The partition of regional sea level variability

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Abstract

The existing altimetric record offers an unprecedented view of sea level (ζ) variability on a global scale for more than 2 decades. Optimal inference from the data involves appropriate partition of signal and noise, in terms of relevant scales, physical processes and forcing mechanisms. Such partition is achieved here through fitting a general circulation model to altimeter and other datasets to produce a “best” estimate of ζ variability directly forced by the atmosphere—the signal of primary interest here. In this context noise comes primarily from instrument errors and meso-scale eddies, as expected, but spatial smoothing effectively reduces this noise. A separate constraint is thus formulated to measure the fit to monthly, large-scale altimetric variability that unlike the daily, pointwise constraint shows a high signal-to-noise ratio.

The estimate is explored to gain insight into dynamics, forcing, and other factors controlling ζ variability. Contributions from thermo-steric, halo-steric and bottom pressure terms are all important depending on region, but slopes of steric spectra (red) and bottom pressure spectra (white) are nearly invariant with latitude. Much ζ variability can be represented by a seasonal cycle and linear trend, plus a few EOFs that can be associated with known modes of climate variability and/or with topographic controls. Both wind and buoyancy forcing are important. The response is primarily basin-bound in nature, but uneven patterns of propagation across basin boundaries are clearly present, with the Pacific being able to affect large portions of the Indian and Atlantic basins, but the Atlantic affecting mostly the Arctic.

Keywords:

ALTIMETRY; MODELLING; ESTIMATION; FREQUENCY ANALYSIS; STERIC SEA LEVEL; WAVE PROPAGATION.

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1. Introduction

This study assesses the various contributions to the 20-year altimetric record of regional variability, quantitatively, on a global basis, and with a primary focus on the large-scale, low-frequency forced response to the atmosphere. A broad range of statistical and dynamical analyses are applied to the multi-mission altimetric data set. This approach is complementary to historical reviews (e.g. Fu and Cazenave, 2001; Stammer et al., 2013) and detailed analyses of specific regions and phenomena (e.g. Ponte and Gaspar, 1999; Tamisiea et al., 2010; Piecuch and Ponte, 2013).

Our understanding of regional variability in sea level (ζ) has been developed over, at least, sixty years. Much of the theoretical foundations go back to the fifties and seventies. At the time the focus was largely on the response to atmospheric forcing (Pattullo et al., 1955; Veronis and Stommel, 1956; Gill and Niiler, 1973; Philander, 1978; Willebrand et al., 1980), numerical modeling was in its infancy, and sea level measurements were limited to tide gauges (Pattullo et al., 1955; Wunsch, 1972; Chelton and Davis, 1982).

Developments in satellite altimetry and general circulation models (GCMs) came to fruition in the nineties. The continuous growth in computing power allowed for GCMs to become of widespread use. Their results largely confirmed and extended our basic theoretical understanding of the forced ζ response to the atmosphere (Stammer, 1997b; Fukumori et al., 1998; Frankignoul et al., 1997). It is now well established that the importance of winds, buoyancy, and/or mass forcing is a strong function of location and time scale.

Building upon the successes of SEASAT (Wunsch and Gaposchkin, 1980; Fu, 1983), the launch of TOPEX-Poseidon in 1992 was a major turning point in observational oceanography. The wealth of data it provided over the global ocean soon confirmed the predominance and geography of meso-scale eddies seen in GCMs (Stammer et al., 1996; Stammer, 1997a) and, along with analyses of numerical models of increasing resolution (Hurlburt and Hogan, 2000), greatly improved our understanding of geostrophic turbulence (e.g. Chelton et al., 1998; Tulloch et al., 2009; Chelton et al., 2011).

Over the last decade, in situ hydrography (e.g. Argo) and space-based gravity measurements (e.g. GRACE) provided complementary and crucial information on the nature of altimetric variability (Willis et al., 2004; Chambers, 2006; Forget and Wunsch, 2007) and its relation to steric sea level (ζ_ρ)

and bottom pressure (p_b) variability. The mounting global data record (more than 2 decades of altimetry, and 1 decade of Argo and GRACE data) begins to allow for a comprehensive examination of the large-scale ζ variability on annual and longer time scales, which is a focus of this study.

