperature and Depth) usually from scientific cruises, moored buoys (TAO/TRITON in the Pacific, PIRATA in the Atlantic, RAMA in the Indian Ocean; see McPhaden et al. 2010) and Argo floats (Freeland et al 2010). Salinity (mainly from Argo and CTDs), and altimeter-derived sea-level anomalies (SLAs, since approximately 1993, Wilson et al. 2010) are also assimilated. The latter usually need a prescribed external Mean Dynamic Topography (MDT), which can be derived indirectly from gravity missions such as GRACE (Gravity Recovery and Climate Experiment) and, in the near future, GOCE (Gravity field and steady-state Ocean Circulation Explorer) (Knudsen et al. 2010).

Figure 5 (left column) shows the number of subsurface temperature (top) and salinity (bottom) observations in the depth range 400m-600m as a function of time, illustrating the large increase in observations associated to the advent of Argo. The right panels of figure 5 show the spatial observation coverage in June 1980 (top) and in June 2009 (bottom). The properties of spatial and temporal sampling varies substantially between instruments: the XBTs usually follow commercial ship routes, CTDs are associated with intense scientific missions, the moored array samples the equatorial oceans at few selected fix positions; Argo, is only observing system that sample uniformly the subsurface of the ocean, measuring temperature and salinity up to depth of 2000m. Altimeter sea-level (not shown) also samples the surface of the ocean quite uniformly, but a good relation between sea level variations and subsurface structure is only possible in regions of strong stratification (the tropics).

