Improving seasonal forecasting through tropical ocean bias corrections

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Improving seasonal forecasting through tropical ocean bias corrections

David P. Mulholland, Keith Haines and Magdalena Alonso Balmaseda

1. Introduction

The initialization of coupled atmosphere–ocean dynamical models for forecasting on seasonal time-scales (∼3–9 months) currently poses a challenge to forecasters (Weisheimer et al., 2009; Barnston et al., 2011; MacLachlan et al., 2014; Saha et al., 2014). Observational information must be incorporated into both components of the models, particularly the ocean component, in order to realise skilful forecasts, but the optimum strategy for achieving this in the presence of biases that exist in all numerical climate models is not yet known (Balmaseda and Anderson, 2009; Magnusson et al., 2013; Smith et al., 2013; Thoma et al., 2015). One requirement of a successful model initialization procedure is that it avoids the generation of initialization shocks (Rahmstorf, 1995; Chen et al., 2011; MacLachlan et al., 2014; Saha et al., 2014). Observational information must be incorporated into both components of the models, particularly the ocean component, in order to realise skilful forecasts, but the optimum strategy for achieving this in the presence of biases that exist in all numerical climate models is not yet known (Balmaseda and Anderson, 2009; Magnusson et al., 2013; Smith et al., 2013; Thoma et al., 2015). One requirement of a successful model initialization procedure is that it avoids the generation of initialization shocks (Rahmstorf, 1995; Chen et al., 1997; Zhang et al., 2007; Zhang, 2011; Mulholland et al., 2015; Smith et al., 2015), due to inconsistencies or imbalances in the initial model state, at the beginning of the forecast, a problem which stretches back to the numerical weather predictions of Richardson (1922).

In coupled models, initialization shocks may be particularly prevalent in the Tropics, where the ocean and atmosphere are strongly coupled. In particular, close to the Equator, any imbalances between zonal wind stress and the zonal pressure gradients in the upper ocean can lead to the generation of subsurface ocean waves which propagate along the thermocline, later affecting sea surface temperatures (SST) in the eastern part of the ocean basins where the thermocline lies close to the surface (Harrison and Giese, 1988; Vecchi and Harrison, 2000). Via reflections at the basin boundaries, such signals can then remain in the ocean for O(1 year), and potentially longer via coupled feedbacks (Fedorov, 2002). Further, through atmospheric teleconnections, signals in tropical SST can exert a global impact (e.g. Trenberth et al., 1998; Mason and Goddard, 2001; Mathieu et al., 2004; Sanchez-Gomez et al., 2016). Zonal imbalances can easily arise when tropical mooring data, such as from the Tropical Ocean–Atmosphere (TAO) array (Hayes et al., 1991) are assimilated, leading to changes in ocean zonal pressure gradients. Although this problem is well known (Bell et al., 2004), it is still unclear whether this results in degradation in seasonal forecast skill, via nonlinear interactions which cannot be corrected by linear post-processing drift correction (Stockdale, 1997).

Fundamentally, this problem arises because of the relatively large uncertainties associated with atmospheric reanalysis wind speeds in the Tropics (Kent et al., 2013) and errors in the parametrization of the vertical propagation of turbulent wind
stress through the upper ocean. These result in biases in thermocline structure and in SST along the Equator, in both ocean models forced with reanalysed winds, and free-running atmosphere–ocean coupled models. Data assimilation attempts to correct these biases, using subsurface density information, but this creates large spurious circulations in the ocean analysis when the model effectively ‘rejects’ these corrections to the thermocline, due to the imbalance between zonal pressure gradient and wind stress forcing, leading to large adjustments at each analysis time step.

To preserve dynamical balance, and avoid these circulations, the ‘pressure correction’ bias scheme of Bell et al. (2004) was developed, and is now commonly used in operational systems, e.g., at the Met Office (Blockley et al., 2014) and ECMWF (Balmaseda et al., 2013). The pressure correction scheme modifies the pressure gradient forces in the tropical upper ocean, in order to allow the correct average thermocline structure (and hence realistic SST) to exist in the presence of erroneous wind stresses and/or vertical ocean mixing. The correction term may have a slowly varying (seasonal cycle) component, using a monthly climatology from a previous run of the ocean reanalysis, along with a higher frequency component, calculated from errors occurring on a time-scale of a few days (Balmaseda et al., 2007; Mogensen et al., 2012).