The complementarity of observations and models is essential to refined analyses of ζ variability, and one can distinguish two basic approaches. On one hand simplified models (e.g., Fu and Qiu, 2002; Qiu, 2002; Cabanes et al., 2006; Weijer, 2012; Piecuch, 2013) are used to understand specific processes and events seen in observations. Historical development of this approach includes Gill and Niiler (1973), Philander (1978), and Willebrand et al. (1980). On the other hand general circulation models are used as an integral part of data processing and synthesis (Stammer et al., 2002; Wunsch and Heimbach, 2007; Forget et al., 2015a). The resulting ocean state estimates (or model-data syntheses) allow for extended analyses of altimetric data in terms of known dynamics and closed ζ budgets (Forget, 2010; Piecuch and Ponte, 2011, 2012).

The present study brings this latter line of research forward on a number of levels. Its guiding thread is the partition of altimetric ζ variability (i.e. its decomposition) in terms of contributions from signal and noise, steric height and mass, wind and buoyancy forcing, etc. The analysis focuses on the Radar Altimeter Database System (RADS) (Scharroo et al., 2004), which is a unified data base of along-track altimetry, and the ECCO v4 (Estimating the Circulation and Climate of the Ocean, version 4) state estimate, which includes RADS and complementary data constraints (Forget et al., 2015a). The composite nature of regional ζ variability leads us to approach the problem from a variety of complementary point of views. The various sections of the paper, while integrated with each other, can thus also be read individually, and are complemented with technical appendices.

Section 2 reviews data filtering methods that allow the partitioning of altimetric variability. The partition of ζ variability is then assessed in terms of signal and noise (section 3), intrinsic and forced variability (sections 3 and 4), frequency (sections 4 and 6), vertical structure (sections 4 and 6), spatio-temporal modes of variability (section 5), mechanisms of interannual variability (section 6), and local or non-local responses to surface forcing (section 7). New insights are summarized and perspectives are drawn in section 8.

2. Data Filtering

Aside from incorporating decades of research from numerous international collaborators, RADS efforts towards cross-calibrating the various instruments lead us to select their data set as our starting point. The along-track altimeter data from TOPEX-Poseidon/Jason (TPJ), ERS/Envisat (EE) and GEOSAT Follow-On (GFO) are obtained from RADS (Scharroo et al., 2004) for years 1992 to 2011. Relevant quality checks and corrections provided by RADS are first applied (see Appendix Appendix A), before bin-averaging the along-track data daily to a grid of 1° nominal resolution (see Appendix Appendix B). Filters of varying degree of sophistication can then be applied to isolate processes and signals of particular interest within the observed ζ variability. Here we delineate three classes of filtering methods and motivate their application to altimetry.

2.1. Outlier Filters

The most basic data partitioning is between valid data points and suspicious outliers: removing the latter is often a necessary prerequisite for robust analysis and statistics. For example the ice-covered sea level data points distribution in the Ross Sea shows a suspicious positive long tail (Figure 1). In fact, most outliers in the overall RADS data distribution are simply removed by masking out ice-covered pixels (an option of the RADS software; see Appendix Appendix A). A generic filter is applied to treat remaining outliers.

The distribution of each altimeter data set (TPJ, EE, GFO) at each grid point is treated individually. First, the spread of the observed distribution is calculated using the median absolute deviation, an estimator that is robust to outliers. Second, all data points that are more than 4 times the spread away from the median are rejected. If the data were following a normal distribution, the chance of finding a data point that satisfies this criterion would be about $1/25000$. In any case, the chosen filter is fairly conservative and rejects only a small fraction (0.9%) of the data points. For comparison, previously masked out, ice-covered pixels amount to 3.6% of the data points.