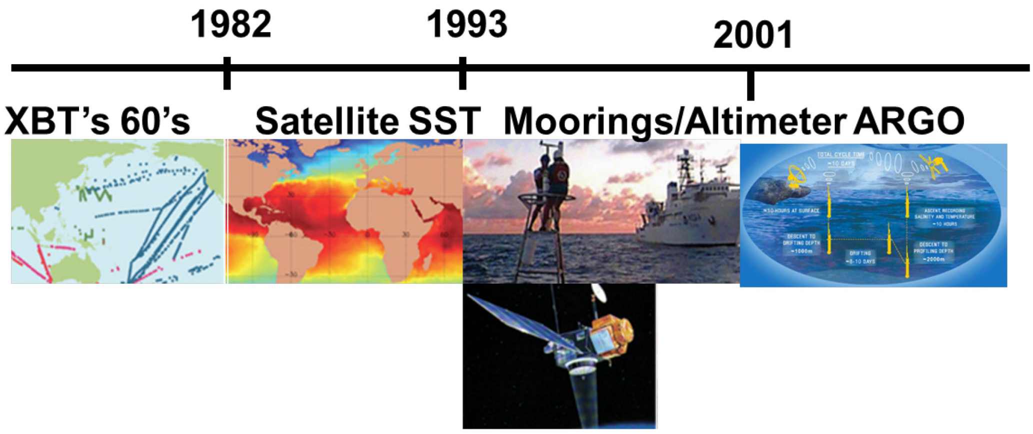

Figure 4: Time evolution of the ocean observing system by instrument

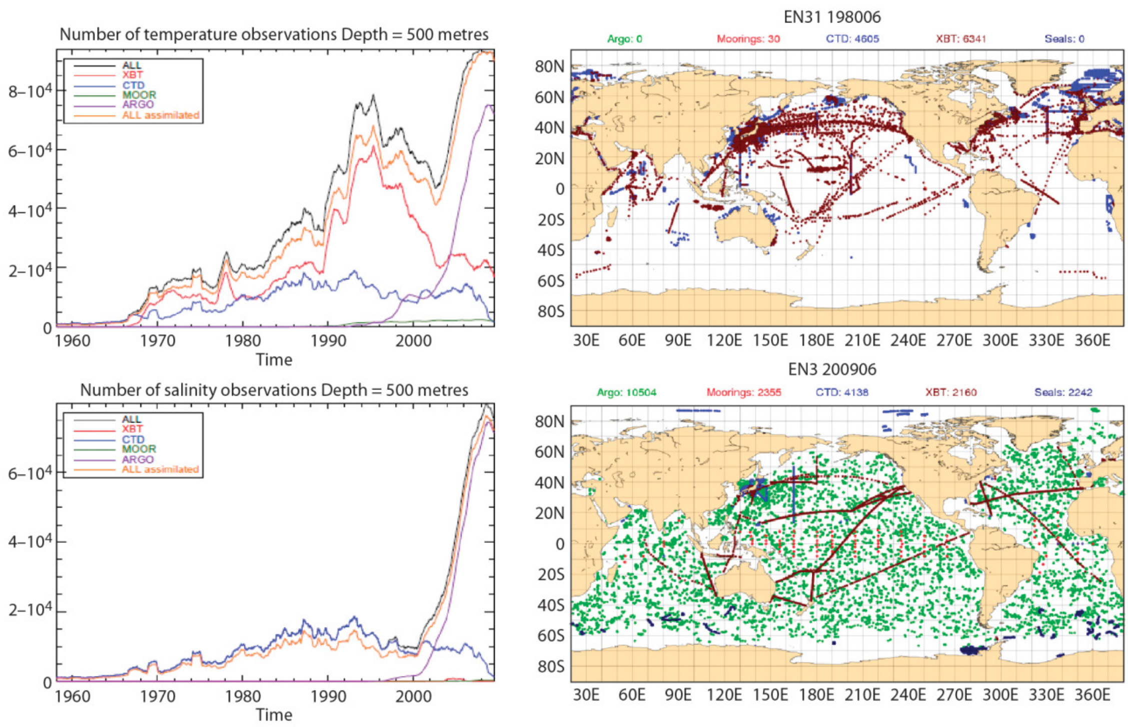

Figure 5: (left) Number of temperature (top) and salinity (bottom) observations within the depth range 400m-600m as a function of time per instrument type. The black curve is the total number of observations. The orange curve shows the number of assimilated observations in the ORAS4 reanalysis (from Mogensen et al 2012). Right: Typical observation coverage in June 1980 (top) and in June 2005 (bottom). Note that the colour coding for the instruments is not the same in the left and right panels.

3.3 Assimilation Increment and Model Error: Need for bias correction

Figure 6 shows the 1987-2001 average of a longitude-depth section of the assimilation increments along the equator from a previous ECMWF ocean analysis (system 2). The non-zero mean increment is indicative of systematic model error. In this particular case, the large scale dipolar structure of the increment can be interpreted as a correction in the slope of the thermocline (making it deeper in the western Pacific and shallower in the eastern Pacific). This kind of error could appear if the equatorial winds were too weak, although it may be due to incorrect ocean mixing.

Regardless of the source of error, figure 6 shows that the data assimilation is correcting the system bias, whereas the scheme assumes the first guess given by the model background is unbiased. In practice, the presence of systematic error may introduce spurious temporal variability in regions where the observation coverage is not uniform in time, which may be a serious problem when the ocean analysis is used to predict interannual variability (Balmaseda et al. 2007) . This is illustrated in figure 7, which shows the evolution of D20 in the Equatorial Atlantic for three experiments. The CNTL, (black line) corresponds to an ocean simulation forced by reanalysis fluxes. ASM (red line) is an equivalent experiment where subsurface temperature is being assimilated. There is a clear jump around 1999 caused by the advent of the PIRATA moorings, which started around that time. The data from PIRATA is correcting the position of the model thermocline, and in doing so it introduces a large jump contaminating the interannual variability. The blue curve corresponds to an assimilation experiment where a bias correction scheme (see later) is being applied to the model (or first guess) before each analysis cycle. The bias correction corrects the model mean error, thus avoiding spurious signals each time that there are changes in the ocean observing system. The following section summarizes the current ECMWF reanalysis system (ORAS4), and provides more details on the bias correction algorithm.

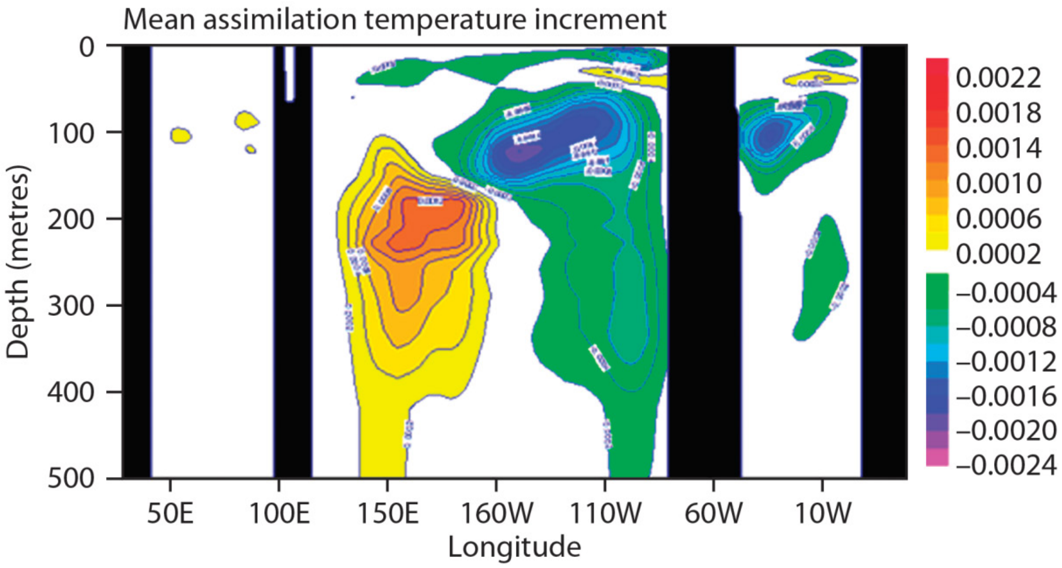

Figure 6. Equatorial longitude-depth section of mean assimilation temperature increment from a previous ECMWF ocean analysis system (ORAS2). The contour interval is 2×10−4◦C/hr. The mean corresponds to the time-average during the period 1987-2001. From Balmaseda et al 2008.

