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Assessing the impact of observations on ocean forecasts and reanalyses: Part 1, Global studies

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Under GODAE OceanView the operational ocean modelling community has developed a suite of global ocean forecast, reanalysis and analysis systems. Each system has a critical dependence on ocean observations routinely assimilating observations of *in situ* temperature and salinity, and satellite sea level anomaly and sea surface temperature. This paper demonstrates the value and impact of ocean observations to three global eddy permitting forecast systems, one global eddy permitting model independent analysis system, one eddy resolving reanalysis system, and two seasonal prediction systems. All systems have been used to assess the impact of Argo profiles, including scenarios with no Argo data, and a degraded Argo array unanimously concluding that Argo is a critical data set the most critical for seasonal prediction, and as critical as satellite altimetry for eddy permitting applications. Most systems show that TAO data are as important as Argo in the tropical Pacific, and that XBT data have an impact that is comparable to other data types in the vicinity of XBT transects. It is clear that no currently available data type is redundant. On the contrary, the components of the global ocean observing system complement each other remarkably well, providing sufficient information to monitor and forecast the global ocean.

Introduction

Global ocean forecasting is important for a range of public-good and commercial applications (Davidson et al. 2009). Reliable ocean forecasting has the potential to positively impact a broad range of these applications; providing timely and accurate estimates of the current and future state of the ocean. Maintenance of each component of the Global Ocean Observing System [GOOS; www.ioc-goos.org] depends, to some extent, on an ongoing demonstration of the value of the collected observations for all the applications mentioned above. This paper provides an evidence-based community perspective of the value of observations from the GOOS to the ocean forecasting community. It presents a synthesis of the results obtained under the framework of the GODAE OceanView Observing System Evaluation (OSEval) Task Team. It includes results from Observing System Experiments (OSEs), where different components of the GOOS (e.g. satellite altimetry, Argo profiles) are systematically withheld from an assimilating system. For each experiment, the degradation of each system's performance is quantified when different observation types are withheld.

Earlier studies conducted by the GODAE community that involved OSEs, and related approaches, have been documented in the published literature (Oke et al. 2009). The most common method for quantifying the impact of observations on a forecast/analysis system is the use of traditional OSEs (Balmaseda 2007; Oke & Schiller 2007; Smith & Haines 2009). This paper includes several traditional OSEs, plus some novel implementations of OSEs, including a series of near-real time (NRT) OSEs (Lea 2012; Lea et al. 2013) and a 'total-denial' OSE. The NRT OSEs were performed in parallel with an operational ocean forecast system, where data were systematically withheld from the NRT OSE, to provide an up-to-date demonstration of the impact of each component of the current GOOS on operational ocean forecasts. The 'total-denial' OSE, while not produced in NRT, demonstrates the impact of a total loss of observations to a forecast system, quantifying the degradation of the forecast system over time. This paper also presents some results related to the investigation of alternative methods that allow a direct assessment of the relative impact of ocean observations in a given system.

This paper provides an update on this community's contribution to this field, under the auspices of GODAE OceanView. Many studies have previously quantified the impact of each GOOS component. However, the GOOS

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is always changing, with the number, constellation, and sampling of satellite altimeters varying every few years, the number of Argo floats increasing (until recently) and the distribution of Argo floats and XBT surveys rarely replicating. It is, therefore, important for studies that evaluate the GOOS for different applications, including ocean forecasting, to be repeated regularly; so that published results are up-to-date and relevant. Continuous efforts to quantify the impact of observations, demonstrating their importance to the society and institutes deploying observation platforms are also essential for sustaining the indispensable ocean observation system in an efficient state. This paper seeks to provide an update on the GODAE OceanView community's efforts to demonstrate the value of observations to assimilating global ocean models. Additionally, this study demonstrates the evolution, and perhaps the coming of age, of observing system evaluation studies. Such studies are becoming less focused on the evaluation of historical observing systems, and more focused on evaluation of the current observing system. Several studies reported in this paper highlight this change, which is in response to the growth and importance of operational oceanography. A companion paper, focusing on regional observing system evaluation studies, complements this review paper (Oke et al. 2015).

In this paper, details of the forecast systems are first introduced, followed by results, a short discussion, and a series of recommendations.

Models

The systems used in this study include the 1/4°-resolution global ocean forecast systems developed by Mercator Océan (Lellouche et al. 2013), the Met Office (Storkey et al. 2010; Blockley et al. 2013) and the Canadian consortium (Smith et al. 2014), a 1/10°-resolution reanalysis system developed under Bluelink (Oke et al. 2013a; Oke et al. 2013b), a 1/4°-resolution model-independent analysis system developed at CLS (Guinehut et al. 2012), two operational seasonal prediction systems, currently operated at JMA (Takaya et al. 2010; Fujii et al. 2012) and ECMWF (Balmaseda et al. 2013). Several of these systems share a common source code for the model (i.e. NEMO), similar grids and topography; but in most cases, different data assimilation systems and different surface forcing. Each system is run independently, and assimilated observations are prepared and processed differently.

In this paper, results using global eddy-permitting systems are presented for a traditional set of OSEs using the Mercator system; for a series of NRT OSEs – a novel twist on the traditional OSEs – using the Met Office system; for a single 'total denial' scenario, where it is assumed that all observations are unavailable, using the Canadian system; and analysing some alternative diagnostics using the CLS system. These studies represent a cross-section of approaches to demonstrate the value of observations on eddy-permitting forecast and analysis systems. These studies are complemented by a series of traditional OSEs using the Japanese and European seasonal prediction systems.

It is important to note that the results from the types of OSEs presented in this paper depend on the details of the model and assimilation system used.

It is important to note that the results from the types of experiments presented in this paper depend on the details of the model and assimilation system used. This includes the model resolution, model physics, assimilation method, estimated background error covariance, observation error estimate and method of initialisation. The results provide a meaningful representation of the impact of assimilated observations on each system, given their strengths, weaknesses, assumptions and limitations. Furthermore, it is anticipated that although some of the studies presented below focus on observation impacts in specific regions, for specific times, the results are indicative of observation impacts in other regions with similar dynamics and for other systems using similar methods or approaches. To avoid misleading conclusions resulting from these deficiencies, results from a number of different, independent systems are employed here; with the intention of identifying the most robust and reliable results from the operational oceanography community.

Results

Several studies presented below include results showing statistics computed from the difference between two OSE simulations, where OSE_{X+Y} assimilates observation types X and Y, and OSE_Y that assimilates only observation type Y. The difference between OSE_{X+Y} and OSE_Y does not necessarily quantify the 'improvement' attributable to observation type X. However, it does faithfully quantify the 'impact' of assimilating observation type X. It is preferable to quantify the improvement, not just the impact, but the availability of sufficient independent observations is a common problem for systems that seek to assimilate all available observations.