2.2. Simple Data Filters

Gridding the data, one way or another, implies a choice of scale truncation. Daily bin-averaging the along-track data to a grid of 1° nominal resolution attenuates the smallest scale noise, including instrument errors, but

Figure 1: Altimetric ζ sample distribution (horizontal axis in m) in the Ross Sea with ice-covered points included (top panel) or excluded (second panel) and for only ice-covered points (third panel). Superimposed magenta curves are from a gaussian fit to each distribution. Bottom left: altimetric ζ standard deviation (in cm, log scale) including all data points. Bottom right: same after removing ice-flagged points and applying the generic outlier detection algorithm.

retains meso-scale eddy variance (Fig. 2). For analyses focusing on larger scales, further smoothing is necessary. Thus Figure 3 is obtained by first applying a 35-day boxcar window ($\mathcal{B}$), and then applying a spatial smoother ($\mathcal{D}$) that removes the variability on scales smaller than 3 grid points (3°).

The chosen 35-day smoothing scale (in $\mathcal{B}$) coincides with the longest repeat cycle amongst altimeters (that of ERS) and yields nearly full maps (between 65°S and 65°N) of ζ anomalies for effective smoothing in space. The $\mathcal{D}$ spatial smoother is implemented as the time integration of a diffusion equation starting from the input field as initial condition (after Weaver and Courtier, 2001, and references therein). This operation is equivalent to convolving the input field with a gaussian kernel which spatial scale is set by the

product of diffusivity and integration time (as demonstrated in Weaver and Courtier, 2001). Here the smoothing scale is set to 3 grid points, which is the approximate scale beyond which the difference in variance level between altimetry and the ECCO v4 model plateaus (not shown).

After applying the $\mathcal{DB}$ smoother, the more homogeneous, and often much reduced, variance seen in Fig. 3, as compared with Fig. 2, is characteristic of the larger scale variability induced by atmospheric forcing. The removed variability, in turn, is a rough estimate of meso-scale eddy variability (see Appendix Appendix C). This physical interpretation of the partition realized by the $\mathcal{DB}$ smoother is reasonable due to the separation between ocean meso-scale of $O(100 \text{ km})$ and atmospheric synoptic scale of $O(1000 \text{ km})$.

Other partitions are certainly possible using different cut-off scales or other statistical filters (e.g., Fourier analysis, principal component analysis) but it is worth emphasizing that any filter (purely statistical or otherwise) implies a model for the physical behavior of the system. Aside from purely statistical filters, one can rely on simple physical models to begin partitioning the observed variability in terms of known physical processes.

Figure 2: Altimetric ζ variance (in m^2 , log scale) using all altimeters jointly for daily pointwise data. Along track data is simply averaged over 1-day windows and 1° grid cells.

The most common, and simplest, altimetric example is the so-called inverted barometer (IB) effect (a term coined by Doodson, 1924). The basic model is that of a static sea level response η to an anomaly in surface atmospheric pressure p' in the form of $\eta = -\frac{p'}{\rho_0 g}$, where ρ_0 is sea water density and g is the acceleration of gravity. This equilibrium model is generally a very good approximation (Ponte, 1993; Wunsch and Stammer, 1997) and is routinely used to compute an IB correction (from uncertain atmospheric surface pressure estimates) that can then be subtracted from the data.

Figure 3: Same as Fig. 2 but after applying a 35-day boxcar window, then a diffusive smoother to remove scales smaller than 3° . The 35-day boxcar window is sufficient to provide nearly full spatial coverage over the global ocean on scales larger than 1° . Note that the color axis was shifted by half order of magnitude compared with Fig. 2 (m^2 , log scale).

Another altimetric signal that is commonly filtered out is the contribution of the barotropic ocean tides. While the forcing is very accurately known from astronomy, the physics are more elaborate than for IB case — the shallow water equations are typically used and solutions are far from equilibrium. Tide solutions based on data inversions (Ray, 1999) and hydrodynamic models with data assimilation (Lyard et al., 2006) are, however, of sufficient accuracy to warrant subtracting the resulting tide correction from the data.

