Science and Technology Infusion Climate Bulletin
NOAA's National Weather Service
40th NOAA Annual Climate Diagnostics and Prediction Workshop
Denver, CO, 26-29 October 2015

A Real-time Multiple Ocean Reanalyses Intercomparison Project for Quantifying the Impacts of Tropical Pacific Observing Systems on Constraining Ocean Reanalyses and Enhancing our Capability in Monitoring and Predicting ENSO

Y. Xue[1], C. Wen[1], A. Kumar[1], M. Balmaseda[2], Y. Fujii[3], G. Vecchi[4], G. Vernieres[5], O. Alves[6], M. Martin[9], F. Hernandez[10], T. Lee[7], D. Legler[8], and D. DeWitt[1]

[1]*Climate Prediction Center, NOAA/NWS/NCEP, College Park, Maryland, USA*

[2]*European Center for Medium-Range Weather Forecasts, Reading, UK*

[3]*Japan Meteorological Agency, Tokyo, Japan*

[4]*Geophysical Fluid Dynamics Laboratory, NOAA/OAR, Princeton, NJ, USA*

[5]*Goddard Space Flight Center, NASA, Greenbelt, MD, USA*

[6]*Bureau of Meteorology, Melbourne, Australia*

[7]*Jet Propulsion Laboratory, NASA, Pasadena, CA, USA*

[8]*Climate Program Office, NOAA, Silver Spring, MD, USA*

[9]*UK Met Office, Exeter, Devon, United Kingdom*

[10]*Mercator Ocean, France*

ABSTRACT

To quantify uncertainties in the current generation of ocean reanalysis products, CLIVAR Global Synthesis and Observations Panel (GSOP) and the GODAE OceanView (GOV) jointly initiated Ocean Reanalysis (ORA) Intercomparison Project (ORA-IP). For those ocean reanalyses produced by operational centers for initialization of climate models or short-range ocean forecast models, there is an opportunity to conduct ORA intercomparison in near real-time, and to use the ensemble approach to quantify the signal (ensemble mean) and noise (ensemble spread) in our estimation of ocean climate variability. Motivated by the Tropical Pacific Observing System (TPOS) 2020 Workshop held in January 2014 in La Jolla, CA, with support from NOAA Climate Observation Division, the CPC initiated and led a Real-Time ORA-IP. An ensemble of *nine* operational ORAs is been routinely collected, and they are used to monitor consistency and discrepancy in the tropical Pacific temperature analysis in real time in support of ENSO monitoring and prediction.

The role of the TAO/TRITON buoy data on constraining the ocean reanalyses is assessed by root-mean-square error (RMSE) and anomaly correlation (AC) with the buoy temperature data directly. The ensemble mean is shown to have a higher accuracy (smaller RMSE and larger AC) than individual product, suggesting the ensemble approach is an effective tool in reducing uncertainties in temperature analysis for ENSO. The spread among the ensemble mean and its time variability measures how uncertainties vary with location and time. The temporal variability of the spread can be partially linked to the temporal variability of in situ observations which reduce ocean analysis errors and increase consistency among them. The important outcomes of the project are to 1) provide estimation where uncertainties are large and if sustained or enhanced ocean observations are needed to reduce uncertainties, 2) to provide the most reliable estimate of climate signal such as ENSO, and 3) to provide the signal to noise ratio for the climate signal in real time.

Correspondence to: Yan Xue, 5830 University Research Court, Climate Prediction Center, NOAA/NWS/NCEP, College Park, Maryland; E-mail: Yan.Xue@noaa.gov.

1 Introduction

Ocean reanalyses (ORAs) aim to provide an optimal estimation of 3-dimensional structures of the ocean by combining model solutions with ocean observations via data assimilation methods. However, the time evolution represented by an ORA will be sensitive to the temporal variations of the observing system, to the errors of the ocean model, atmospheric fluxes and assimilation systems, which are often flow-dependent, and not easy to estimate. A crude and pragmatic way of estimating uncertainties in ORAs is to carry out an intercomparison of ORAs within the framework of an ensemble approach.