Mercator OSEs

Mercator Océan generates operational ocean and ice analyses and forecasts using a global 1/4° model, using NEMO as the base code. This modelling system assimilates SST, *in situ* temperature and salinity profiles, and along-track SLA using an assimilation scheme called SAM2 (Lellouche 2013); a multivariate reduced-order extended Kalman filter, a variant of Ensemble Optimal Interpolation (Oke et al. 2002; Evensen 2003).

To assess the impact of Argo observations on the global ocean forecast system, the Mercator system is used to perform a series of OSEs that assimilate all available Argo data, half of the available Argo data, and no Argo data – in addition to SST and SLA. All OSEs are initialised with identical initial conditions, forced with identical surface forcing, and are run for one year, starting in January 2012. To evaluate each OSE, the Observation minus Background (OmB) values for temperature and salinity are analysed using all Argo data. The OmB statistics provide an indication of the forecast error, quantifying the misfit to observations immediately before assimilation.

Figure 1 shows the global root-mean-squared difference (RMSD) between the observations and the background temperature and salinity fields immediately before assimilation for 2012 for all OSEs. When no Argo data are assimilated the OmB values increase by 40–45% compared to the OSE that assimilates all Argo data. The relative degradation is approximately uniform down to 2000 m depth. When data from only half the Argo floats are assimilated, the OmB values increase by about 15% for temperature and salinity. The regional impact of Argo floats is sometimes very large (not shown). The neglect of Argo data degrades the properties in the mixed layer and at depth in key regions, such as the Mediterranean outflow and in the Labrador Sea during periods of convection (not shown), which are known model weaknesses. This shows the importance of Argo data for initialising crucial aspects of the ocean circulation, such as the depth of the Mediterranean outflow. In the Labrador Sea, when no Argo data are assimilated, the warmer water between 200 and 400 m depth beneath the thermocline under the winter convection events (Yashayaev & Loder 2009), are not generated or maintained (Figure 2). The impact of Argo data on the upper ocean indicates that Argo is critical for constraining the broad scale properties of the ocean, upon which the mesoscale circulation depends.

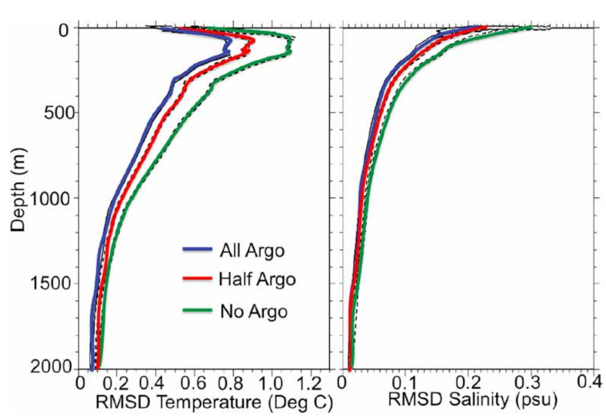

Figure 1. Global mean root mean squared difference (RMSD; OmB) profile for 2012 in temperature (left) and salinity (right): in the Mercator run assimilating all Argo floats, half Argo floats, and no Argo floats.

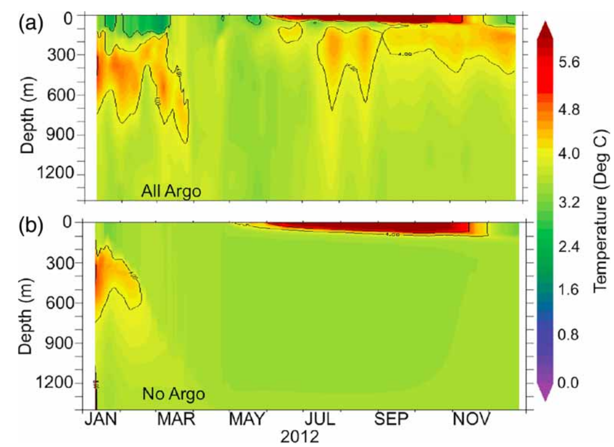

Figure 2. Time evolution of the temperature profile in the Labrador Sea at 55°W 59.3°N for two Mercator OSEs: (a) all Argo data assimilated; and (b) no Argo data assimilated.

FOAM NRT OSEs

A number of NRT OSE experiments were performed in 2011 with the UK Met Office's operational ocean forecasting system, FOAM (Storkey et al. 2010; Lea 2012, Lea et al. 2013; Blockley et al. 2013). These experiments adopt the same approach as that described above for the Mercator system, except that they were performed by running a parallel, identical version of the UK operational system, with different data types systematically withheld. Each month a single additional OSE is performed alongside the operational system. The operational system assimilated all available data. On average, each month, the operational system assimilates 120K XBT, 900K TAO, 1.1M altimetric, 30M SST, and 1.3M Argo observations (where K denotes thousands, and M denotes millions). For each OSE, a different set of observations was excluded from the assimilation. By comparing the results of the run excluding a particular observation type with the operational run, the impact of the withheld observations on the FOAM system was assessed.

Each month an OSE was initialised with fields from the operational system, and then a different observation type was excluded from the assimilation for that month. During the month the operational and OSE runs were run independently. The observation types excluded in the OSE runs were XBT in February, TAO/TRITON in March, Jason-2 altimeter in April, all altimeter data in May, AVHRR sea surface temperature (SST) in June (AATSR, AMSRE, and *in situ* SST data were assimilated, totally 17.8M assimilated SST observations, with 8.8M with-held SST observations) and Argo data in July.

Results are summarised in Table 1, showing the number of withheld observations, the 90th percentile, mean, and maximum of the absolute differences between each OSE and the control (operational) run for temperature at 100 m depth (T100), salinity at 100 m depth (S100), and sea-

Table 1. Statistics of the differences between each FOAM NRT OSE run and the control run showing the 90th percentile (pc) of the absolute difference, the mean absolute difference, and maximum absolute difference for key variables including the sea surface height (SSH), and temperature and salinity at 100 m depth (T100 and S100 respectively), over the entire globe and over the Tropical Pacific. Also shown is the number of withheld observations for each OSE. Note that 'No SST' withheld AVHRR and METOP, but assimilated 17.8M SST observations from AATSR, AMSRE and *in situ* sources.