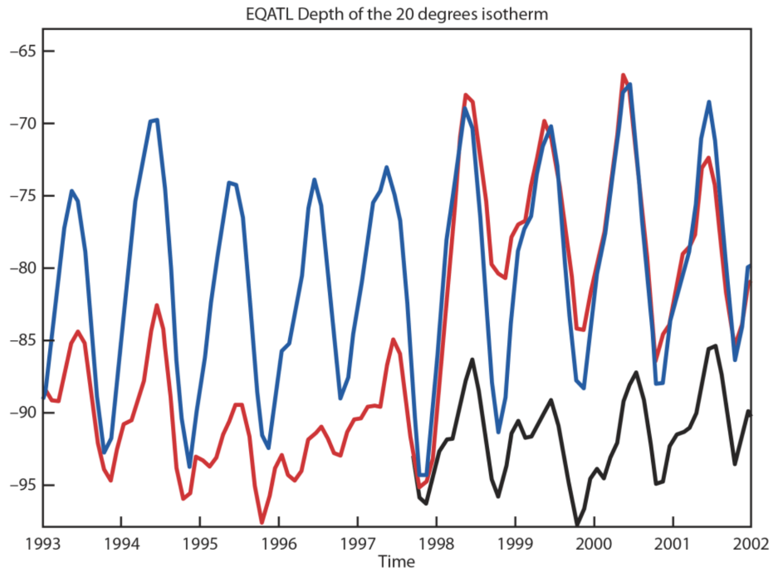

Figure 7: Time evolution of the depth of the 20 degree isotherm in the equatorial Atlantic in an ocean model simulation (CNTL, black), in a data assimilation experiment without bias correction (ASM, red) and in a data assimilation experiment with bias correction (blue). The model has too deep thermocline, that the PIRATA observations are correcting for, introducing a spurious interannual variability. By applying a bias correction, the depth of the thermocline is corrected before and the changes in the observing system do not translate into spurious signals.

3.4 An example of ocean initialization system: the ECMWF ORAS4

The ORAS4 (Ocean Reanalysis System 4, Balmaseda et al 2013, Mogensen et al 2012) provides ocean initial conditions for the ECMWF Seasonal Forecasting System 4 (Molteni et al 2008). ORAS4 has been produced by combining, every 10 days, the output of an ocean model forced by atmospheric reanalysis fluxes with quality controlled ocean observations.

ORAS4 uses the NEMO ocean model [Madec, 2008] with a horizontal resolution of approximately 1 degree, and the NEMOVAR [Daget et al. 2009, Mogensen et al., 2012] data assimilation system in its 3Dvar configuration. The ocean model is forced by daily atmospheric-derived daily surface fluxes of solar radiation, total heat flux, evaporation-minus-precipitation and surface wind stress. These are from the ERA-40 reanalysis [Uppala et al., 2005] from the September 1957- December 1989, and ERA-Interim (Dee et al. 2011) thereafter. The heat fluxes are adjusted using a strong relaxation to gridded SST products. The fresh-water flux is also adjusted using ocean observations: i) globally, by constraining the global model sea-level changes to the variations in the altimeter-derived value, and ii) locally, via a weak relaxation (1 year time scale) to a monthly climatology of surface salinity.

The analysis cycle is 10 days, and it is summarized in equation (1). The state $\mathbf{x}^f$ produced by integrating the NEMO model forced by daily surface fluxes and relaxed to SST, is bias corrected with a bias term $\mathbf{b}^f$ to produce the first guess ($\mathbf{x}^f+\mathbf{b}^f$), which is contrasted with each available observation $\mathbf{y}$ at its appropriate time and position via the observation operator $\mathbf{H}$.

$$
\begin{aligned}
x^a &= x^f + b^f + K\left[y - H\left(x^f + b^f\right)\right] \\
b^a &= b^f + L\left[y - H\left(x^f + b^f\right)\right]
\end{aligned}
\tag{1}
$$

The observations consist of temperature and salinity (T/S) profiles from the Hadley Centre's EN3 data collection [Ingleby and Huddleston, 2007], which includes XBTs, CTDs, TAO/TRITON/PIRATA/RAMA moorings, Argo profiles Autonomous Pinniped Bathythermograph (APBs or elephant seals, T/S). Altimeter-derived along track sea level anomalies from AVISO are also assimilated. The quality controlled model-observations departures are passed to the 3D-Var minimization to compute the optimal assimilation increment. This is applied as a tendency forcing during a second model integration spanning the same time window as for the first guess, thus producing the analysis $\mathbf{x}^a$. The analysis increments are also used to correct the bias first guess $\mathbf{b}^f$, producing an update of the bias state $\mathbf{b}^a$. The model bias correction scheme (equation 2) comprises an adaptive component ($\mathbf{b}'$), estimated on-line from previous observations according to the second expression in equation (1), and a-priori component ($\overline{\mathbf{b}}$), derived off line from a monthly climatology of model errors estimated during the data-rich Argo period (2000-2008) and applied to ORAS4 from the beginning of the record.

$$\mathbf{b}_k^f = \overline{\mathbf{b}_k} + \mathbf{b}_k'^f \tag{2}$$

Figure 8 shows the offline temperature bias correction term used in ORAS4, for the depth range 300m-700m. Clearly visible are the corrections needed by the western boundary currents, which the low resolution of the model prevents resolving properly.