The multi-analysis ensemble approach is adopted by the Ocean Reanalyses Intercomparison Project (ORA-IP) jointly coordinated by the CLIVAR Global Synthesis and Observation Panel (GSOP) and GODAE OceanView (Balmaseda *et al.* 2015). Some ORAs in the ORA-IP are continuously updated in real-time in operational centers for initialization of seasonal forecast models or short-range ocean forecast models. Those real-time ORAs, often referred to as operational ORAs, have the additional advantage that they allow monitoring of climate variability such as El Niño/Southern Oscillation (ENSO) and those beyond ENSO (Xue *et al.* 2010). The operational ORAs are now routinely used at national climate centers for ENSO monitoring, and prediction efforts.

The quality of the ORAs for monitoring ENSO depends critically on the Tropical Pacific Observing Systems (TPOS), which was initially populated by the Tropical Atmospheric Ocean (TAO) array in early-1980s (McPhaden *et al.* 1998), and was later enhanced by the Triangle Trans-Ocean Buoy Network (TRITON) array in the western tropical Pacific (west of 160˚E) after 2000 (Ando *et al.*, 2005). The TAO/TRITON array is considered as the cornerstone of the ENSO observing system, as it systematically measures upper ocean temperature, current and air-sea fluxes *etc.* at geographically fixed locations. The implementation of the TAO/TRITON array stimulated a rapid development of operational ocean reanalyses (*e.g.* Behringer *et al.* 1998; Alves *et al.* 2004; Zhang *et al.* 2007; Yin *et al.* 2011; Balmaseda *et al.* 2013).

§**Table 1** List of ocean reanalysis products entering the inter-comparison.

Product	Forcing	Configuration	Data Assim. Method	Analysis Period
GFDL/NOAA (ECDA)	Coupled DA	1°x1/3° MOM4 coupled	*EnKF (T/S/SST)*	1979-present
GMAO/**NASA** (MERRA Ocean)	Merra + Bulk	0.5° MOM4	*EnOI (SLA/T/S/SST/SIC)*	*1979-present*
NCEP/NOAA (**GODAS**)	NCEP-R2 Flux.	1°x1/3° MOM3	*3DVAR (SST/T)*	*1979-present*
NCEP/NOAA (**CFSR**)	Coupled DA	0.5°x1/4°	*3DVAR (SST/T)*	*1979-present*
CAWCR/**BOM** (PEODAS)	ERA40 to 2002; NCEP-R2 thereafter. Flux	1°x2° MOM2	*EnKF (T/S/SST)*	*1979-present*
ECMWF (ORAS4)	ERA40 to 1988; ERAi thereafter. Flux.	1°x 1/3° NEMO3	*3DVAR (SLA/T/S/SST)*	*1979-present*
MRI/**JMA** (MOVE-G2)	JRA-55 corr+ CORE Bulk	1°x0.5° MRI.COM3	*3DVAR (SLA/T/S/SST)*	*1979-present*
UK **MET** (GloSea5)	ERAi+CORE Bulk	1/4° NEMO3.2	*3DVAR (SLA/T/S/SST/SIC)*	*1993-present*
MERCATOR (GLORYS2V3)	ERAi corr+ CORE Bulk	1/4° NEMO3.1	*EnKF+3DVAR (SLA/T/S/SST/SIC)*	*1993-present*

§ The data assimilation column lists the observation types used for their estimation (T/S for temperature and salinity; SLA: altimeter-derived sea level anomalies; SST: sea surface temperature, SIC: sea-ice concentration), as well as assimilation techniques used for reanalysis: Ensemble Optimal Interpolation (EnOI), Ensemble Kalman Filter (EnKF), variational methods (3D-Var). The atmospheric surface forcing is usually provided by atmospheric reanalyses, using either direct daily fluxes, or different bulk formulations. There are also systems that use fluxes from coupled data assimilation systems (Coupled DA), which come in multiple flavours (parameter estimation, EnKF, weakly coupled).

Table 2 Root-mean-square error (RMSE, the second column) and normalized RMSE (NRMSE, the third column) of temperature anomaly from TAO observations averaged in upper 300m in 1993-2014 for the ensemble mean (EM). NRMSE is RMSE divided by standard deviation (STD) of TAO temperature anomalies expressed as percentage (%). Positive (negative) difference of NRMSE of each ORA from EM (the 4th-11th column) indicates increased (decreased) NRMSE from that of EM (values higher than 15% are in bold). Shown are the values calculated for each TAO/TRITON buoy and averaged in the eastern equatorial Pacific (170^{o}W-90^{o}W, 2^{o}S/0/2^{o}N, EEPac), the western equatorial Pacific (120^{o}E-180^{o}W, 2^{o}S/0/2^{o}N, WEPac), the northeastern subtropical Pacific (170^{o}W-90^{o}W, 5^{o}N/8^{o}N, NEPac), the northwestern subtropical Pacific (120^{o}E-180^{o}W, 5^{o}N/8^{o}N, NWPac), and the southern subtropical Pacific (120^{o}E-90^{o}W, 5^{o}S/8^{o}S, SPac).