	No XBT	No TAO	No J2	No ALT	No SST	No Argo
Number of with held observations	128 K	816 K	495 K	1.1M	8.8M	1.3M
T100: Global (Deg C)						
90th pc	0.080	0.105	0.511	0.805	0.120	0.698
Mean	0.037	0.050	0.187	0.290	0.048	0.270
Max	5.421	7.228	9.848	11.080	6.628	10.529
T100: Tropical Pacific (Deg C)						
90th pc	0.112	0.429	0.583	1.050	0.134	0.872
Mean	0.046	0.167	0.255	0.452	0.055	0.374
Max	3.024	6.005	6.275	9.098	3.153	4.786
S100: Global (psu)						
90th pc	0.007	0.016	0.067	0.100	0.011	0.097
Mean	0.003	0.007	0.024	0.037	0.005	0.039
Max	0.981	1.458	1.575	1.792	0.849	1.355
S100: Tropical Pacific (psu)						
90th pc	0.012	0.051	0.087	0.129	0.016	0.117
Mean	0.005	0.019	0.036	0.055	0.007	0.049
Max	0.368	1.091	0.768	1.373	0.849	0.543
SSH: Global (cm)						
90th pc	0.27	0.35	2.46	7.23	0.47	2.94
Mean	0.13	0.18	1.05	3.77	0.19	1.33
Max	26.95	23.76	79.88	80.61	14.95	49.76
SSH: Tropical Pacific (cm)						
90th pc	0.18	0.83	2.14	8.17	0.32	1.70
Mean	0.08	0.34	0.98	4.55	0.15	0.76
Max	6.27	23.76	16.78	49.38	7.42	11.77

surface height (SSH), for the entire globe and for the Tropical Pacific.

One of the main conclusions from this study is that there is complementary information in different data types (Lea 2012; Lea et al. 2013). More specifically, while XBT data do not impact global metrics significantly they do have significant local impacts (with T100 differences of up to 2°C along XBT transects; see Lea et al. 2013, Figure 2; see also the global mean and maximum differences for the 'No XBT' OSE in Table 1). Data from the TAO/TRITON array also have a large impact locally in the Tropical Pacific, where Argo data are relatively sparse. Altimeter data have a strong impact on the model sea-surface height (SSH) and a positive impact on the fit to mesoscale velocities (Lea 2012; Lea et al. 2013) (not shown). AVHRR SST data has significant impacts between the surface and the bottom of the surface mixed layer, but has little impact at greater depths. By contrast, Argo data impacts the temperature and salinity globally, down to 2000 m depth (Lea 2012; Lea et al. 2013) (not shown); consistent with the results from the Mercator system, described above. Furthermore, by correcting for model drifts, Argo data enables the forecast system to more accurately forecast SSH and surface velocities (Lea 2012; Lea et al. 2013) (not shown).

Globally, altimeter and Argo data have the largest and comparable impacts on model temperature, salinity, and SSH. If the impact is assessed more locally, in the Tropical Pacific, TAO/TRITON has a similar impact to both altimetry and Argo data (compare the 'No TAO' statistics with 'No ALT' and 'No Argo' in Table 1). XBT data still shows a much smaller impact overall but the maximum differences in the immediate vicinity of XBT lines show some large and persistent impacts in temperature that are often around 1 degree C, and sometimes greater (see the maximum differences for 'No XBT' in Table 1).

GIOPS OSEs

The Canadian Operational Network of Coupled Environmental Prediction Systems (CONCEPTS) consortium have taken a different approach to demonstrate the value of observations on an ocean forecast system – answering the question: how long does it take for a system to degrade after data stops being assimilated? This approach is motivated by recognizing the importance of considering the tolerance of an operational ocean forecasting system to delays, or dropouts, in the NRT delivery of observations to forecast centers. For example, if a particular *ftp* server used to obtain observations was shut down temporarily, for how long could a given operational system continue to provide useful forecasts before it should be stopped because it is too inaccurate? Clearly, this depends on the particular observation dataset, forecasting system and application. Regardless, such knowledge is required to ensure product quality for users.

To provide a rough estimate of the decrease in analysis and forecast skill for such an event, a simple OSE is performed using the experimental Canadian Global Ice Ocean Prediction System (GIOPS) (Smith et al. 2014). All observations that would normally be assimilated are simply withheld from the forecast system and the misfit between the model fields and observations is assessed over time.

GIOPS has been running experimentally in operations at the Canadian Meteorological Centre (CMC) since March 2014, producing daily analyses and 10-day ice-ocean forecasts using the 1/4° global resolution NEMO-CICE modeling system and the Mercator assimilation system, referred to above. Ocean analyses are blended with ice concentration analyses produced using a 3DVar method (Smith et al. 2014).

Figure 3(a) shows the global RMSD of OmB for temperature using all available *in situ* observations (Argo, moorings, etc.). The experiment was initialised in January 2011 from a GIOPS analysis and run for 2 months before denying all observations, starting in March 2011. As GIOPS uses a 7-day assimilation window, RMSD between the trial and observations can be considered to be representative of roughly 1–7 day forecast error. When observations are not assimilated the forecast errors begin to grow, with a 50% increase after a few months. Only after 6 months of integration without data assimilation, the errors begin to saturate. While significant regional variations are present (not shown); this nonetheless gives an indication of the system tolerance to observation dropouts.

In Figure 3(b)-(c), the global SST mean and RMSD with the CMC SST analysis are shown. A reference experiment with no assimilation is also shown. The SST errors show a similar response to that seen for *in situ* observations with errors growing rapidly over a 1–2 month period. While the mean errors (biases) saturate fairly quickly (2 months), the RMS errors only reach background values after 6 months. In general, SLA errors grow more quickly (not shown).

The majority of data streams for assimilated observations (e.g. Argo, XBT, and altimetry) in operational oceanography are not 'operational' (i.e. not 24-7 supported). As a result, data-dropouts are common. As such,

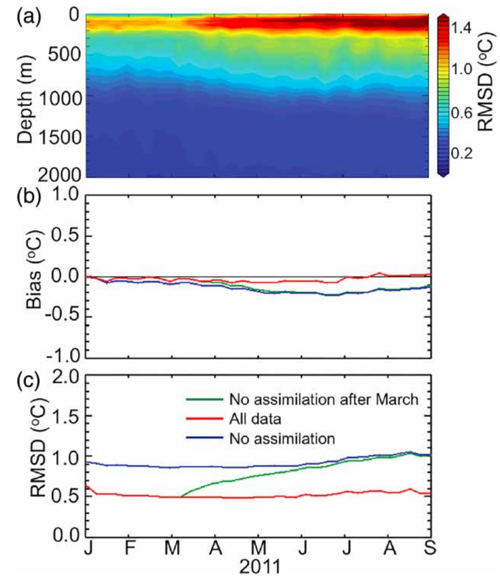

Figure 3. (a) RMSD between GIOPS temperature and *in situ* temperature observations for an OSE where there is no data assimilated after March 2011. (b) bias (mean difference) and (c) RMSD between GIOPS SST and CMC operational SST analyses for an OSE where no data are assimilated after March 2011 (green) when all data are assimilated (red), and for a run with no history of assimilation (blue).

knowledge of the impact of data-dropouts is especially important to guide users. The large impact on forecast errors found here, when *in situ* observations are denied (i.e. a 50% increase in error), highlights the potential benefits of transitioning ocean observational to operational programs.