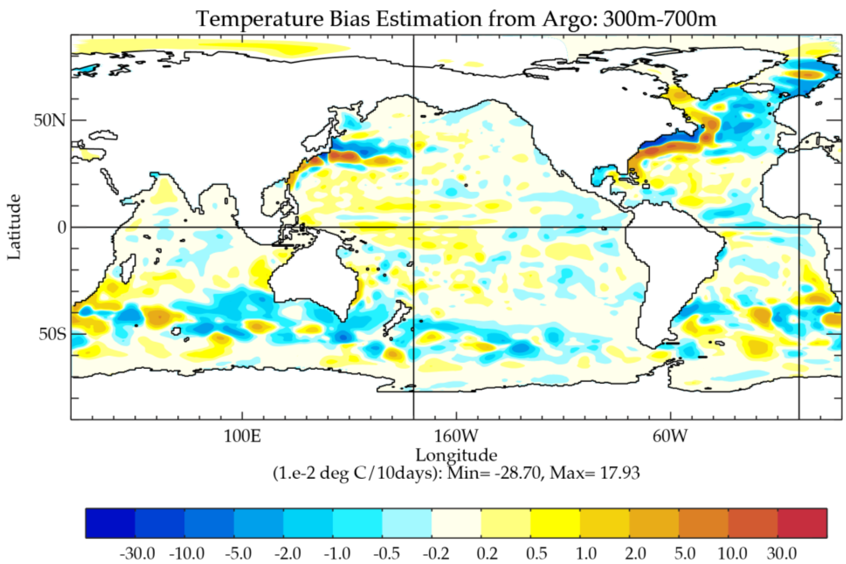

Figure 8. Temperature bias correction term estimated offline for the depth range 300m-700m. The term is used ORAS4 as a tendency term in the evolution equation to correct the first guess. Units are degrees C per hour. From Balmaseda et al 2013.

ORAS4 consists of 5 ensemble members spanning the period 1958 to present. The 5 ensemble members of ORAS4 sample plausible uncertainties in the wind forcing, observation coverage, and the deep ocean. To account for the uncertainty in the deep ocean, five different ocean states from an ocean model integration sampled at 5-year intervals from 1960 to 1980 are used to initialize each of the ensemble members of ORAS4. The impact of this step in the deep ocean is noticeable in the first 20 years of the reanalysis

Quality improvements in ORAS4 relative to earlier ocean reanalyses are due to the use of atmospheric surface fluxes from the ERA-Interim reanalysis, various improvements in ocean modeling and data assimilation, and more comprehensive and improved quality-controlled ocean data sets, including important corrections to the ocean observations. Balmaseda et al 2013 have evaluated ORAS4 using different metrics, including comparison with observed ocean currents, RAPID-derived transports, sea-level gauges, and GRACE-derived bottom pressure. They show that compared to a control ocean model simulation, ORAS4 improves the fit to observations and the interannual variability, and consistently results in improved seasonal forecast skill of SST.

4 Impact on Forecast Skill

The skill of seasonal forecasts is often used to gauge the quality of the ocean initial conditions. This may not always be appropriate, since the quality of the coupled model is also important - if the major source of forecast error comes from the coupled model, improvements in ocean initial conditions would have little impact on forecast skill. This is something to bear in mind when interpreting results of the impact of ocean data assimilation on seasonal forecasts. Several studies have demonstrated the benefit of assimilating ocean data on the prediction of ENSO (Alves et al 2003, Balmaseda et al 2008, among others). The benefits are less clear in other areas, such as the equatorial Atlantic, where model errors are large and there is no long history of moored observations, as in the Pacific. Ultimately, the impact of initialization in a seasonal forecasting system will depend on the quality of the coupled model (Stockdale et al 2006, Balmaseda and Anderson, 2009).

The contribution of the different sources of observational information in seasonal forecast skill has been quantified by Balmaseda and Anderson, (2009). They used a previous of the ECMWF seasonal forecasting system (S3), evaluate three different initialization strategies, each of which uses different observational information. Strategy i) uses ocean, atmospheric and SST information, strategy ii) uses atmospheric information and SST, and strategy iii) uses only SST, as in Keenlyside et al 2008. In method (i), the coupled system thus starts close to the observed state but it is not obvious that this leads to the most skilful forecasts as the method can have undesirable initialization shocks. Method (iii) can reduce the initialization shock since the atmospheric and ocean models will be in closer balance at the start of the coupled integrations. The three experiments can also be seen as observing system experiments. Differences between (i) and (ii) are indicative of the impact of ocean observations, and comparison of (ii) and (iii) are indicative of the impact of the atmospheric observations that were used to produce the atmospheric reanalyses. Results show that the initialization strategy has an impact on both the mean state and the interannual variability of coupled forecasts (Figure 9). They also show that, in this particular system, initialization shock does not preclude forecast skill, and the most skilful forecasts are those obtained when the initial conditions are closer to the “real ocean state”, even if this causes sizable adjustment processes.