However, in forecast mode no ocean observations are available, so the correction scheme is usually switched off, since ocean wind stress errors develop rapidly in the free-running coupled model, making the calculated pressure correction term inappropriate. The model ocean must then adjust to establish a new balance between the zonal wind stress forcing (which it now ‘sees’ fully for the first time) and its density structure. This is the initialization shock which we will address in this article, and it occurs even before the free-running coupled model winds deviate from the winds used to force the ocean analysis, due to the instantaneous loss of the bias correction term. Forecast model winds will also drift from the truth, due to the existence of systematic biases, and this quickly dominates overall errors. However, the shock due to the removal of the bias correction term may interact nonlinearly with other drifts, and with the evolving forecast state, complicating the task of post-process forecast drift correction.

This choice of initialization methods is one example of a wider issue of seeking to find an optimum balance between creating accurate initial conditions close to the observed state, and allowing the model to remain consistent with its own, biased climatology, in order to avoid rapid adjustments in forecast mode when observational information is no longer available. It is similar to the choice between ‘full-field’ and ‘anomaly’ initialization (Pierce et al., 2004; Smith et al., 2007), in which anomalies from an observed climatology are assimilated into the model’s own biased climatology. Anomaly initialization avoids large forecast drifts at the expense of a realistic mean state, which can adversely affect the anomaly forecasts. It is not yet clear whether or in what circumstances the anomaly initialization method might be superior to full-field assimilation (e.g., Meethl et al., 2009; Magnusson et al., 2013; Smith et al., 2013; Polkova et al., 2014).

In this article we investigate the impact of the use, and subsequent removal, of the pressure correction term within the seasonal forecasting system at the European Centre for Medium-range Weather Forecasts (ECMWF), and evaluate the performance of different initialization methods which avoid the instantaneous removal of the bias correction term. We test our hypothesis that avoiding or minimizing initialization shocks in the tropical oceans can lead to improved forecast skill at several months’ lead time and beyond. The model used and the forecast sets performed are described in section 2. The results of the experiments are presented in section 3. Interpretations of the results and issues regarding the use of the various methods are discussed in section 4. Finally, the key results are summarised in section 5.
The final set of forecasts, DAMP, also used the bias correction, but with a scaling factor which decreases linearly to zero over a time window of 20 days from the beginning of the forecast. This was chosen to match the drifts in near-surface zonal wind along the Equator, which occur over ~10 days in the ECMWF system, while still ensuring that the correction term was not removed too rapidly. This aims to avoid prolonged use of a sub-optimal correction field while at the same time avoiding the initialization shock that is potentially present in OP due to the instantaneous removal of the field. Note that the methods PERS and DAMP require no future information, as they use only the climatological bias correction term, so are viable strategies for real-time forecasting.

To measure seasonal forecast skill, the root-mean-square error (RMSE) and anomaly correlation coefficient (ACC) were calculated for SST using NOAA’s Extended Reconstructed SST dataset (ERSSTv4; Huang et al., 2015) as the common reference for all forecast sets. The ACC and RMSE results presented here do not differ greatly if ORAS4 or ORAS4_nobc SST are used as references instead. ACC is insensitive to mean forecast drift, so ACC differences between forecast methods should be due to nonlinear interactions that cannot be removed through an a posteriori drift removal. The statistical significance of differences in ACC or RMSE time series between pairs of forecast sets was computed using a bootstrap sampling method over the 16-date forecast sets (Appendix). However, ‘climatologies’ for each forecast set are computed separately for each of the four seasons using only four dates, so values contain further uncertainty resulting from undersampling of climate variability in each season, and must still be viewed with caution.