Bluelink water mass analysis

Analysis of eddies in the Western Boundary Current (WBC) regions in a free run of the near-global, 1/10°-resolution, Bluelink Ocean Forecasting Australia Model [OFAM (Oke et al. 2013a)], with no data assimilation, shows that the water mass properties of eddies in different regions are distinctive [Figure 4(a)]. The analysis, shown in Figure 4(a), is from an 18-year composite of eddies for each WBC. The individual eddies that compose the mean are manually identified based on SLA fields (Rykova et al. 2014). Differences in the properties of each WBC are explained by the circulation and forcing in each region. The differences between anticyclonic and cyclonic eddies are explained by the formation mechanisms (Rykova et al. 2014). The temperature-salinity (TS) relationship in eddies is non-linear.

Most data assimilation systems used for operational oceanography exploit statistical (typically linear) relationships (i.e. model-based covariances) between observed and unobserved variables (Oke et al. 2008; Lellouche

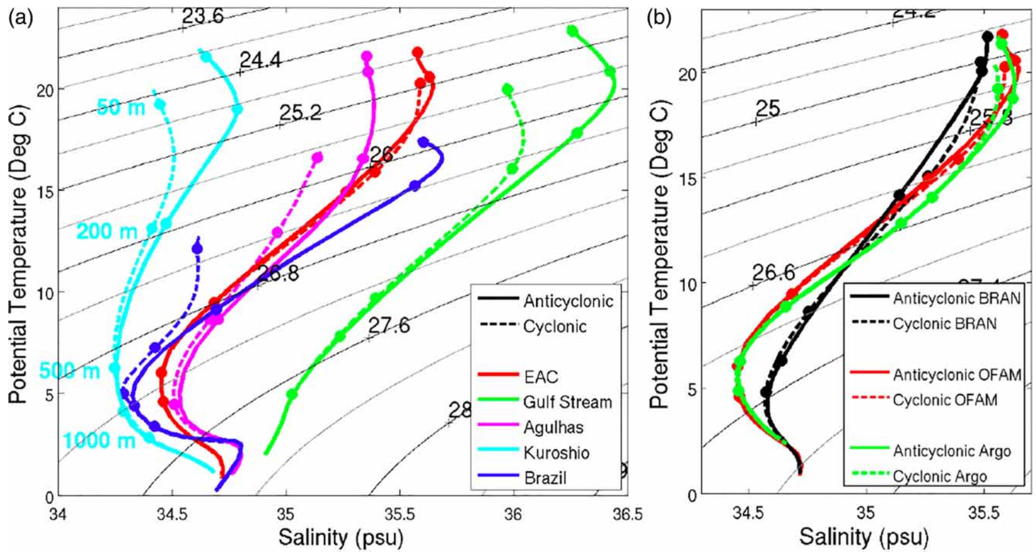

Figure 4. TS plots of cyclonic (dashed) and anticyclonic (solid) eddies in (a) the five major western boundary currents in a free run of OFAM; and (b) a comparison of TS plots in OFAM (Oke et al. 2013a) the latest BRAN (Oke et al. 2013b) and Argo in the EAC region (Rykova et al. 2014 with the dots indicating depths along the profiles).

et al. 2013; Storkey et al. 2010). The ability of these data assimilation systems to realistically reproduce the ocean's water masses is a major challenge. Analysis of the eddy water mass properties in the latest Bluelink ReANalysis [BRAN (Oke et al. 2013b)] indicates that indeed, a data-assimilating eddy-resolving ocean model struggles to accurately represent the water masses [Figure 4(b)]. Indeed the water mass properties in OFAM, with no data assimilation, compares better with observations (using Argo profiles within eddies) than BRAN [Figure 4(b)]. Of course, BRAN provides a better representation of the actual circulation, with eddies in the right place at the right time (Oke et al. 2013b) for example; but OFAM with no data assimilation more faithfully reproduces the ocean's water mass properties [Figure 4(b)].

Note that the water mass properties in the East Australian Current (EAC) region are the most well-defined (with the TS relationship nearly linear) of all the WBC regions [Figure 4(a)] and with the properties of anticyclonic and cyclonic eddies almost the same. However, despite this relative simplicity, the water mass properties in a data-assimilating model (Oke et al. 2013b) are somewhat unrealistic compared to properties observed using Argo floats [Figure 4(b)], with water masses overly mixed, and the structure of the TS-relationship poorly reproduced in BRAN (note that BRAN withheld data from about half the Argo profiles in the region of interest (Oke et al. 2013b)). Note that assimilating systems, like BRAN or operational forecast systems typically assimilate satellite observations that resolve the mesoscale, plus *in situ* data (e.g. Argo) that doesn't resolve the mesoscale. The analysis in Figure 4(b) indicates that either more advanced (or different), or more carefully configured data assimilation systems are needed to realistically reproduce the ocean's water masses – or more *in situ* observations are needed to initialise and constrain eddy-resolving ocean models. This result is consistent with the FOAM NRT OSEs summarised above (Lea 2012; Lea et al. 2013), where it was shown that SSH comparably degraded when either data from Argo or Jason-2 were with-held (Table 1), confirming the need for both profile and altimetric data for ocean initialisation.

Argo impact on ARMOR3D

ARMOR3D (Guinehut et al. 2012) is an analysis system that combines data from satellite altimetry, SST, and *in situ* temperature and salinity to produce three-dimensional gridded fields of temperature and salinity. Firstly, satellite observations are projected vertically, to generate synthetic temperature and salinity profiles. Secondly, *in situ* profiles are combined with synthetic profiles using optimal interpolation, to construct gridded fields of temperature and salinity on a 0.25°-resolution global grid down to 1500 m.

In order to assess the relative impact of satellite and *in situ* data for constructing the ARMOR3D temperature and salinity fields, the Degree of Freedom of Signal (DFS) are computed. DFS is an influence matrix diagnostic, first developed for the atmosphere (Oke et al. 2008) and recently adopted for ocean applications (Oke et al. 2009; Dibarboure et al. 2011a; Sakov et al. 2012). It provides a measure of the information content of each assimilated observation, based on the assumed error estimates used in the assimilation or analysis system. The implementation used here is similar to that described by Dibarboure et al. (2011a).

DFS is calculated as the trace of the $H\mathbf{K}$ matrix, where H is the observation operator that interpolates the background field to the observation location, and $\mathbf{K}$ is the Kalman gain matrix. The optimal interpolation method used in the ARMOR3D system uses a Gauss-Markov estimator that computed $H\mathbf{K}$ explicitly, along with the error covariance matrix or formal mapping error (Bretherton et al. 1976). The DFS is computed on each $H\mathbf{K}$ matrix, so that the local mapping 'gain' in information from each dataset (here, *in situ* and satellite data) can be computed. The partial DFS is associated with a particular dataset and is computed from the partial trace of the $H\mathbf{K}$ matrix, taking only elements associated with the dataset to be analysed. Partial DFS associated with the dataset i is written as DFS(i). Here, the fraction of the percentage of the overall information content (%IC) is computed for *in situ* data and satellite data (%IC = DFS(i) / Σ_iDFS(i) x 100); and the fraction of information of each data type actually exploited by the optimal interpolation system (i.e. the amount of information not lost to duplicate data and measurement error) (%$IC_{exploited}$ = DFS(i) / N(i), where N(i) is the actual number of observations from each dataset i).