	RMSE of EM (^{o}C)	NRMSE of EM (%)	NRMSE Difference from EM (%)								
			NCEP GODAS	JMA	ECMWF	GFDL	NASA	BOM	UK MET	MERCATOR	NCEP CFSR
EEPac	0.26	21	7	10	5	14	13	7	-3	9	**19**
WEPac	0.25	24	8	11	4	**19**	10	8	1	14	**17**
NEPac	0.33	38	**15**	14	2	**17**	**27**	**16**	-11	6	**24**
NWPac	0.29	27	7	11	0	**20**	13	**19**	-4	10	**20**
SPac	0.21	24	3	7	3	**27**	12	10	-2	11	**23**

The rapid decline of the TAO array after summer 2012 and anticipating substantial reduction in the TRITON array in next few years raised a serious concern among the ocean data assimilation community if the quality of the operational ORAs has been compromised due to the data loss. One of the recommendations from the TPOS 2020 workshop (http://www.ioc-goos.org/tpos2020) is to monitor the consistency and discrepancy across the operational ORAs in real time to support ENSO forecast, and to monitor the impacts of the TAO/TRITON data loss on the quality of ORAs (Fujii *et al.* 2015).

With the support from NOAA Climate Observation Division, the Climate Prediction Center (CPC) of National Centers for Environmental Prediction (NCEP) initiated and led the Real-Time ORA-IP following the TPOS 2020 Workshop. An ensemble of nine operational ORAs (Table 1) is been routinely collected, and an experimental web site has been constructed to display the ensemble ORA products with a focus on monitoring the consistency and discrepancy in tropical Pacific temperature analyses in real time in support of ENSO monitoring and prediction (http://www.cpc.ncep.noaa.gov/products/GODAS/multiora_body.html for the 1981-2010 climatology; http://www.cpc.ncep.noaa.gov/products/GODAS/multiora93_body.html for the 1993-2013 climatology that is partially finished). The objectives of the project are to 1) provide estimation where uncertainties among operational ORAs are largest and if sustained or enhanced ocean observations are needed to reduce uncertainties, 2) to provide the most reliable estimate of climate signal such as ENSO, and 3) to provide the signal to noise ratio for climate signal in real time.

2 Results

2.1 Comparison with the TAO/TRITON data

In the tropical Pacific, in addition to assimilating the TAO/TRITON data, ORAs also assimilate temperature and salinity observations from the Argo floats and expendable bathythermographs (XBTs). It is important to know how well each ORA fits to the TAO/TRITON data. The temperature observations from 66 buoys that have more than 10 year record of monthly values are included in the comparison. The buoy data are linearly interpolated onto the same vertical grid (with 10m interval) as that in the ORAs. For the comparison, each ORA is sampled identically in time as the buoy data and temperature anomalies are constructed by removing the climatology for each ORA and buoy data separately. The root-mean-square error (RMSE) and anomaly correlation (AC) are then calculated at each level for every buoy site. Normalized RMSE (NRMSE) is calculated as the RMSE divided by the standard deviation (STD) of TAO temperature anomalies at each level for every buoy site. To get an integrated measurement of the fit to the buoy data, RMSE, NRMSE and AC are averaged at all levels in the upper 300m.

Table 2 shows the averaged RMSE and NRMSE over the upper 300m in five regions. The NRMSE of each ORA is compared with that of the ensemble mean (EM), defined as the average of the nine ORAs, which