2.3. Effect of the bias correction term

Differences in the initial conditions of OP and NOBC are shown in Figure 1 for ocean density and zonal velocity along the Equator, averaged over all 16 start months. Seasonal variations (not shown) are fairly small but not negligible, particularly in the Indian Ocean. In the equatorial Pacific, the effect of the pressure correction is to increase the density (reduce the temperature by up to 1 °C) and raise the thermocline by ~2 m around 100–150 °W, and to deepen the thermocline by 1–2 m close to the dateline and at the eastern boundary. The associated circulation response is upward and eastward at the depth of the thermocline at 120 °W, and westward at the surface. A similar pattern is seen in the Atlantic basin, while the response in the Indian basin includes a slightly weaker shallowing of the thermocline at 40–60 °E.

These differences make the initial conditions of OP (and PERS and DAMP) more consistent with observations, whereas NOBC is placed at a disadvantage by the neglect of bias correction in its initial conditions (Balmaseda et al., 2013). However, this also implies that the initial surface and subsurface temperature distributions in OP cannot be sustained by the model with the bias correction field, so OP forecasts are expected to drift rapidly in the opposite direction to the fields shown in Figure 1. That is, for example, a downwelling adjustment should occur in the eastern Pacific thermocline depth at 100–150 °W, and an upwelling adjustment should occur along the thermocline at around 180 °E. Also, westward surface currents should decelerate in the central Pacific and eastern Atlantic oceans. These adjustments, or initialization shocks, will be superimposed on ocean drifts that are driven by the atmospheric model during the first few days of the forecasts; e.g. if near-surface winds strengthen over the central Pacific, this could reverse the surface zonal current response to be one of acceleration, and could enhance the upwelling adjustment occurring in the underlying ocean.

3. Results

3.1. Thermocline response to initialization shock

The ensemble mean time series of the 20 °C isotherm depth averaged in Niño-4 (160 °E–150 °W, 5 °N–5 °S) for the first 30 days of each forecast set are shown in Figure 2(a), alongside the reanalyses ORAS4 and ORAS4_nobc. A shallow (linear) drift of the forecasts relative to the reanalyses is clear, caused by model biases. Variability with period 4–5 days is apparent in all forecasts, and some variability on this time-scale can also be seen in the reanalyses. Waves at this high frequency are slightly stronger in OP relative to the other forecasts, and there is an additional small (less than 1 m) upward thermocline adjustment in the first 1–2 days, as was predicted in the previous section to occur at 170–180 °E following the sudden removal of the bias correction field. The phase of the high-frequency wave in OP is also shifted by roughly half a cycle, while the other forecasts remain roughly in phase with the reanalyses out to 30 days’ lead time. (The slight downward adjustment from the reanalyses seen on day 1 in all forecast sets is another form of shock, and occurs as a consequence of the neglect of surface currents in the wind stress applied to ORAS4 and ORAS4_nobc, possibly combined with atmospheric wind drifts within the first 24 h; section 3.2.)

The frequency spectra in Figure 2(b) show clearly the additional wave energy present in the OP forecasts compared to the others,

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with a clear peak in the spectrum at $0.20–0.25\text{d}^{-1}$ (period $4–5$ days). This enhancement in wave energy in OP can be regarded as the signature of an initialization shock that occurs following the instantaneous removal of the bias correction term. The spectra confirm that the additional thermocline variability is not present in PERS, and in DAMP it appears to have been almost entirely removed. There is greater power at a range of frequencies in the two reanalyses, due to the forcing of the thermocline by assimilated subsurface observational data, particularly where these data capture mesoscale eddy processes that are at the limit of the model’s horizontal resolution ($30 \times 110$ km at the Equator).

Figure 3(a) confirms that day 1–15 differences in $20^\circ\text{C}$ isotherm depth temporal variability between OP and NOBC are initially largely confined to the Tropics ($15^\circ\text{N}–15^\circ\text{S}$), where the pressure correction method was applied in ORAS4. This is further evidence that the differences between OP and NOBC are due to the sudden removal of the bias correction term at the beginning of the OP forecasts, rather than the different initial model states (Figure 1) per se. At days 16–30 (Figure 3(b)), differences in $20^\circ\text{C}$ isotherm depth variability have spread to higher latitudes, suggesting that the long-term effects of initialization shock are not limited to the region in which the bias correction term is applied.