Time series of the global average of two DFS metrics are presented in Figure 5 for the temperature at 100 m depth, and the information content of each satellite altimeter is shown in Figure 6. Figure 5 shows the impact of *in situ* data (Argo, moorings, XBTs, and CTDs) and synthetic profiles that are derived from satellite data (altimeter and SST) and climatology (Gaillard & Charraudeau 2008). Results indicate that 1/3rd (2/3rd) of the overall information come from the *in situ* (satellite) data at the beginning of the period and that this number increases (decreases) to 2/3rd (1/3rd) as the Argo observing system is established. Furthermore, this method can be applied within a given observation system (Dibarboure et al. 2011a) to assess the impact of a sub-set of observations. Figure 6 shows that when data from one altimeter is unavailable (e.g. Loss of Jason-1), the information drawn from other altimeters (e.g. Jason-2) temporarily increases.

The fraction of the information from the *in situ* data actually exploited by the optimal interpolation method is quite constant over time (Figure 5) with mean values around 65% and associated mean standard deviation of about 20%. This number is really determined by the decorrelation lengthscales used in the optimal interpolation

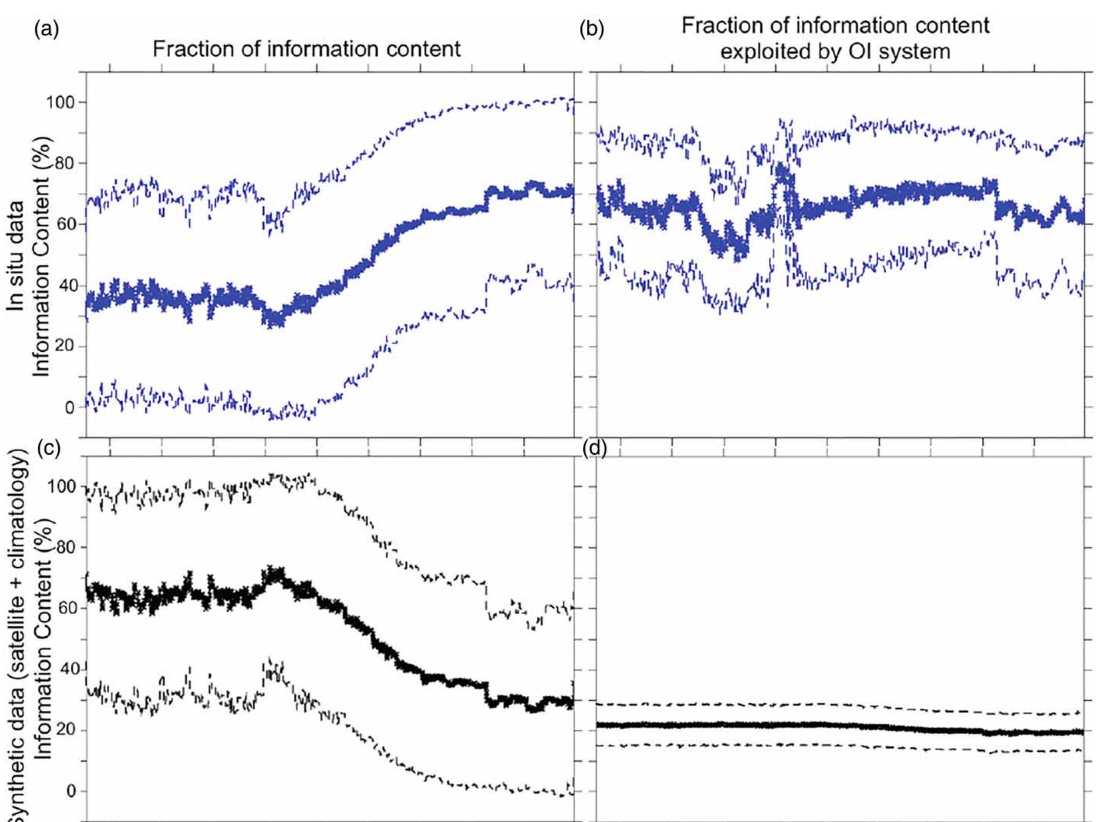

Figure 5. Time series of the spatial mean (thin lines) plus/minus the standard deviation (dashed lines) of the information content (pre sented as a percentage), computed from the DFS, for the ARMOR3D temperature at 100 m depth. The *in situ* data refers to Argo profiles, and the synthetic data refers to the profiles generated by projecting satellite data over depth.

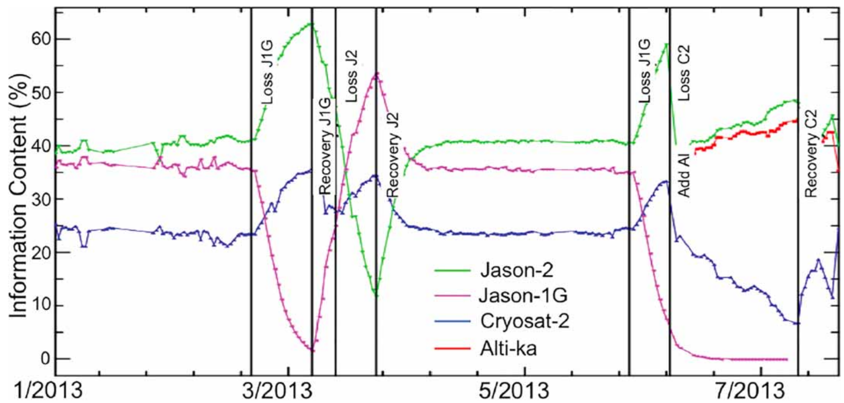

Figure 6. Time series of the relative information content for each satellite altimeter for the DUACS system, based on DFS calculations.

method and by the space/time distribution of observations. In some areas, redundant *in situ* observations show lower values for the information content, and isolated observations (like in the Southern Ocean) have values close to 100%. Similarly, the fraction of the information from the synthetic field dataset actually exploited by the optimal interpolation method is also quite constant over time with mean values around 20% and associated mean standard deviation of the order of 6%. These numbers are dictated by the way the synthetic fields are used (i.e. as the background field for step 2 of the method) and the measurement errors applied to those fields.

ECMWF OSEs

A series of OSEs has been performed using the ECMWF's ocean reanalysis ORAS4 (Balmaseda et al. 2013), which is used to initialise the operational monthly and seasonal forecasts. The study includes an experiment that assimilates: all observations (ORAS4), no mooring data (ORSA4 NoMoor), no Argo data (ORSA4 NoArgo), no altimetry (ORAS4 NoAltim), no data (ORAS4 NoDA), plus an experiment with no bias correction (ORAS4 NoBias). The OSEs presented here span the period 2001–2009.