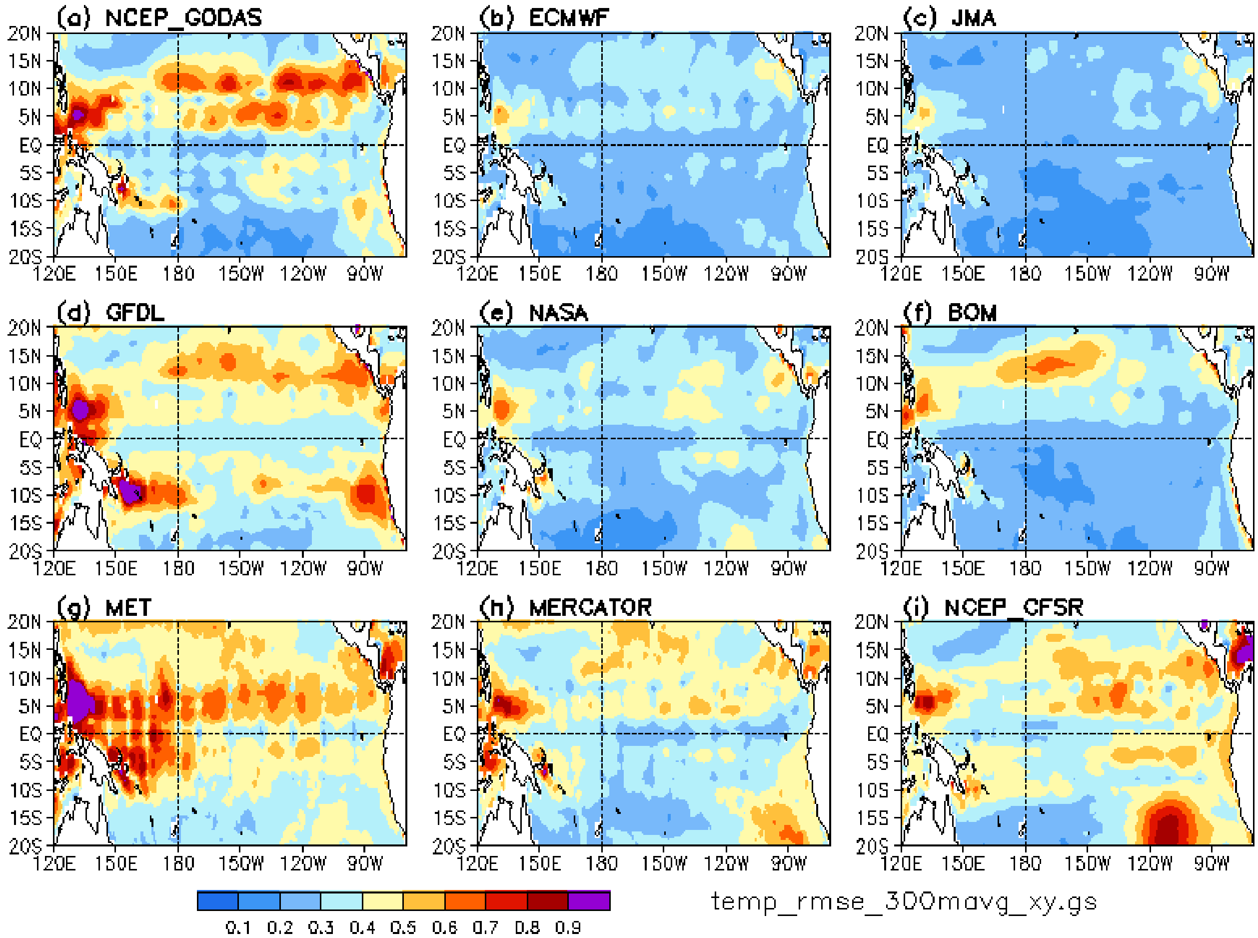

Fig. 1 Root-mean-square error (RMSE) of temperature anomaly for (a) NCEP_GODAS, (b) ECMWF, (c) JMA, (d) GFDL, (e) NASA, (f) BOM, (g) MET, (h) MERCATOR, and (i) NCEP_CFSR computed against the ensemble mean and averaged in upper 300m. The RMSE is computed over 1993-2014. Unit is ^{o}C.