Substantial initialization shocks are present in the western parts of all three tropical basins (Figure 3(a)), where the thermocline is deepest. Anomalies in thermocline depth tend to propagate eastward as equatorial Kelvin waves, so the subsurface shock in the west can later influence the eastern parts of the basins, adding to any shock experienced locally there. Further, any shock effects felt in tropical SST have the potential to affect the global atmosphere via teleconnections. Extratropical weather patterns have been noted to be particularly sensitive to SST anomalies in the western/central tropical Pacific area (Barsugli and Sardeshmukh, 2002).

The amplitude and persistence of the initialization shocks in OP, NOBC and DAMP can be seen in Figure 4, which shows averaged wavelet spectra (Torrence and Compo, 1998) for Niño-4 $20^\circ\text{C}$ isotherm depth, for the first 60 days of the forecasts. Spectra were calculated for each of the 16 ensemble mean forecast series, and averaged for each forecast set and for ORAS4. The ORAS4 spectrum shows stronger power in the $4–8$ day band at $10–20$ days’ forecast lead time, despite being averaged over multiple start dates, indicating that edge effects are present in the calculation even beyond the marked ‘cone of influence’. Nevertheless, the initialization shock can be seen primarily as the enhancement of power at $4–8$ days’ period at $10–50$ days’ lead time in OP (Figure 4(a)) relative to the other forecasts (Figure 4(b, c)). In DAMP (Figure 4(c)), the power at $4–8$ days’ period is weaker than in OP by a similar amount to NOBC over the first 50 days, confirming that the initialization shock has been largely avoided.
in DAMP, by virtue of the more gradual removal of the correction field. The strong appearance of the initialization shock in the 4–8 days band is likely due to the excitation of a gravity wave mode, perhaps with some numerical interaction with the model spatial resolution, or the surface flux or SST forcing time-scales imposed in ORAS4.

There are also suggestions of reduced power at longer periods as the forecasts progress, at lead times of 40–60 days (Figure 4(b, c)) and longer (not shown). This is a possible pathway for initialization shock to affect seasonal forecast skill (sections 3.3 and 4.1).

### 3.2. Interaction with model drifts

We now look at the rate of development of model errors, since these will also affect forecast skill. Figure 5 shows the forecast drift in equatorial surface zonal wind stress, compared to ERA-Interim wind stresses, which were applied directly in ORAS4 (Balmaseda et al., 2013). Errors develop rapidly, and become fairly steady after around 10 days, when they can reach 25–50% of climatological wind stresses. Therefore, after around 10 days the bias correction field, which was derived for ERA-Interim wind stress forcing, is no longer valid. Its effect on the forecasts of PERS will vary regionally, depending on the structure of the correction field relative to the model drifts. Note that wind stress drifts on this time-scale are comparable to the formation of westerly wind bursts, so can be expected to impact tropical dynamics (e.g. Philander, 1981; Latif et al., 1988; Fedorov and Philander, 2001), in addition to initialization shocks.

In the western and central Pacific and the Indian Ocean, wind stress drift is negative, denoting strengthening easterly winds. This raises the thermocline around the dateline, via Ekman suction, as seen in Figure 5, generating an upwelling Kelvin wave which propagates eastward. By referring to Figure 1 it can be seen that the bias correction term acts in the opposite direction, increasing the depth of the thermocline, in the central Pacific (170–180°E), and to some extent the eastern Indian Ocean (80–90°E). In these regions, the mean drift in thermocline depth in the first month is reduced in PERS through the continued application of the bias correction term (e.g. Figure 2(a)), and the Kelvin wave generated is weaker than in OP as a result. Similarly, in the central equatorial Atlantic (~40°W), the shallowing effect of the bias correction term acts against the deepening that is caused by weakened wind stresses. In contrast, in the western and eastern edges of the Atlantic Ocean, the bias correction acts in the same direction as the initial drifts in wind stress, with respect to the thermocline, thereby accelerating the drifts.

In contrast to Niño-4, the Niño-3 (150–90°W, 5°N–5°S) thermocline initially adjusts downwards, with approximately twice the magnitude in OP as in the other forecasts, as...
the shallowing effect of the bias correction term is removed. Continuing the bias correction reduces initial drift errors in the first few days in the Niño-3 thermocline depth in PERS and DAMP. However, the longer-term drift in Niño-3 is a shallowing of the thermocline, beginning around month 2, caused by the arrival of an upwelling Kelvin wave generated in the western Pacific, following the strengthening of easterly wind stresses there. This shallowing of 5–10 m is then amplified if the bias correction term is continually applied, resulting in a 1–2 m shallower thermocline in months 3–7 in PERS (not shown).