Results are summarised in Figure 7(a), showing the RMSD of temperature, averaged over the top 300 m depth, between each OSE and ORAS4. The overall impact of data assimilation is significant (Figure 7), with errors growing significantly when no data are assimilated. The results show that the impact of the mooring observations, TAO and Pirata, is limited to within about ten degrees of the equator in the Pacific and Atlantic Ocean. In those regions, the impact of the mooring observations is about half the impact of Argo (in terms of reducing the RMSD), and is greater than altimetry. Notably, the impact of TAO/TRITON at the Equator and that of the PIRATA moorings is about the same as Argo in the very low latitudes in the vicinity of the moorings. The impact of altimetry is greatest in the centre of the south Indian and Atlantic basins and in the vicinity of the Gulf Stream extension [Figure 7(c)]; perhaps indicating that assimilation of altimetry impacts the large-scale gyres. Argo data clearly have the largest impact on the tropics and the extratropics. Argo is also the observing system that has an overwhelming impact in global salinity (not shown), in agreement with the results reported elsewhere (Balmaseda et al. 2008).

The experiments ORAS4, ORAS4 NoArgo, ORAS4 NoAltim and ORAS4 NoMoor include a bias correction scheme (Balmaseda et al. 2013). The bias correction involves an adjustment to the temperature and salinity fields estimated from a previous data assimilation experiment. These experiments therefore implicitly include some information from all the observing systems about the climatology of model errors. In the OSEs presented here, the data assimilation is mainly correcting the temporal variability. The experiment with no bias correction is included here to illustrate the role of the observations in correcting the mean. Clearly, in several regions the underlying model has significant errors, and the removal of the bias correction term results in large values of the RMSD.

Note that the fields presented in Figure 7 are based on the differences between two model runs; namely each OSE and ORAS4. These fields accurately quantify the data-impacts, as noted above, but do not necessarily quantify the change in forecast error. To better understand this, the profiles of the RMSD between each OSE and ORSA4 [Figure 8(a)] are computed, along with the profiles of the RMS error (RMSE) between all OSEs and the *in situ* observations [Figure 8(b)]. The former RMSD fields represent the data-impact on the model; and the latter RMSE fields represent the data impact on the error (assuming that the observation errors are negligible). It is found that in the tropical Pacific, whenever any data type is withheld, the fit to *in situ* temperature profiles degrades. Note that the impact of the mooring data from the TAO array is greater than the impact of Argo in the equatorial Pacific [Figure 8(b)]. This indicates that all data types contribute some unique information to the data assimilating system.

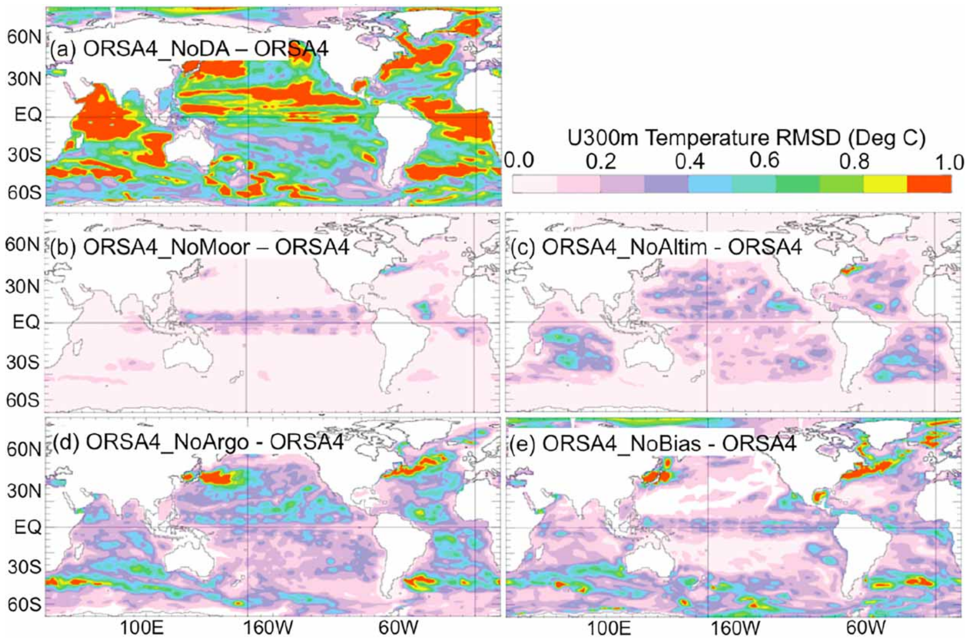

Figure 7. RMSD between each OSE and the ORAS4 run that assimilates all observations, for temperature, averaged over the top 300 m.

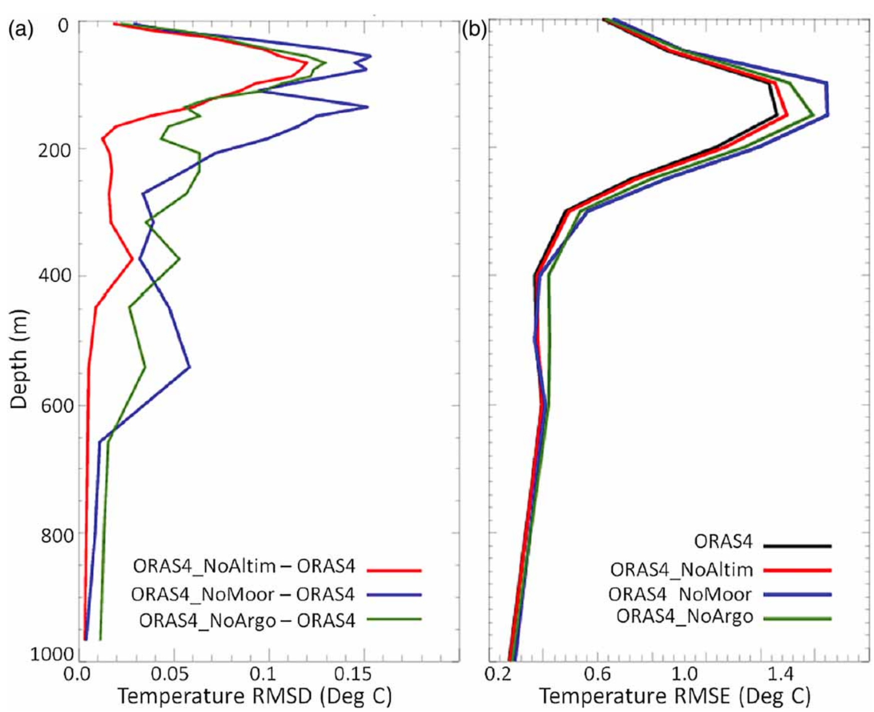

Figure 8. Profiles of the (a) RMSD for temperature in the equatorial Pacific between the OSEs and the ORAS4 run that assimilates all observations; and (b) the RMSE for temperature in the equatorial Pacific, computed by comparing the temperature in each experiment with all *in situ* observations.