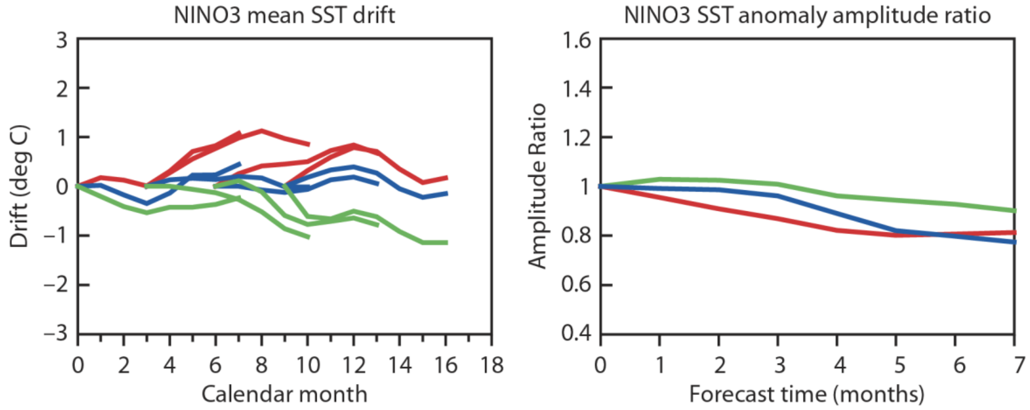

Figure 9. Impact of initialization strategy in forecast drift (left) and normalized interannual variability (right). Green uses SST only, blue uses SST and atmospheric reanalyses, and red uses SST, atmospheric reanalyses and ocean observations. All the forecasts have been conducted with the same coupled model. From Balmaseda and Anderson 2009.

Fig.10 (upper panel) shows the relative reduction in the monthly mean absolute error (MAE) resulting from adding information from the ocean and/or atmospheric observations for the 1-3 month forecast range in the regions defined in the inset table. Observational information has the largest impact in the western Pacific (EQ3), where the combined information of ocean and atmospheric observations can reduce the MAE more than 50% . With the exception of the equatorial Atlantic (EQATL), the best scores are achieved by strategy i). This means that for the ECMWF system, the benefits of ocean data assimilation and the use of fluxes from atmospheric (re)analyses more than offset problems arising from initialization shock. Seasonal forecast skill can also be used to evaluate the ocean observing system.

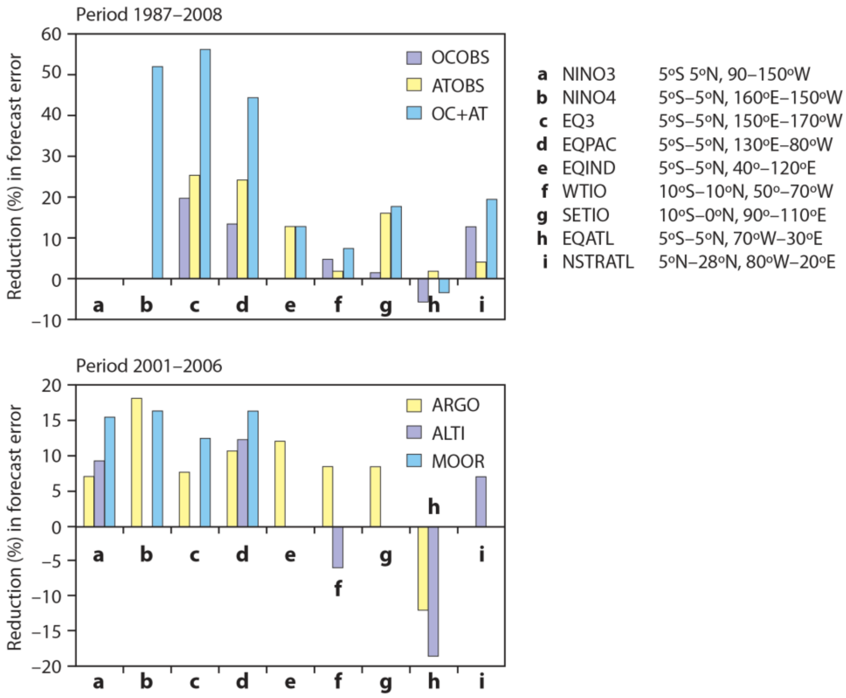

Figure 10. Impact of observations in forecast skill for different regions in table above, as measured by the reduction in mean absolute error for the forecast range. (top) ocean observations (OCOBS), atmospheric observations (ATOBS) and both, for the forecast range 1-3months, period 1987-2008. (bottom) Impact of Argo, altimeter and moorings for the period 2001-2006.

The lower panel of Fig.10 shows the impact on forecast skill of Argo, moorings and altimeters. The statistics have been calculated only for the (rather short) Argo period 2001-2006 and so the impacts are best considered as indicative rather than definitive. The figure shows that no observing system is redundant. Argo has a dominant impact in the western Pacific (NINO4) and equatorial Indian Ocean. Argo is the only observing system with a significant positive impact on the WTIO (Western Tropical Indian Ocean) and SETIO (South-eastern Tropical Indian Ocean) regions. The information from the moorings is still dominant in most of the equatorial Pacific, although in the NINO4 region it is less important than that from Argo. Meanwhile altimetry has a significant positive impact in the equatorial Pacific, and is the only observing system with positive impact in the north subtropical Atlantic. Again, for this period, all the observing systems have a negative impact on the EQATL region. The impact of the TAO/TRITON array and Argo float data has also been evaluated with the Japan Meteorological Agency (JMA) seasonal forecasting system (Fuji et al 2008) by conducting data retention experiments for the period 2004-2007. The results (not shown) are consistent with the above ones, indicating that TAO/TRITON data improves the forecast of SST in the eastern equatorial Pacific (NINO3, NINO4), and that Argo floats are essential observations for SST prediction in the tropical Pacific and Indian Oceans.