is expected to have the smallest RMSE. For the eastern equatorial Pacific (EEPac), the RMSE of EM is 0.26^{o}C and NRMSE is about 21% of STD. Individual ORA tends to have larger NRMSE (5-19% STD) except the MET. This is consistent with the wisdom that the ensemble mean tends to cancel out noises in individual ORA and to provide a better analysis than individual ORA. In the western equatorial Pacific (WEPac), the RMSE and NRMSE are similar to those in EEPac and the EM is generally superior to individual ORA. In the northeastern Pacific (NEPac), the RMSE (0.33^{o}C) and NRMSE (38%) are considerably higher than those in other regions. Compared to the EM, individual ORA has higher NRMSE except the MET which has smaller NRMSE. For the northwestern Pacific (NWPac) and southern Pacific (SPac), the conclusion is similar to the above. Individual ORA tends to have larger NRMSE than the EM except the MET. We will discuss next why the MET fits to the buoy data much better than other ORAs. If the NRMSE in the five regions is averaged, the ORAs ranked from the lowest to highest NRMSE are MET, ECMWF, NCEP GODAS, MERCATOR, JMA, BOM, NASA, GFDL and NCEP CFSR. We will explain in next section that the better fit to the buoy data at limited buoy sites may not represent a better analysis when all the grid points are considered.

2.2 Comparison with the ensemble mean

It is shown earlier that the ensemble mean (EM) tends to be superior to individual ORA in the fit to the TAO/TRITION data. Another advantage of the EM is that it has a uniform coverage of all grid points and provides us the best estimation of climate signal in locations where not covered by the isolated mooring sites.