Throughout this study (incl. in Figs. 1, 2 and 3) IB and tide corrections provided by RADS are thus subtracted from the data (see Appendix Appendix A for details). Before we turn to more advanced combinations of models and data, it is useful to stress that satellite observations, and altimetry in particular, rely on atmospheric re-analyses and hydrodynamical models as part of low level data processing. In other words, the distinction between models and observations is readily blurred to some extent through basic data processing steps that carry some uncertainty (see section 2.2). In addition, interpolating the data (even without dynamics) requires an uncertain model for the covariance of ocean variability (see Le Traon et al., 1998; Wunsch, 2010).

2.3. Full Dynamical Filters

Available GCMs provide a convenient tool for advanced data filtering. Unlike for IB or shallow water equations, the ocean stratification and baroclinic variability are included in GCMs. There is a price, computational and technical, to pay for the added generality but our premise is that fitted GCMs will eventually become a routine and integral part of altimetry data processing — as is already the case with data-assimilating tide models.

In this study, the ECCO v4 state estimate serves as a prototype. Forget et al. (2015a) provides a general presentation of ECCO v4 and Appendix B recalls specifics that are of direct relevance to the synthesis and analysis of altimetric variability. The state estimate is a (laminar) GCM solution that resolves the large scale mass-, buoyancy- and wind-driven ζ variability and is fitted to altimetry (amongst other data sets) over the period from 1992 to 2011.

The limited model resolution (nominally 1°) implies that only large-scale responses can emerge from the surface forcing. The state estimation procedure furthermore excludes sequential data assimilation state increments, and imposes that surface forcing fields can only be adjusted at large scales. These settings (along with the least squares formulation in section 3) yield a dynamically consistent filter of data noise and meso-scale signals.

Apart from ζ , the state estimate provides related quantities of steric sea level (ζ_ρ) and bottom pressure (p_b). As formulated by Gill and Niiler (1973), under the hydrostatic and Boussinesq approximations

$$\zeta = \frac{1}{\rho_0 g} (p_b - p_a) + \zeta_\rho \quad (1)$$

where p_a is sea surface atmospheric pressure (which is omitted hereafter), ρ_0 is a constant density, g is the acceleration due to gravity, H is the ocean bottom depth and $\zeta_\rho = \frac{1}{\rho_0} \int_{-H}^0 \rho dz$. By virtue of Eq. 1, estimates of ζ_ρ and p_b allow for extended interpretation of altimetric ζ . In the ECCO v4 state estimate, the temporal evolution of Eq. 1 can furthermore be budgeted precisely in terms of air-sea fluxes, advection and diffusion (see Appendix Appendix F).

3. Partition of Signal and Noise

For context it is useful to stress the duality of the following perspectives:

- If the primary objective is to estimate meso-scale eddies, then large scale fluctuations driven by the atmosphere are a source of noise.
- If the primary objective is to estimate climate fluctuations, then individual meso-scale eddies are a source of noise.

Here we adopt the latter point of view. Thus, ECCO v4 is typically set up as an attempt to partition the RADS variability into: large scale fluctuations due to surface buoyancy, mass and wind forcing (resolved by the fitted dynamical model); geophysical noise due to tides, atmospheric pressure load and eddies (omitted by the fitted dynamical model); and instrumental noise. Here we revisit this estimation problem, the underlying error budget, and associated skill metrics.

3.1. Problem Formulation

The partition of observations into signal and noise is formalized as a constrained minimization problem. The daily pointwise distance between model and altimetry is written as

$$J_{a,pt} = (\zeta_e - \zeta_a)^T W_{a,pt} (\zeta_e - \zeta_a) \quad (2)$$

where ζ_a denotes the daily bin-averaged altimetry (RADS), ζ_e are the corresponding model sea level anomalies (ECCO v4), and $W_{a,pt}$ denotes the inverse error covariance matrix. As in previous realizations of ECCO, covariance matrices are approximated as diagonals. Indeed full error covariance matrices, and their inversion, remain intractable when the size of ζ_a is $O(10^7)$.