5 Assessment of initialization strategies.

Systematic model error leads to difficulties in the forecasting process. This can happen when transferring information between the observation space and the model space, namely at the initialisation stage and when issuing the forecast. At the initialisation stage, information needs to be transferred from observations to model space. When issuing the forecast, the model output needs to be calibrated using reliable information about the real world. In numerical weather prediction (NWP) the forecast covers typically the range 1-15 days, and, because of the relatively short forecast time, the difference between model and observed climatologies can be ignored (i.e. the model error is neglected). At longer lead times (monthly, seasonal and decadal time scales) the systematic model error cannot be ignored and strategies for accounting for model error are needed. Below is a description of three different strategies (Full Initialization, Anomaly Initialization and Flux Correction), followed by a summary of the results from Magnusson et al 2012a,b, who produced an assessment of the different forecast strategies.

5.1 Full initialization

The full initialization strategy follows the NWP approach, i.e. the model (in this case the ocean model) is initialized from an ocean analysis performed via data assimilation. The analysis is a combination of the latest observations together with a short-range forecast (typically 10 days). By continuously using the information from the observations the analysis state is kept close to the attractor of the nature (although in poorly observed areas, a difference could still be present), and often an explicit bias correction is used. During the forecast, the state of the model will diverge from the state of nature both due to the loss of predictability, related to high sensitivity to initial conditions and development of systematic errors. At long lead times (monthly, seasonal and decadal time scales), the model bias is often large compared with the random component of the forecast error. In these cases the model bias cannot be neglected and the strategy for accounting for the model systematic error is the a-posteriori removal of it. The bias is corrected by applying a lead-time dependent bias correction in post-processing. The bias correction is also made dependent of the seasonal cycle. This is the strategy is commonly used in monthly and seasonal forecasts (Stockdale, 1997). For example, in an operational seasonal forecast issued every month with a typical leadtime of 7 months, the estimation of 7x12=84 bias correction terms is needed to account for all lead times and all starting dates. The robust estimation of this large number of bias fields requires a large data set of hindcasts (retro-perspective forecasts).

This strategy will fail if the bias is non-stationary, and can lead to sub-optimal forecast skill. The non-stationarity of the bias may be due to non-stationary errors on the initial conditions (Kumar et al., 2012), or to flow-dependent bias arising from the non-linear nature of the system (Balmaseda and Anderson, 2009). Generally speaking, if the systematic error bias is large enough, the non-linear terms will become non-negligible and therefore a mere linear calibration process will reveal insufficient.

The full initialisation strategy may also be affected from the so-called initialisation shock, a term referring to rapid adjustment processes caused by the imbalance between the initial conditions and the forecast model. This can occur if the forecast model is different from the initialization model, or if the initialization does not preserve physical constrains. In the case of the full initialization, the imbalance can be induced by the fact that the forecast model is coupled, while the initialization has taken place in uncoupled mode.

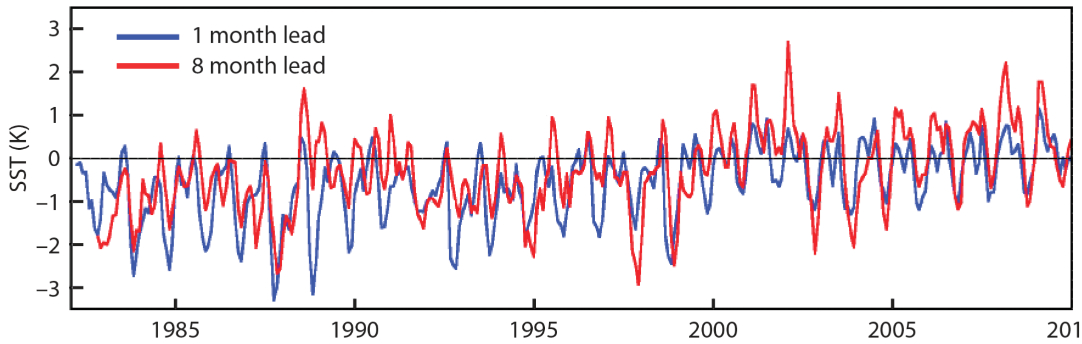

Figure 11. Time evolution of the SST forecast bias in the NCEP CFS version 2. The figure shows the bias at 1-month and 8-months lead time, and it illustrates the non-stationarity of the bias. From Kumar et al 2012.

Figure 11 from Kumar et al 2012 illustrates the non-stationarity of the SST bias in the NCEP CFS model (version 2). It shows that the bias depends on the lead time and the seasonal cycle, a dependency that is accounted for in the a-posteriori removal of the bias. The figure also shows a non-stationary behaviour at interannual time scales, contrary to the assumptions in the a-posteriori bias correction. This can lead to degradation of forecast skill. The figure also hints to the presence of initialization shock: the negative extreme values in the 1-month leadtime are reduced in 8-month leadtime bias..