In summary, on the monthly time-scale, the continued application of bias correction in PERS interacts with coupled model drift and may improve or degrade the upper ocean forecast, depending on the region. In the first 10 days, the bias correction term can either amplify or dampen Kelvin wave signals generated along the thermocline by rapid drifts in surface wind stress. In the Niño-4 region, where the largest initialization shocks occur in OP, the bias correction term partially cancels the effects of wind stress drift in the short term, which may be of benefit to the forecast. This effect occurs in both PERS and DAMP, but only DAMP avoids drift interactions on longer time-scales.

3.3. Effect on forecast skill

We now examine whether the responses in the equatorial thermocline to initialization shocks and persisted bias correction have any longer term impact on the skill of the coupled forecasts. The ACC for the monthly SST forecasts, evaluated against the Extended Reconstructed Sea Surface Temperature (ERSSTv4), is shown for the Niño-4 and Niño-3 regions in Figure 6(a) and (b), respectively. In Niño-3, where the most substantial area of high skill beyond ~3 months’ lead time exists, ACC for OP and NOBC are fairly similar over months 1 to 6. In fact, in the first month ACC is larger in NOBC, significant at the 90% level, and in the last 2 months ACC in NOBC again rises above that of OP, reaching 95% significance in month 7. In Niño-4, OP and NOBC are very similar from month 4 onwards. Therefore, despite the more accurate initial conditions used in OP, we suggest that the initialization shock from the removal of the bias correction has prevented significantly more skilful forecasts being achieved in the equatorial Pacific.

Over all 7 months, SST forecast skill in Niño-3 is highest in DAMP. ACC in DAMP is superior to OP from month 3 onwards, at the 95% level in months 4 and 7 (in month 7, differences are more than 0.05), and at the 90% significance level in month 6. DAMP is also superior to NOBC in months 3 to 6, with this difference being significant in months 3 and 4 (not marked). In Niño-4, DAMP again performs best, particularly in the first 3 months.

Figure 6(c) and (d) show the uncalibrated SST RMSE (i.e. including the mean drift), in Niño-4 and Niño-3, respectively. Mean error in Niño-3 is significantly lower in NOBC in the first 2 months (Figure 6(d)), perhaps due to better agreement between ORAS4 Nobc and ERSSTv4 in this region than between ORAS4 and ERSSTv4, and this may contribute to the increased ACC in NOBC in month 1. However, the increased skill in NOBC in months 6 to 7 (Figure 6(b)) cannot similarly be attributed to reduced mean drift, since the mean state appears to be largely independent of initialization procedure by this stage in the

Figure 6. SST ACC versus ERSSTv4 for (a) Niño-4 and (b) Niño-3, for all four forecast sets. Filled (open) squares show values that are different from the OP value at the 95% (90%) significance level, calculated using the bootstrap method. (c, d) are as (a, b), but show raw RMSE (°C) versus ERSSTv4.
forecasts. Similarly, in Niño-4, the increase in skill in DAMP in months 2 and 3 (Figure 6(a)) occurs despite slightly increased mean error (Figure 6(c)). The mean drift is also decreased slightly in DAMP in Niño-3 (Figure 6(d)) from month 3 onwards, although not significantly so, which likely contributes to the improved ACC skill at these lead times.

PERS performs worst of the four methods in Niño-3 (Figure 6(b)), although differences from OP are only significant in one of the 7 months. It does somewhat better in Niño-4 (Figure 6(a)), despite a significantly larger mean drift from month 2 onwards (Figure 6(c)), the occurrence of which shows that the favourable interaction between the bias correction and the mean drift that was seen initially in the Niño-4 thermocline depth (Figure 2(a)) is not felt in SST at longer lead times.