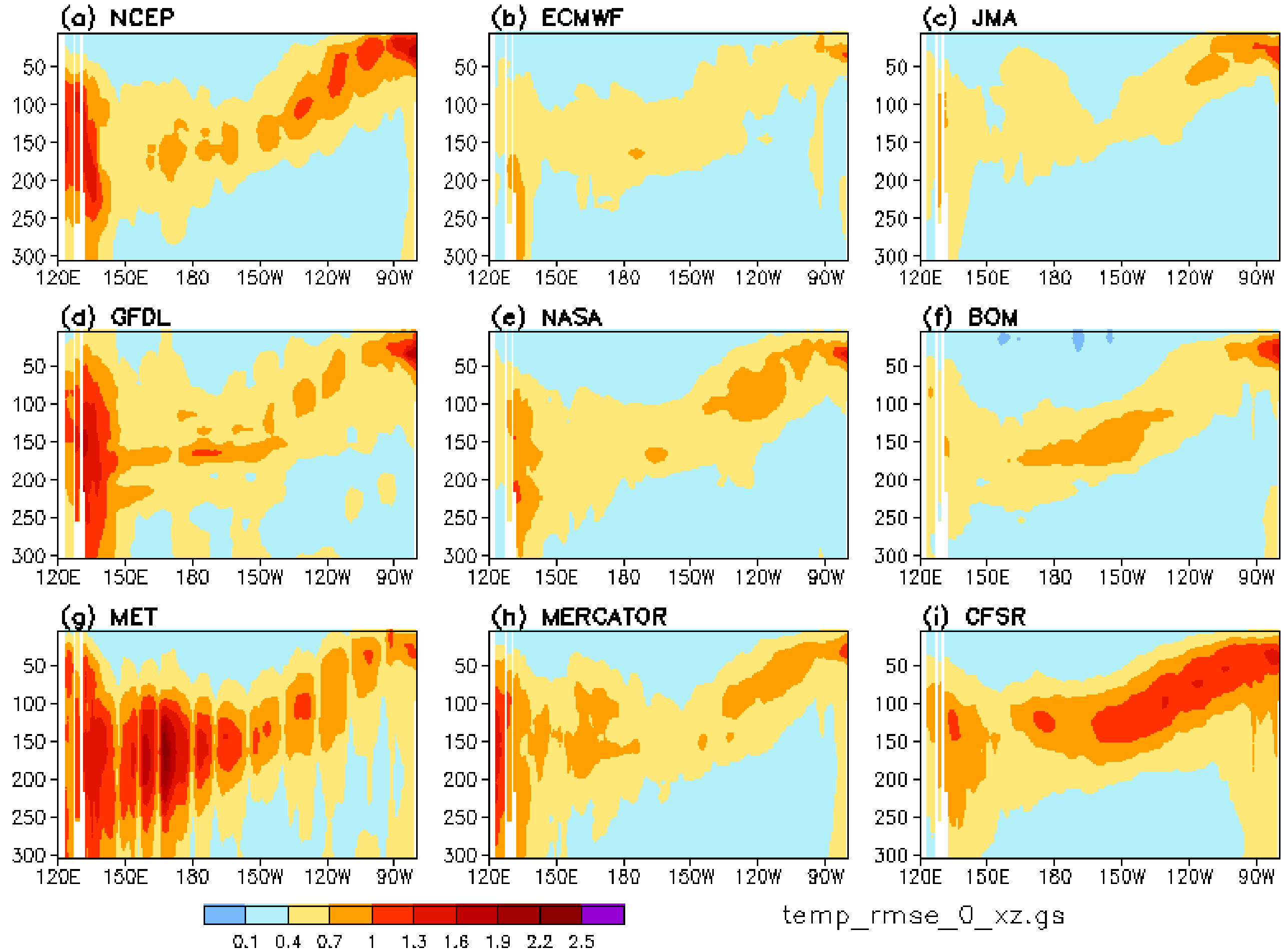

Fig. 2 Root-mean-square error (RMSE) of temperature anomaly at the equator for (a) NCEP_GODAS, (b) ECMWF, (c) JMA, (d) GFDL, (e) NASA, (f) BOM, (g) MET, (h) MERCATOR, and (i) NCEP_CFSR computed against the ensemble mean. The RMSE is computed over 1993-2014. Unit is ^{o}C.

In the ensemble approach, the true signal in the ocean state is estimated as the ensemble mean (EM) based on all ORAs

$$\text{EM}\,(\text{t}) = \frac{1}{N}\sum_{k=1}^{N} X_k(t) \qquad (1)$$

where $X_k(t)$ denotes an individual ORA and N is the total number of ORAs. The root-mean-square error (RMSE) relative to the EM measures how well each ORA agrees with the EM. Fig. 1 shows that the RMSE is generally small (< 0.3^{o}C) in the equatorial belt where TAO observations help constrain the analysis. A noticeable exception is larger values in the MET west of 180^{o}E, and in locations between the mooring sites. Another exception is larger values in the CFSR (> 0.4^{o}C) east of 150^{o}W and in the GFDL west of 150^{o}E. The RMSE is much larger in the off-equatorial belt, and the MET, the NCEP_GODAS and NCEP_CFSR, along with the GFDL product, stand out as the ones with the largest RMSE.

The RMSE at the equator (Fig. 2) shows that the largest error is located near the mean thermocline. The UK MET and the two NCEP reanalyses have the largest departure from the EM. The large RMSE in the UK MET is largely due to a too strong fit to observations in the presence of large model biases. The large RMSE in the NCEP CFSR can be partially attributed to a sudden shift in climatology near 1999 (Xue et al. 2011), and for the GODAS is largely due to the warm biases before 1990.

2.3 Uncertainties among ocean reanalyses

The uncertainty in the ocean state estimation can be quantified by the spread of ocean reanalyses from the ensemble mean

$$ES(t) = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(X_k(t) - EM(t))^2} \quad (2)$$

$$\sigma_{ES} = \sqrt{\left(\frac{1}{M}\sum_{t=1}^{t=M}(ES(t))^2\right)} \quad (3)$$

where M is the number of samples in the time series.

To see how temporal variations in ocean observations contribute to reduce σ_{ES}, Fig.3 shows the σ_{ES} and the corresponding data counts during the period

a) prior to the completion of TAO array (1985 to 1993),
b) after the completion of TAO array but prior to the ARGO (1994 to 2003), and
c) 2004 to 2011 after the full deployment of TAO/TRITON and ARGO.

The full deployment of the TAO array significantly reduces the analysis uncertainty in the equatorial Pacific, and the availability of Argo reduces the analysis uncertainty in off-equatorial regions, thus clearly highlight the positive influence of ocean observations on constraining the ocean analysis. However, there is still large spread in the northwestern tropical Pacific, in the SPCZ region and central and northeastern tropical Pacific. Fig. 3 also indicates that the data assimilation systems tend to constrain the solution very locally, only where there are in situ observations. This suggests that enhancing ocean observing systems should go hand in hand with improving ocean data assimilation systems such that ocean observations can be optimally utilized by those systems.

Considering the significant loss of the TAO data in the equatorial eastern Pacific in 2012-13, we examined the temporal variations of the spread in the equatorial eastern Pacific (EEPac), and related it to the temporal variability of signal and data counts. Fig. 4 shows that the spread is relatively large before 1990 when where was little data, and stays relatively low from 1990 to 2005 except during the 1982/83 and 1997/98 El Nino. However, there is a gradual increase of the spread after 2005 and a noticeable peak in 2012-2013 when there was a significant loss of the TAO data.