A new formulation of J_a is introduced, as a practical alternative, in order to distinguish between pointwise and large-scale errors. The smaller spatial scales and shorter time scales are filtered out consistently in model and observations by applying the $\mathcal{DB}$ smoother (section 2.2) to $\zeta_e - \zeta_a$. This approach yields a simple measure of the differences between ECCO v4 and RADS at the scales they both resolve:

$$J_a = \mathcal{DB}(\zeta_e - \zeta_a)^T W_a \mathcal{DB}(\zeta_e - \zeta_a) \quad (3)$$

3.2. Pointwise and Large-Scale Error Budget

Appropriate prescription of weights W is a critical consideration in the evaluation of model-data distances. Given the contrasting variances seen in Fig. 2 and Fig. 3, very different error budgets are expected for $J_{a,pt}$ and J_a .

Figure 4: Pointwise daily error budget (m^2 log scale) for altimetric anomalies averaged in bins of 1 day and 1 grid cell (1° box). The 5 error contributions are based on variances of: differences between TOPEX-Poseidon and ERS-Envisat over 1993-2010 (top left), differences in inverted barometer (IB) corrections calculated using ECMWF and NCEP pressure fields (top right), dynamic response to surface pressure forcing not treated by the IB correction (middle left), differences between tide models (middle right) and representation errors due to monthly meso-scale eddies (bottom left). The total error estimate ($\sigma_{a,pt}^2$; Eq. 4) combining the 5 error contributions is shown in the bottom right panel (see section 3.2 and Appendix Appendix C for details).

Following Ponte et al. (2007), the pointwise error variance $W_{a,pt}^{-1}$ in $J_{a,pt}$ accounts for 5 different error contributions: instrumental noise, geophysical noise due to meso-scale eddies, IB errors (σ_{IB}), dynamic pressure-forced signals (σ_{DP}) and tide errors (σ_{tide}). The total error variance is thus estimated as

$$\sigma_{a,pt}^2 = \sigma_{tme}^2 + \sigma_{mms}^2 + \sigma_{IB}^2 + \sigma_{DP}^2 + \sigma_{tide}^2 \quad (4)$$

where $\sigma_{tme}^2 + \sigma_{mms}^2$, taken together, accounts for the sum of instrumental noise and geophysical noise due to eddies. Updated estimates for the five error contributions are derived in Appendix Appendix C and depicted in Fig. 4.

The total error variance $\sigma_{a,pt}^2$ is dominated, over the bulk of the global ocean, by either instrumental errors (quieter areas) or eddy representation error (energetic areas). The basic level of instrumental error is about 2.7 cm pointwise (see Appendix Appendix C). Eddy representation error (see Fig. 4; bottom left) shows the expected energetic regions at mid-latitudes, which contrasts with the low variance seen in the tropics. The low variance seen south of the ACC may also be a robust feature, although the limited sample size adds uncertainty.

The geophysical noise due to IB, DP and tides is generally small but can become significant in particular regions. Atmospheric pressure fields are most uncertain in the Southern Ocean. Dynamic response to pressure load is largest in the Southern Ocean and in shallow and constricted regions (e.g., Hudson Bay). Tide errors are most important in shallow regions.

The large scale error budget consists of the same, albeit modulated, five terms, and is thus estimated as

$$\sigma_a^2 = \mu_{tme}^2 + \mu_{mms}^2 + \mu_{IB}^2 + \mu_{DP}^2 + \mu_{tide}^2 \quad (5)$$

Each of the terms essentially is the residual of daily pointwise errors coming out of the $\mathcal{DB}$ smoother (see Appendix Appendix D and Fig. 5).

Each of the error contributions is reduced in the large scale error budget (Fig. 5) as compared with the pointwise error budget (Fig. 4), and particularly the DP and meso-scale terms. Effects of DP are expectedly small at time scales beyond a few days (Ponte, 1993). Regions of strong meso-scale activity can still be detected in σ_a^2 but the homogeneous instrumental error term is much more predominant than in $\sigma_{a,pt}^2$. The basic level of instrumental error is about 0.8 cm at large scales (see Appendix Appendix D).