MOVE-G OSEs

Several activities for evaluating ocean observations have been performed using MOVE/MRI.COM-G (MOVE-G) by the JMA/MRI group (Takaya et al. 2010). MOVE-G is an ocean data assimilation system that underpins the operational seasonal forecasting at JMA. MOVE-G uses a near-global configuration of the MRI.COM [MRI Community Ocean Model (Tsujino et al. 2010)]. The grid spacing is 1° in the zonal direction, and changes from 0.3° (within 5.7°S-5.7°N) to 1° (Poleward of 16°S and 16°N) in the

Table 2. Statistics of the absolute model differences for temperature at different depths for REGULAR and NOSAL in the equatorial Pacific (2°S 2°N, 130°E 80°W). Bias and RMSD: averaged difference and RMSD between modelled and reference values (modelled minus reference). ACC: Correlation coefficient between anomalies of modelled and reference values. Anomalies are calculated as the deviation from the World Ocean Atlas 2009 (Fujii et al. 2011)

	Bias (°C)		RMSD (°C)		ACC	
Depth	NOSAL	REGULAR	NOSAL	REGULAR	NOSAL	REGULAR
10 m	−0.134	0.029	0.572	0.487	0.795	0.828
50 m	−0.120	0.079	0.620	0.553	0.860	0.880
100 m	−0.471	0.030	2.386	1.121	0.561	0.645
150 m	−0.584	0.120	1.893	1.536	0.522	0.651
200 m	−0.350	0.129	1.391	1.202	0.447	0.553

meridional direction. A multivariate three-dimensional variational analysis scheme, MOVE (Multivariate Ocean Variational Estimation) (Fujii et al. 2003; Fujii et al. 2005; Tsujino et al. 2010) is employed to assimilate along-track SLA from altimeters, gridded SST data from satellite and *in situ* profiles from Argo, XBT, and moorings.

Table 2 reports results from two experiments: REGULAR – that assimilates almost all data (temperature, salinity, and SLA; withholding only Argo data from floats where the last digit of the World Meteorology Organization (WMO) ID is ‘4’); and NOSAL - that is the same as REGULAR, except all salinity observations are withheld and no update to salinity is applied (i.e. for NOSAL, the covariances between temperature-salinity and SLA-salinity are assumed to be zero). Table 2 demonstrates that salinity observations (mainly from Argo floats) improve the accuracy of the analysed temperature in the top 200 m in the equatorial Pacific. This improvement is largely due to the multivariate nature of the MOVE-G data assimilation system (Fujii et al. 2011). For both of these experiments, Argo data from the withheld floats are used for independent evaluation. In NOSAL (Table 2) there is a cold bias in the equatorial temperature field due to density instability that results from updating temperature, but not salinity. However, assimilating salinity observations (REGULAR) using the multivariate analysis framework in MOVE-G effectively reduces this bias, and improves the temperature variability, as indicated by the reduced RMSDs and increased Anomaly Correlation Coefficients (ACCs). This shows the importance of assimilating salinity data and also highlights the benefits of a multivariate data assimilation system.

In a second OSE study using MOVE-G, the impact of Argo data is demonstrated. Figure 9 shows the results from a series of OSEs designed to assess the impact of assimilating data from a different number of Argo floats (Fujii et al. 2015) using the multivariate capabilities of MOVE-G. In these OSEs, 5 experiments that assimilate data from approximately 80%, 60%, 40%, 20%, 0% of the available Argo float profiles were performed for the period 2000–2010. Here, the last digit of WMO number is again used for the selection of the assimilating Argo floats. For example, Argo floats where the digit is 0 or 1 (0, 1, 2 or 3) are used in the OSE with 20% (40%) of Argo, and similarly for the other OSEs. The accuracy of these runs was evaluated by comparing output from each run with data from the 20% of Argo float profiles that were withheld from all assimilation runs (Figure 9). The percentage improvement of RMSD is defined as ($RMSD_{NoArgo}$ - $RMSD_{OSE}$) / $RMSD_{NoArgo}$ x 100, where $RMSD_{OSE}$ denotes the RMSD between the simulated and observed values for each OSE, and $RMSD_{NoArgo}$ denotes the RMSD between the simulated and observed values for the OSE where all Argo data are withheld. The results indicate that the accuracy monotonically improved with increase in the number of assimilated Argo floats from 0% to 80%. This indicates that any further increase in the number of Argo floats has a potential to further improve the accuracy of our assimilating model. It is also clearly demonstrated that the impact of Argo floats on salinity is larger than the impact on temperature; indicating that other observation types provide more constraint on temperature. This result is consistent with the conclusions of an earlier study (Oke & Schiller 2007) using the eddy-resolving Bluelink system. In addition, the impact was found to be quite large on salinity in the eastern equatorial Pacific, relatively large in both temperature and salinity of the subtropical Pacific, and relatively small in the mid-latitudes of the North Pacific. The reason for these regional differences relates to system errors (e.g. surface fluxes, mixing) that differ from place to place.

In a third OSE study using the MOVE-G system, a series of OSEs were performed to evaluate the relative impact of Argo floats and TAO/TRITON buoys on ENSO forecasts using an operational seasonal forecasting system (Fujii et al. 2011). First, three data assimilating runs are prepared using MOVE-G. All available data are assimilated in one run, but Argo floats or TAO/TRITON buoys data are systematically withheld in the other two runs. Forecasts are started at the end of January, April, July and October 2004–2008. Thirteen-month, 11-member ensemble

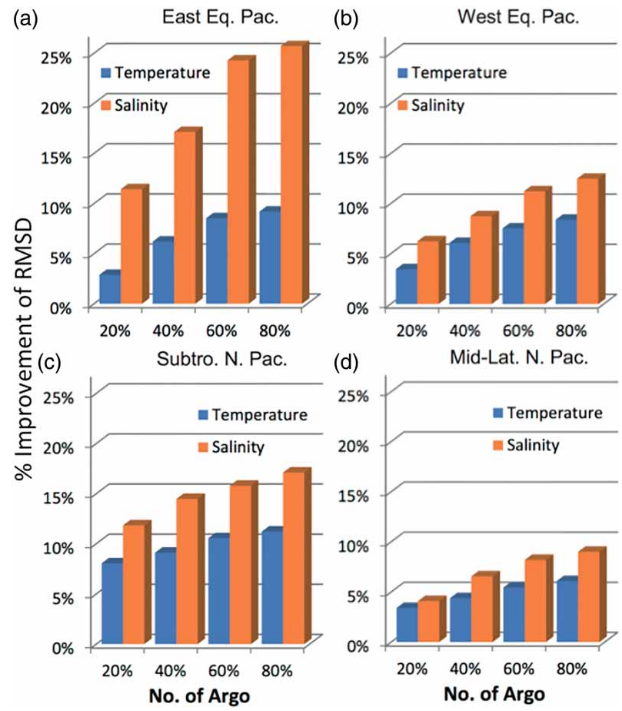

Figure 9. Percentage improvement of RMSDs (positive values indicate that assimilation improves the skill) for 0 300m averaged temp erature and salinity by assimilating 20%, 40%, 60% and 80% of Argo profiles. (a) Eastern Equatorial Pacific (5S 5N, 170 80W). (b) Western Equatorial Pacific (5S 5N, 170 80W). (c) Subtropical North Pacific (5 20N, 130E 90W). (d) Mid latitude North Pacific (30 60N, 130E 120W).