Although the full initialization strategy follows the NWP approach, its practical implementation in monthly/and seasonal differs from NWP in three main elements: i) the model bias is explicitly corrected during the data assimilation, ii) the forecast error needs to be removed a-posteriori and iii) the forecast and initialization models are not the same. The later can lead to initialization shock, and it prevents using the bias information obtained by the data assimilation in the forecast stage.

5.2 Anomaly initialization

The idea of using anomaly initialisation is to avoid the non-stationary model drift and initialisation shock, by initializing the model around its own climatology. The procedure is to calculate anomalies in the observations with respect to the observations climatology and add such anomalies to the climate of the model climatology. The method has been very popular for decadal forecasts (Smith et al. 2007, among others).

In the anomaly initialization only the anomaly state $\mathbf{x'^a}$ is analyized. Equation (3) describes the procedure, which is often called bias-blind data assimilation: the presence of bias is acknowledged, but there is no attempt to correct it. In the full initialization (equation 1), the bias was also corrected by the data assimilation.

$$x'^a = (x^f - \overline{x}) + K\left[(y - \overline{y}) - H\left(x^f - \overline{x}\right)\right] \tag{3}$$

The procedure of the anomaly initialisation is not without problems. The estimation of the anomaly requires the knowledge of the model climate observed climatology ($\hat{y}$). This introduces two kind of difficulties. On one hand, it is important that the sampling period used for the observed climatology is consistent with that used for the model climatology (for instance, a model climatology estimated for the pre-industrial era should not be used for the anomaly initialisation of decadal forecast post 1960's, with an observed climatology estimated during the period 1970-2005). The other kind of problem is related with defining the climatology of new or sporadic observations. For instance, some regions like southern oceans had not been observed prior to advent of Argo. Most of the deep ocean has only been observed sporadically with cruise data, and there is not enough information to extract a long term climatology. To avoid this problem, the anomaly initialisation often uses gridded fields from existing reanalysis. In this way, it turns an initial weakness into a good advantage, since it means that different coupled modelling groups can initialise their decadal forecasts with external ocean reanalysis, without the need of having to develop data assimilation systems for their own models.

The problem with non-linear interaction between mean state and anomaly is even more acute in the anomaly than in full initialisation, since the mean error is fully developed during the coupled model integrations. Although it is often claimed that the anomaly initialization avoids initialization shock, this is by no means guaranteed since it depends how the anomaly is assimilated into the model. The structure of the observed anomaly may not be consistent with the model mean state. An example are anomalies associated with displacement of sharp fronts or gradients which are in different locations in model and observations, when simply adding the anomaly can lead to rapid adjustment process (examples are anomalies associated with vertical displacements of the equatorial thermocline, Gulf Stream or sea-ice edge).

A more interesting advantage of the anomaly initialisation, which is often not discussed, is the avoidance of model drift. By avoiding model drift, the a-posteriori correction of the forecast does not require the bias dependence on the forecast lead time (so typically only the 12-month climatology of the bias is required), and the bias estimators can be more robust. This is more relevant for decadal forecast ranges, when it is also more expensive to conduct the calibrating hindcasts. The procedure requires however a long integration to estimate the model climatology.

5.3 Flux correction

It is clear from a variety of studies that strong non-linear interactions between mean state and anomaly are at play in the coupled model forecasts. Model improvement is the ultimate way of reducing model biases. However this is a slow process, especially if the systematic errors related to model resolution (as in the case of the correct Gulf Stream). A temporary solution, until the problems in the model is detected and solved, is to compensate for the systematic errors by applying empirical corrections.

One specific correction is the so-called flux correction, applied only in the coupling between the atmosphere and the ocean. The aim of the strategy is to avoid (or limit) the model drift by adding a correction term to the model during the simulation, to avoid non-linear interactions between model mean state and variability. In this strategy the empirical correction of the forecast is done during the model integration rather than only in the final calibration phase. Magnusson et al 2012a,b investigate using both momentum-flux correction and a combination of momentum and heat-flux correction.

5.4 Assessment

Full initialization, anomaly initialization and flux correction have been implemented in the ECMWF coupled forecasting system. The three strategies have been evaluated at seasonal and decadal timescales. The results are presented in Magnusson et al 2012a,b where they also discuss the practical implications of the different strategies.

Magnusson et al 2012a investigate the impact of the mean state on the properties of ENSO in a set of coupled decadal integrations, where the mean state and its seasonal cycle have been modified by applying flux correction to the momentum-flux and a combination of heat and momentum fluxes. They show that correcting the mean state and the seasonal cycle improves the amplitude of SST inter-annual variability and also the penetration of the ENSO signal into the troposphere and the spatial distribution of the ENSO teleconnections are improved. An analysis of a multivariate PDF of ENSO shows clearly that the flux correction affects the mean, variance, skewness and tails of the distribution. The changes in the tails of the distribution are particularly noticeable in the case of precipitation, showing that without the flux correction the model is unable to reproduce the frequency of large events. For the interannual variability the momentum-flux correction alone has a large impact, while the additional heat-flux correction is important for the teleconnections.