The spatial distribution of SST ACC differences at 6 months’ lead time is shown for DAMP relative to OP in Figure 7. Differences are regionally dependent, but there is an overall predominance of positive values. The regional variability is probably due in part to an insufficient number of start dates, although it is plausible for skill to be degraded by the use of bias correction in the first 20 days, in areas where this increases the mean drift in DAMP relative to OP. More generally, the reduction in initialization shock in DAMP would be expected to increase forecast skill, if anything, and this is indeed the case on average (global mean ACC is 6% higher in DAMP than in OP), and in the tropical Pacific in particular, where SST skill is most important for driving atmospheric teleconnections.

Since differences in skill at the gridpoint scale may suffer from undersampling of forecast start dates in the 16-date sets used here, it is better to compare performance on a globally averaged basis. Table 1 shows several such metrics for SST ACC in month 6. OP performs best in none of the categories, though often differences between methods are small. Overall, DAMP performs best, including showing the largest global mean skill at this lead time. PERS also performs well in several of the metrics, but does poorly in the Niño-3 region. In month 7 (not shown), the performance of DAMP relative to the other methods increases further in several metrics.

The four methods are compared globally at other lead times in Figure 8, which shows the fraction of ocean gridpoints, weighted by area, with SST ACC greater than 0.5 in each forecast month, relative to the fraction above 0.5 in OP. By this measure, NOBC develops an advantage over OP at around month 4, and maintains this advantage at subsequent lead times, although the difference only reaches the 90% confidence level in month 7. DAMP, however, emerges as at least as good as any other method from month 4 onwards, and its superiority over OP increases over months 5 to 7. OP ranks last of the four sets in each month from month 4 onwards, although by this metric it is only inferior at the 90% significance level in month 7.

The ACC was also calculated for atmospheric variables such as precipitation rate and 500 hPa geopotential averaged over months 5–7, measured against ERA-Interim, but estimates were noisy and most differences were not statistically significant. A larger number of forecasts would be needed to assess differences in skill in these fields. Since forecast skill in atmospheric variables is expected to be largely derived from skilful predictions of SST, it is still an important step to demonstrate the improvements in SST here.

Finally, the four forecast sets may be compared using the El Niño–Southern Oscillation (ENSO) forecasting ‘figure of merit’ (FOM), defined as the average mean absolute error in predicted SST (in °C) over months 1–6, calculated for Niño-4, Niño-3.4 (120°W–170°W, 5°S–5°N) and Niño-3, added together and multiplied by 1000 (Molteni et al., 2011). To calculate this, the forecasts were first calibrated by removing the mean drift, calculated separately for each of the four seasons. The FOM for OP, NOBC, PERS and DAMP respectively are 785, 793, 834 and 739. With this metric (which extends only to month 6), it can be seen that OP and NOBC are roughly equivalent, but both are clearly outperformed by DAMP. The improvement in FOM of ∼40 points, achieved through the Niño-3 and Niño-3.4 components, is comparable to the differences seen between successive versions of the ECMWF operational system (Molteni et al., 2011). These FOM values cannot be compared directly to the operational scores given by Molteni et al. (2011) due to the different start dates involved in each calculation, and several other differences in experimental set-up (ensemble size and generation method, use of separate calibration hindcasts).

3.4. Understanding the improvement in DAMP

Figure 9 shows the mean difference in °C isotherm depth (averaged over 5°N–5°S) between OP and DAMP. Eastward propagating signals are present in the first month, consistent with the bias correction field in Figure 1; that is, an upwelling signal originating around 170°E, and downwelling signals originating around 50°E, 130°E, 150°W and 40°W. These signals capture the component of the thermocline shocks present in OP but not in DAMP. These signals propagate at ∼50° (month)−1, so can be identified as Kelvin waves, and together they affect virtually all longitudes within ∼50 days. There is also evidence of slower, westward Rossby wave propagation, in the Pacific: a downwelling
signal originates at around 120°W and moves westward at ~10°/month, passing Kelvin waves moving eastward at around 40 and 70 days’ lead time. Any interactions between these waves, or between waves close to the surface and the atmosphere via convective coupling (Straub and Kiladis, 2002), will be highly nonlinear and cannot be corrected for by post-processing drift removal, and therefore have the potential to degrade forecast skill.