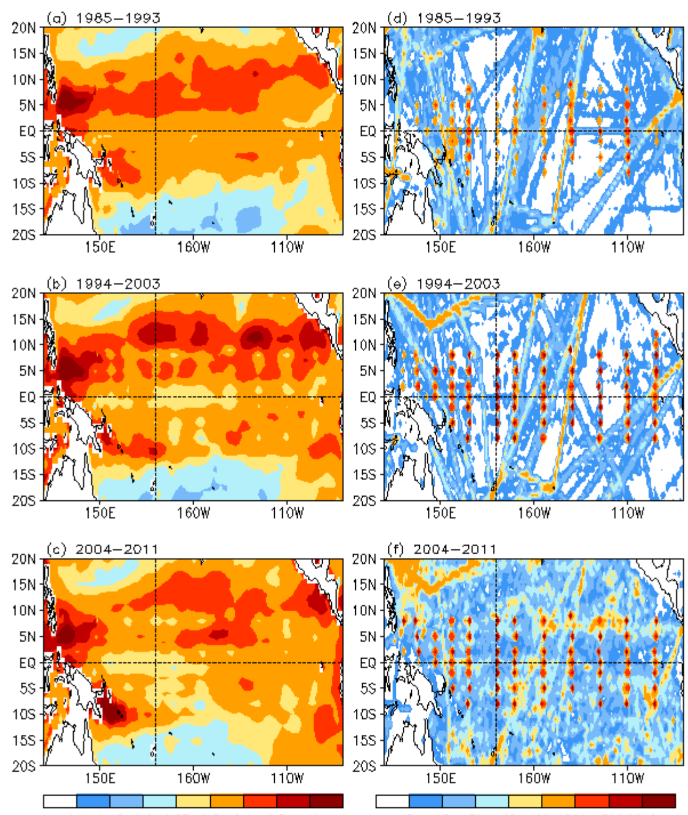

Fig. 3 (Left column) The ensemble spread of temperature anomaly averaged in the upper 300m in (a) from 1985 to 1993, (b) from 1994 to 2003, and (c) from 2004 to 2011, along with (right column) the associated data counts (number of daily temperature profiles in each 1x1 degree box).

3 Summary and discussions

Since the inception of this project at CPC in 2014, major accomplishments include:

- Establishing protocols for routine collection of ocean reanalyses from different operational centers;
- A web page to display ocean reanalyses

and uncertainty among them;

- An ability to provide a sanity check for potential issues among various ocean reanalyses;
- A demonstration of possible issues with NCEP ocean reanalyses systems, *i.e.*, GODAS and CFSR;
- Evidence for the influence of temporal variations *in situ* data on the uncertainty among ocean reanalyses, viz a reduction in *in situ* data leading to an increase in analysis uncertainty.

As the data delivery from external centers is now mostly routine, we plan to devote additional time in better quantification of the impacts of evolution of TPOS on the ocean analysis and uncertainty among them. In future, results from this project will

a) provide support for the framework of TPOS 2020 (http://tpos2020.org/) project on the design of the future tropical Pacific observing system;
b) continue to deliver real-time information to the user community with stake in ENSO monitoring and prediction, and
c) support a comprehensive assessment of the next generation of ocean reanalysis at NCEP.