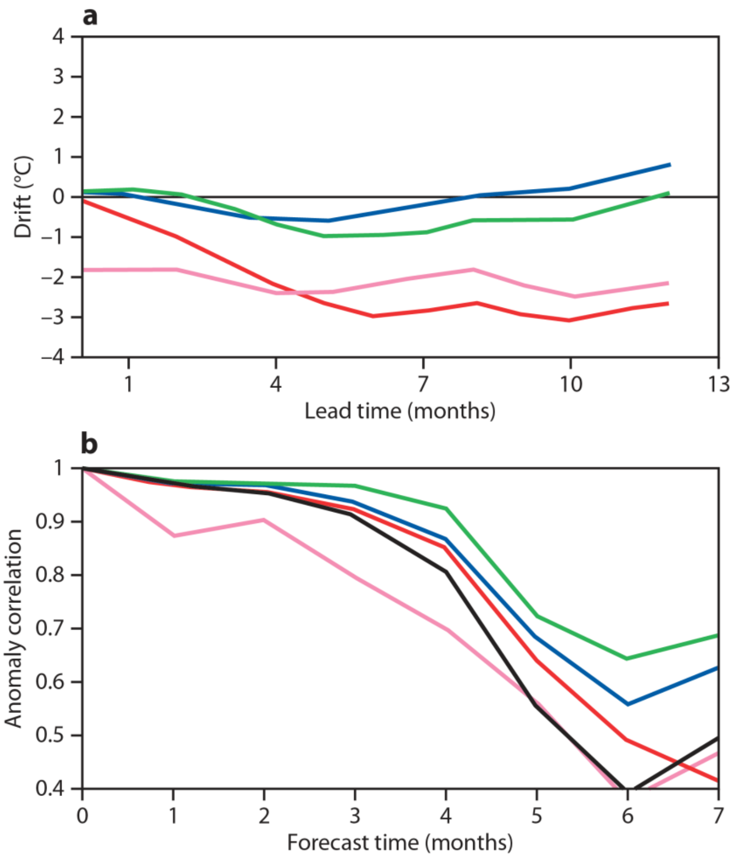

Figure 12. Forecast drift in SST (a) and skill in precipitation (b) in the Central Pacific from different forecast strategies: Full Initialization (red), Anomaly Initialization (pink), Momentum Flux Correction (green) and Momentum + Heat Flux Correction (blue). Black is persistence. The best skill is achieved by the Momentum Flux Correction. From Magnusson et al 2012b.

Magnusson et al 2012b show that full initialization results in a clear model drift towards a colder climate (although for other models the drift could be towards a warmer climate). The anomaly initialization is able to reduce the drift, by initializing around the model mean state. However, the erroneous model mean state results in degraded seasonal forecast skill. The best results on the seasonal time- scale are obtained using momentum-flux correction, mainly because it avoids the positive feedback responsible for a strong cold bias in the tropical Pacific. These results are illustrated in Figure 12. It is likely that these results are model dependent: the coupled model used here shows a strong cold bias in the Central Pacific, resulting from a positive coupled feedback between winds and SST. At decadal time-scales it is difficult to determine whether any of the strategies is superior to the other. Similar conclusions are reached by Smith et al 2012, using the Met Office forecasting system.

6 Summary

It has been shown that seasonal forecasting of SST is an initial condition problem. In order the initialize the upper thermal structure of the ocean it is important to assimilate ocean observations. Assimilation of ocean observations reduces the large uncertainty (error) due to the forcing fluxes. Using information from SST, surface fluxes from atmospheric reanalyses, subsurface temperature and salinity, and altimeter derived sea level anomalies is instrumental in the ocean initialization improves forecast skill.

Because seasonal forecasts need a-posteriori calibration, a sample of the model performance over a long enough period is required, which is obtained by performing a series of coupled hindcasts during some historical period. A historical record of hindcasts is also needed for skill assessment. Ocean reanalysis with reliable representation of the interannual variability are then required to initialize these hindcasts.

The most common initialization strategy is the so-called full initialization, where the data assimilation corrects the ocean model mean state, as well as the variability. In and in order to avoid spurious variability associated with changes in the observing system, consistent ocean reanalysis requires an explicit treatment of the bias during the initialization procedure. The bias estimation obtained during the initialization procedure could be in principle be used to correct model error during the forecasts. However, this is not possible when the full initialization is conducted in uncoupled mode, which currently is the most common practice. The separate initialization of the ocean and atmosphere systems can also lead to initialization shock during the forecasts. A more balance "coupled" initialization is desirable, but it remains challenging. The anomaly initialization is more frequently used in decadal forecasts, but shows weaker performance than the full initialization, especially at seasonal time scales. In decadal forecasts the anomaly initialization shows practical advantages regarding the computational cost of the calibration data set.

Systematic model error remains a difficult problem for seasonal forecasting and climate predictions. An error in the mean state could affect the variability of the system. Results indicate that the current forecast practices of removing the forecast bias a-posteriori or anomaly initialisation are by no means optimal, since they cannot deal with the strong nonlinear interactions. A consequence of the results presented here is that the predictability on annual time-ranges could be higher than currently achieved. The conclusion from the ECMWF model that the correction of the model mean state by some sort of flux correction leads to better forecasts needs to be assessed in other models. This may also lead to further model improvements since flux correction may be a powerful tool for diagnosing coupled model errors and predictability studies.

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