forecasts were performed with each run using the coupled atmosphere-ocean model in the seasonal forecasting system (Takaya et al. 2010). The forecast scores for 6-month lead-time are improved for NINO3, NINO3-4 and NINO4 SST when Argo floats or TAO/TRITON buoys data are assimilated (compared to the scores when the data are withheld), and this impact is enhanced for 12-month lead-time (Figure 10). The improvement of ENSO forecasts at longer lead time are likely to be due to better subsurface temperature fields achieved via assimilation of Argo profiles. This improvement also positively influences several atmospheric fields (not shown), including the sea

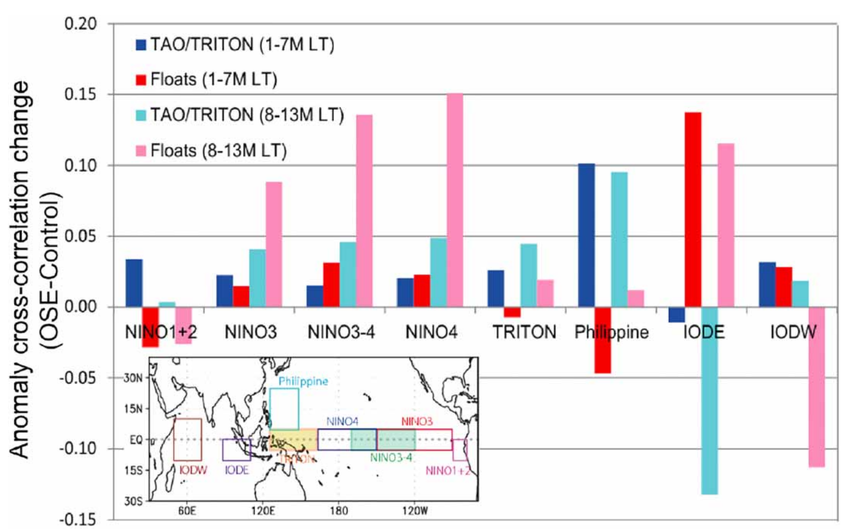

Figure 10. Improvements of the ACC scores by assimilating Argo Floats and TAO/TRITON buoys for SST averaged in the box areas denoted by the left bottom map in 1 7 and 8 13 Lead Time (LT) forecasts. These improvements are calculated by subtracting the scores for OSE runs where Floats (TAO/TRITON) are withheld from the scores for the Control run, when all data are assimilated (Fujii et al. 2011).

level pressure, precipitation, and the divergence in the upper troposphere, demonstrating the value of these data sets to seasonal prediction systems.

Discussion and conclusions

In this study, results are presented from a series of OSEs using eddy-permitting global ocean forecast and analysis systems, and seasonal prediction systems. Each study takes a different approach to quantifying the impact of observations on each forecast/analysis system. This includes traditional OSEs, where data are systematically withheld for a 1-10 year data assimilating model run; a series of 1-month long NRT OSEs (Lea et al. 2013); a total data-denial OSE, where all data are presumed to become unavailable; and an analysis of assimilation/mapping diagnostics (using DFS metrics). These different approaches provide clear demonstrations of the value of different observation types.

In all but one study above, the impact of Argo data is explicitly assessed. All the studies draw the unanimous conclusion that Argo data are a critical data type for ocean forecasting; providing unique and valuable information about the ocean properties and circulation down to depths of 2000 m. Specifically, it is shown that Argo data are important for constraining the mixed layer depths and water mass properties of the ocean interior. Several studies also demonstrate the value of altimeter data and re-confirmed conclusions from previous studies; indicating that it is the most critical data type for initialising the mesoscale ocean circulation (in eddy-permitting systems) where at least a constellation of three altimeters is needed; and also the basin-scale circulation in the extra-tropics and boundary currents (using seasonal prediction systems).

Although TAO/Pirata data are limited in their extent to the tropics; the studies presented in this paper demonstrate that within about 10 degrees of the equator, the TAO/Pirata data are as important for ocean/seasonal forecasting as Argo and altimeter data. These results indicate the possibility that the current degrading of the TAO array system, taking place after the summer of 2012 [see www.ioc-goos.org/tpos2020] might induce serious deterioration in the forecast/analysis systems, and imply that the prompt recovery of the array to the original state is highly desirable. Similarly, although XBT data represent only a small component of the GOOS now that the Argo array is complete, the impact of XBT data in the vicinity of the XBT transects is very significant, with the lack of XBT data degrading forecast systems for some time after their neglect. The experiments conducted by the Japanese group, using the MOVE-G system, is perhaps the most comprehensive assessment of the impact of Argo in the published literature; hinting that future enhancements to Argo, with more floats, may continue to yield benefits to seasonal predictions.

The more novel studies outlined in this paper include a series of NRT OSEs, described in detail elsewhere (Lea 2012; Lea et al. 2013); the 'total-denial' OSE, performed by the Canadian consortium; and the analysis of assimilation metrics, described by the CLS group. These non-traditional studies provide many unique insights. Importantly, from a practical point of view, they represent the types of experiments that could be performed routinely with all operational ocean forecast systems, on an ongoing basis. Indeed, the NRT OSEs, performed by the UK Met Office in 2011 were performed alongside their operational forecast system in NRT. The 'total-denial' OSE performed by the Canadian group could also be easily performed for all operational systems, with minimal computational overhead (just a single month-long model run performed behind real-time); as could the assimilation diagnostics of the CLS group. If these experiments/diagnostics could be computed routinely, then the ocean forecast community could have a NRT, up-to-date, relevant suite of results that demonstrate the value of the present-day GOOS at hand all the time. In recognition of this opportunity, the GODAE OceanView Observing System Evaluation Task Team [OSEval-TT; www.godae-oceanview.org/science/task-teams/observing-system-evaluation-tt-oseval-tt/] has proposed the concept of Observation Impact Statements (OISs). OISs (Lea 2012) are intended to be a concise set of results that demonstrate the value of the present-day GOOS in a way that is easily understood by non-expert users. The details of OISs are being worked through by the OSEval-TT. But it is the vision of the OSEval-TT that all operational systems perform parallel NRT OSEs, or compute equivalent assimilation diagnostics, to provide the broader community, including the observational community and Decision-Makers, with the information that is needed to assess, manage, and maintain the GOOS routinely. By so doing, the GODAE OceanView community could help empower the Decision-Makers to advocate for the maintenance of the GOOS using up-to-date evidence, and consensus results.

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