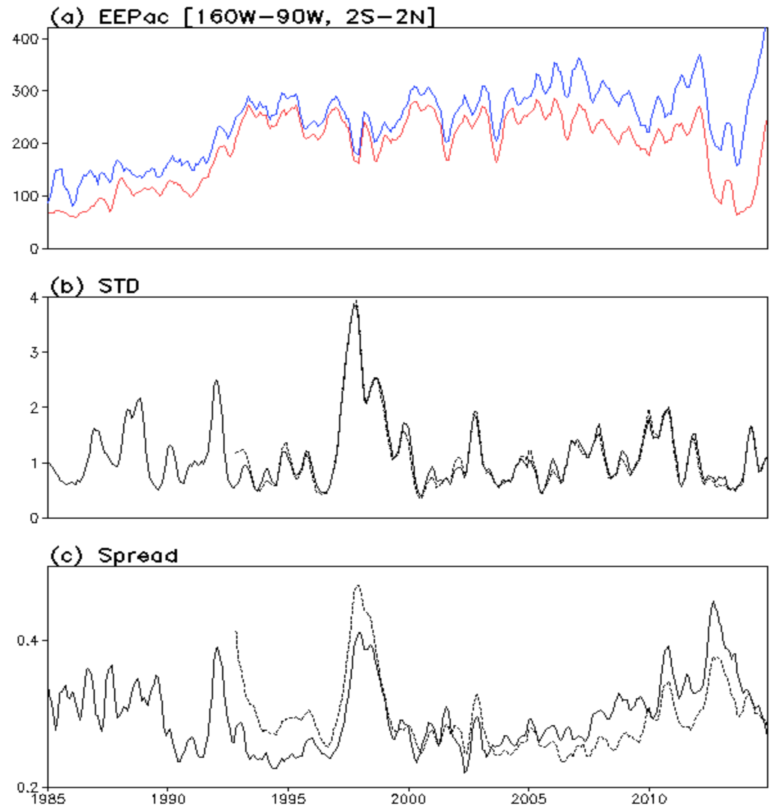

Fig. 4 (top panel) The number of daily temperature profiles from TAO/TRITON (red line), TAO/TRITON/Argo/XBT (blue line), (middle panel) the standard deviation of temperature anomaly of the ensemble mean of seven products (solid line) and nine products (dash line), and (bottom panel) the ensemble spread averaged in the upper 300m based on seven products (solid line) and nine products (dash line) for the eastern equatorial Pacific (EEPac, 160°W-90°W, 2°S-2°N).

References

Alves, O., M. Balmaseda, D. Anderson, and T. Stockdale, 2004: Sensitivity of dynamical seasonal forecasts to ocean initial conditions. *Q. J. R. Meteorol. Soc.*, **130**, 647– 668.

Ando, K., T. Matsumoto, T. Nagahama, I. Ueki, Y. Takatsuki, and Y. Kuroda, 2005: Drift characteristics of a moored conductive-temperaturedepth sensor and correction salinity data. *J. Atmos. Ocean. Technol.*, **22**, 282–291. doi:10.1175/JTECH1704.1

Balmaseda, M.A., and K. Mogensen, A.T. Weaver, 2013: Evaluation of the ECMWF ocean reanalysis system ORAS4. *Q. J. R. Meteorol. Soc.*, **131**, 1132-1161.

Balmaseda, M, and Coauthors, 2015: The Ocean Reanalyses Intercomparison Project (ORA-IP). *J. Oper. Oceanogr.*, **7**, 81–99.

Behringer, D.W., M. Ji, and A. Leetmaa, 1998: An improved coupled model for ENSO prediction and implications for ocean initialization. Part I: The ocean data assimilation system. *Mon. Wea. Rev.*, **126**, 1013-1021.

Fujii, Yosuke, J. Cummings, Y. Xue, A. Schiller, T. Lee, M. A. Balmaseda, E. Rémy, S. Masuda, G. Brassington, O. Alves, B. Cornuelle, M. Martin, P. Oke, G. Smith and X. Yang, 2015: Evaluation of the

Tropical Pacific Observing System from the Ocean Data Assimilation Perspective. *Q. J. R. Meteorol. Soc.*, **141**, 2481-2496. doi:10.1002/qj.2579.

McPhaden, M.J., and Coauthors, 1998: The tropical ocean–global atmosphere (TOGA) observing system: a decade of progress. *J. Geophys. Res.*, **103**, 14,169–14,240.

Xue, Y., B. Huang, Z.-Z. Hu, A. Kumar, C. Wen, D.W. Behringer, and S. Nadiga, 2011: An assessment of oceanic variability in the NCEP Climate Forecast System Reanalysis. *Clim. Dyn.*, **37**, 2511–2539. doi:10.1007/s00382-010-0954-4

—, and Coauthors, 2010: Ocean state estimation for global ocean monitoring: ENSO and beyond ENSO. *Proceedings of ocean obs'09: sustained ocean observations and information for society (vol. 2)*. Venice, Italy, 21–25 September 2009, J. Hall, D.E. Harrison, and D. Stammer, Ed., ESA Publication WPP-306.

Yin, Y., O. Alves, and P. Oke, 2011: An ensemble ocean data assimilation system for seasonal prediction. *Mon. Wea. Rev.*, **139**, 786–808. doi: http://dx.doi.org/10.1175/2010MWR3419.1

Zhang, S., M.J. Harrison, A. Rosati, and A. Wittenberg, 2007: System design and evaluation of coupled ensemble data assimilation for global oceanic studies. *Mon. Wea. Rev.*, **135**, 3541–3564.