The large scale (35 days, 3°) error variance σ_a^2 is thus an order of magnitude smaller, and much more homogeneous, than the pointwise (1 day, 1°) error variance $\sigma_{a,pt}^2$. The key implication is that large scale ζ fluctuations can be tightly constrained by altimetry — much more so than the pointwise error budget may suggest. This expected result was of course the motivation for including a separate large scale altimeter constraint (Eq. 3) in ECCO v4.

Figure 5: Large scale monthly error budget (m^2 log scale) for altimetric anomalies. Cutoff scales are set to 3 grid points (diffusive smoother) and 35 days (boxcar). Panels are organized as in Fig. 4 but the color scale is shifted by an order of magnitude. The net error estimate (σ_a^2 ; Eq.5) combining the 5 error contributions (see section 3.2 for details) is shown in the bottom right panel.

There remain many caveats in the present analysis, and efforts to improve upon the proposed error model are warranted. At least four issues stand out : (1) the neglect of differences in instrumental error between altimeters; (2) the need for independent information to check each error contribution estimate; (3) the lack of a specific treatment of global mean errors (e.g., Ablain et al., 2009); (4) the need for swath altimetry observations of small scale and/or high-frequency motions that profile altimetry does not properly resolve (see

Fu and Ubelmann, 2014). Despite these caveats, the present analysis makes a useful step forward in defining the large scale noise level present in altimetry.

3.3. ECCO v4 Fit to Altimeter Data

The fit between state estimate and altimetry is depicted in Fig. 6, for the monthly large scale and daily pointwise cases, to illustrate how the estimated error budgets provide a useful frame of reference to gauge estimates of large-scale ζ variability (see also Table 1). In the present context 'signal' refers to sea level response to mass, buoyancy, and wind atmospheric forcing, whereas 'noise' refers to any of the contributions in Eqs. 4-5.

Figure 6: Assessment of the fit between the ECCO v4 state estimate and altimetry, for monthly large scale variability (left panels), and for pointwise daily variability (right panels). Top row: normalized model-data distance J_a , $J_{a,pt}$ (unitless; Eqs. 2-3). Middle row: log of signal to noise ratio (unitless; Eq. 7). Bottom row: coefficient of determination R^2 (unitless; Eq. 7).

The average model-data distances (J_a and $J_{a,pt}$) are generally close to one for the state estimate (Fig. 6, top panels). In deep waters, ECCO v4 only underfits altimetry ($J_a > 1$) in a few regions where further optimization (e.g. of forcing fields or parameterized physics) may be needed or σ_a may be underestimated. In marginal and shallow seas, the state estimate more often underfits the data but the 1° model is expected to have limited skill in these regions. There is little sign of the state estimate overfitting altimetry ($J_a < 1$), which indicates that the fitted model approximately rejects the amount of instrumental and geophysical noise predicted in section 3.2.

The skill of dynamical models as filters of un-physical signals is further highlighted in Fig. 7. Remaining misfits to EE and GFO observations are larger than those to TPJ observations, even though the various altimeters are equally weighted in ECCO v4. This non-trivial result is consistent with previous assessments that indicate that EE and GFO suffer from additional systematic errors and noise as compared with TPJ. An increase with latitude is visible in Fig. 7, reminiscent of the significant wave height field (see Ponte et al., 2007). Differences in misfit variance yields an inference of excess pointwise noise, which may range from 2 to 4 cm for EE and GFO.

Figure 7: Excess misfit variance for ERS-Envisat (EE) and Geosat-Follow-On (GFO) altimeters, as compared with TOPEX-Poseidon/Jason (TPJ). Taking EE as an example, $\sigma_{ee}^2 = \mathcal{V}(\zeta_e - \zeta_{a,ee}) - \mathcal{V}(\zeta_e - \zeta_{a,tpj})$ where $\zeta_{a,ee}$ and $\zeta_{a,tpj}$ respectively are EE and TPJ altimetry, ζ_e is the state estimate, and $\mathcal{V}$ is the variance operator. The median of σ_{ee} in 10 degree latitude bands is displayed in cm, and accordingly for σ_{gfo} .