In Figure 10 the individual Niño-3 SST forecasts that are combined to produce the skill scores of Figure 6(b) are examined in more detail. Differences in forecast SST anomalies are small, but it can still be seen by eye that DAMP ensemble means agree slightly better with the ERSSTv4 reference than do OP ensemble means. In a few cases (February 2007, May 1984, while in other cases (August 1980, November 1993) the DAMP advantage emerges only in the last 2 months, as a loss of accuracy in OP becomes apparent. These latter cases perhaps suggest a more complicated route for differences to reach the surface in the eastern Pacific. However, the spread of ensemble members indicates that differences in single forecasts should not be treated as robust. The correlation of SST anomalies with ERSSTv4 show particular improvements in DAMP over OP in the May forecasts, but DAMP values are higher in all four seasons. Calibrated (i.e. after mean drift removal) RMSE values also show a general improvement in DAMP, with largest differences in May. Since there are only four cases in each season, these differences should not be over-interpreted.

4. Discussion

4.1. Impact of initialization shock

Chen et al. (1997) noted that high-frequency signals in the initial conditions act as noise to the coupled model, and degrade forecast skill. They found that, while SST forecast skill at lead times of ≤8 months was improved by reduction in large-scale systematic errors in the initial conditions (as is the case in OP, compared to NOBC), improvement in skill at longer lead times was due primarily to the reduction of random noise in the initial conditions. It is in this context that the effectiveness of PERS and, in particular, DAMP can be understood. By constraining upper ocean adjustment over the first 20 days, spurious variability at 4–8 days’ period is avoided in DAMP, increasing the fraction of the ocean’s total spectral power that is contained in low-frequency modes, compared to OP (Figure 4). Accurate representation of these large-scale patterns can lead to improved forecast skill, particularly at long lead times.

Thoma et al. (2015) reported better surface temperature forecast skill at lead times of 2–9 years, especially in the Pacific, when initializing their coupled model with observed wind stress anomalies only, compared to an OP-style initialization using ORAS4. It appears that these differences can be attributed to a combination of initialization shocks due to atmosphere–ocean initial condition imbalance and bias correction removal in the OP-style initialization, which affect simulated ENSO and Interdecadal Pacific Oscillation variability on multidecadal time-scales. The results of Thoma et al. are therefore further evidence of the potential to improve long-range forecasts by reducing initialization shocks, and suggest that the benefits of DAMP may be seen more clearly still at lead times longer than 7 months.

4.2. Significance of increases in ACC

The non-monotonic form of the curves plotted in Figure 6(a) and (b), in comparison to the relatively smooth curves shown in Figure 5.4.5(a) of Molteni et al. (2011), is a result of the limited number (16) of start dates used in the ensemble. The significance test used gives an estimate of the confidence in the improvement in DAMP over the other sets, but this could be an underestimate if the 16-date ensemble is not fully representative of the period covered. However, further confidence in DAMP is provided by the fact that the DAMP ACC in Niño-3 are consistently higher than those of OP, and that this difference broadly increases with increasing lead time, consistent with the notion of errors gradually accumulating through nonlinear interactions in the upper ocean and at the surface. Also the consistent ranking of DAMP above OP, and often above NOBC, in the other metrics presented in Table 1 and Figure 8, and the clear demonstration of reduced thermocline noise in DAMP, justify the claims of improvement.

Müller et al. (2005) and Shi et al. (2015) suggested that hindcast sets of around 20 start dates are too small to give robust estimates of seasonal forecast skill. However, while individual values in Figure 6(a) and (b) may not be robust estimates of absolute skill levels, greater confidence can be given to differences between the methods, since the same forecast model is used in all cases, such that the variation in potential predictability among forecast dates should be similar for each method. DAMP performs consistently better than OP in various subsets of the 16 start dates used (significance measures in Figure 6(a) and (b), and seasonal breakdowns in Figure 10). Since differences between the OP and DAMP systems are small, differences in forecast SST on a given date arguably provide more information on likely improvements in true forecast skill than would differences between two different models on the same date.
Nevertheless, this new method of handling bias during seasonal forecasts needs to be tested in a larger set of hindcasts to confirm its usefulness for operational prediction. More extensive tests should also investigate how differences between the methods change when larger ensembles are used (ECMWF seasonal forecasts currently use ensembles of 51 members), and how the dynamics of the initialization shock are affected by ocean model resolution.

### 4.3. Further improvements

Several operational centres are moving towards coupled data assimilation methods (Laloyaux et al., 2016; Lea et al., 2015) for producing initial conditions for seasonal and shorter-term forecasts. With a coupled analysis, it should be possible to produce a bias correction field more appropriate to the atmospheric model component of the coupled analysis. Tests using the Coupled ECMWF ReAnalysis system (CERA; Laloyaux et al., 2016) have shown that tropical wind drifts are slower than in all four sets featured here, due to the use of consistent atmospheric model versions in the analysis and forecast phases, and the use of wind stresses accounting for surface ocean currents (which is not possible in an uncoupled atmospheric analysis such as ERA-Interim). With winds that drift more slowly, the bias correction should remain valid for a longer time during the forecast, so an initialization similar to DAMP or PERS could potentially be even more effective when combined with coupled assimilation.

We have not fully explored how forecast skill varies with the time-scale used to dampen the bias correction, and 20 days may not be the optimum value. For coupled initialization, the time-scale may perhaps be lengthened to further reduce the amplitude of the initialization shock. It may be desirable to vary the time-scale regionally, depending on the drifts that occur in the first month or so (Figure 5). It is also possible that a nonlinear damping of the correction field may be more suitable.

### 5. Summary

A number of seasonal forecast strategies, using ocean initial conditions both with and without equatorial bias correction, have been evaluated. It was found that a straightforward use of pressure correction during the ocean analysis phase followed by removal at the beginning of the forecast (set OP), as is current operational practice, leads to the generation of an initialization shock at the equatorial thermocline. It was further shown that this reduces SST forecast skill at lead times of 3 to 7 months. By some measures, using initial conditions formed without bias correction (set NOBC) outperforms this method, but better performance can be achieved using bias-corrected initial conditions by avoiding the sudden removal of the correction term. Continuing to apply the correction indefinitely (PERS) gives at least comparable forecast skill to the operational method but affects the long-term drift, while slowly removing the correction term over the first 20 days (DAMP) performs best of the four methods overall. This largely avoids the generation of noise in the thermocline and leads to more skilful tropical SST forecasts at lead times of 3 to 7 months. The results highlight the importance of the tropical ocean to delivering skilful forecasts on seasonal time-scales, and of the potential for...
unwanted nonlinear interactions among propagating subsurface waves to hinder forecasting efforts. It is recommended that the method DAMP be tested over a larger set of forecast start dates to robustly measure its potential for use in operational seasonal forecasting.

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Appendix
Calculation of ACC and significance testing
The centred version of the anomaly correlation coefficient (ACC) is used, in which anomalies are calculated relative to specific climatologies for each forecast or reanalysis set. Forecast and reanalysis (ORAS4 or ORAS4_nobc) ensemble means for each of the four seasons are used as seasonal climatologies, with respect to which anomalies are computed, at each lead time. Since each season of the climatologies is comprised of only 4 years (4 of the 16 dates), these will be only approximations to the true, long-term climatologies, which could only be obtained using a greater number of start dates for each forecast method. Because of this (as well as other specifics including ensemble size), the resulting ACC values cannot be compared directly to other published values calculated using larger forecast sets, such as those in Molteni et al. (2011).

Instead, ACC are compared among the different forecast methods. In order to account for sampling error due to the finite number of start dates used, a bootstrap method (e.g. Smith et al., 2013) is used to calculate significance levels for difference between OP and the other methods at each lead time. For this, the 16-date set is sampled randomly with replacement, to form 1000 possible forecast sets. Differences between methods are computed for each of these 1000 combinations of start dates, and differences that appear in at least 900 (950) cases are marked as being significant at the 90% (95%) level. However, this sampling method cannot account for possible unsampled climate variability in the four dates used for each season, so differences between values must still be treated with some caution.

Note also that in operational use, climatologies can in fact only be calculated using all forecasts except the one being measured ('leave-one-out'), since it has not yet been verified. By including in the four dates used for each season, so differences between methods in this work, overestimation of their absolute values (in all cases) is not a problem.

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