Besides model-data distances (Eqs. 2-3), it is insightful to examine the corresponding signal to noise ratios defined as

$$\text{SNR}_a = \frac{\langle \mathcal{DB}(\zeta_e) \rangle^2}{\sigma_a^2}, \quad \text{SNR}_{a,pt} = \frac{\langle \zeta_e \rangle^2}{\sigma_{a,pt}^2} \quad (6)$$

and fractions of explained variance defined as

$$R_a^2 = 1 - \frac{\langle \mathcal{DB}(\zeta_a - \zeta_e) \rangle^2}{\langle \mathcal{DB}(\zeta_a) \rangle^2}, \quad R_{a,pt}^2 = 1 - \frac{\langle \zeta_a - \zeta_e \rangle^2}{\langle \zeta_a \rangle^2} \quad (7)$$

The pointwise signal to noise ratio $\text{SNR}_{a,pt}$ is generally near 1 or smaller (Fig. 6, middle right). Values of $\text{SNR}_{a,pt} \geq 1$ are mainly found in the tropics due to the relatively weak meso-scale eddies and the presence of fast equatorial waves that the state estimate can resolve. In the vicinity of energetic subtropical jets though, $\text{SNR}_{a,pt}$ can be as low as 1/100. Thus $J_{a,pt}$ is rather insensitive to the choice of large scale model solution (see Table 1).

The large-scale signal to noise ratio SNR_a is, in contrast, greater than 1 almost everywhere and values of $\text{SNR}_a > 10$ are common (Fig. 6, middle left). The fact that $\text{SNR}_a \gg \text{SNR}_{a,pt}$ implies that the $\mathcal{DB}$ smoother attenuates the noise more than the signal. Some of the least statistically favorable locations are found in the Southern Ocean due to, at least in part, an imperfect filtering of eddies by the $\mathcal{DB}$ smoother (Fig. 5, bottom left). But the key implication of $\text{SNR}_a \gg \text{SNR}_{a,pt}$, even in the Southern Ocean, is that J_a is a much more sensitive model-data distance than is $J_{a,pt}$ (see Table 1).

The skill of the state estimate can further be measured as a fraction of explained altimetric variance (R_a^2 and $R_{a,pt}^2$ in Eq. 7). The Southern Ocean shows smaller R_a^2 (Fig. 6, bottom left) consistent with its smaller SNR_a (Fig. 6, middle left). However, ECCO v4 explains about 80% of the monthly large-scale ζ variability over the bulk of the global ocean (Fig. 6, bottom left). In the tropics $R_{a,pt}^2 > 0.8$ further suggests that ECCO v4 explains about 80% of the daily pointwise variability (Fig. 6, bottom right) but elsewhere it explains a smaller fraction of the noisier daily pointwise altimeter record as predicted by the $\text{SNR}_{a,pt}$ map (Fig. 6, middle right).

The skill of the state estimate is inherited partly from the first guess combination of dynamical model (MITgcm) and re-analyzed atmospheric forcing fields (ERA-Interim), and improved by use of altimetric observations through the adjoint optimization procedure. The control run defined in Appendix Appendix C (ζ_{ERA}) provides a useful reference point, as it omits the skill added by optimization of time variable forcing fields. Value of R_a^2 of

0.7 for ζ_{ERA} (Table 1; left column) confirms that the pairing of MITgcm and ERA-Interim fields has merit as a first guess solution. In comparison, the optimized solution (ζ_e) is on average 37% closer to altimetry at large scales (1.54/2.44; see Table 1) and successfully approaches the expected R_a^2 value given by $1 - \frac{\sigma_a^2}{\langle \zeta_a \rangle^2} \approx 0.85$ (see Table 1).

	control run (ζ_{ERA})	ECCO v4 (ζ_e)
J large scales (J_a)	2.44	1.54
J all scales ($J_{a,pt}$)	1.29	1.19
R^2 large scales (R_a^2)	0.70	0.80
R^2 all scales ($R_{a,pt}^2$)	0.31	0.35

Table 1: Global mean values (area weighted) of model-data distance (J) and coefficient of determination (R^2) for the ECCO v4 state estimate (right column) and for the control run from Appendix Appendix C (left column). Global mean sea level variations are omitted to facilitate comparison of regional ζ variability. Large scale values (J_a and R_a^2) use all altimeters jointly, whereas pointwise values ($J_{a,pt}$ and $R_{a,pt}^2$) are provided for TOPEX-Poseidon/Jason.

4. Partition in Frequency Space

This section addresses the partition of regional ζ variability in terms of different time scales through simple spectral analysis in frequency space. The bi-decadal trend and mean seasonal cycle are set aside before computing power density spectra (see Appendix Appendix E for algorithmic details). We start with atmospherically-forced variability in ζ , ζ_ρ and p_b , as estimated by ECCO v4, and then compare large-scale and meso-scale ζ variability.

4.1. Forced Response

The globally averaged spectrum of ζ (Fig. 8) is pink in color for time scales between 3 months and 3 years ($n = -1.2$). The ζ spectrum is intermediate between the white p_b spectrum ($n = -0.3$) and the red ζ_ρ spectrum ($n = -1.8$). At periods longer than approximately one year, the first order balance is baroclinic, i.e., ζ and ζ_ρ have similar power levels, while p_b shows considerably weaker power. At shorter periods, p_b gradually gains power relative to ζ_ρ and the first order balance becomes more and more barotropic, i.e., with closer correspondence between ζ and p_b and a weaker role for ζ_ρ contributions. The spectral slope steepens at periods less than a month, which is characteristic of high frequency barotropic responses (Willebrand et al., 1980).

Figure 9 (left) demonstrates the near universality of the p_b and ζ_ρ spectral shapes, which are consistent with classic theory of the oceanic response to large-scale atmospheric disturbances (e.g. Veronis and Stommel, 1956; Gill and Niiler, 1973; Willebrand et al., 1980; Frankignoul et al., 1997). The variation of ζ spectral slope with latitude simply reflects large contrasts in the respective magnitudes of baroclinic and barotropic contributions (Fig. 9, middle). For periods between 3 months and 3 years, ζ variability is largely barotropic at high latitudes, but largely baroclinic at low latitudes. This result is consistent with the latitudinal dependence predicted by Gill and Niiler (1973) for the annual period. Thus, ζ spectrum at low latitudes tends to be redder, and whiter at high latitudes (Fig. 9, right).

When examining the pressure field at all depths, steep spectral slopes are a characteristic of the upper ocean (Fig. 10), reflecting the near surface intensification of dominant baroclinic modes (see also Wunsch, 1997). Below the main thermocline white spectra are found at most latitudes, consistent with p_b spectra and a predominance of barotropic fluctuations. The steepest spectra seen in the upper tropical ocean are largely a characteristic of

Figure 8: Power density spectrum for ζ (red), p_b (blue) and ζ_ρ (black) as resolved in ECCO. Trend and seasonal cycle are removed before computing spectra. Global (area-weighted) averages of individual spectra computed at each grid point are shown (not be confused with spectra of global averages). Vertical dashed lines denote, from left to right, periods of 10, 3 and 1 years, 3 months, 1 month and 1 week. Spectral slopes between periods of 3 years and 3 months are reported in the legend.

ENSO. As illustrated in section 5, most of the ζ power at low latitudes is indeed associated with ENSO modes, which can easily be captured through EOF analysis, and which show a predominance of low frequencies. Thus, subtracting the leading EOFs from section 5 yields considerably flatter ζ spectra between 20°S and 20°N (Fig. 11). An interesting question, which is proposed for further study, is whether flat ζ spectra (Fig. 11, red curve) are a characteristic of un-coupled ζ responses to atmospheric disturbances in the tropics (as opposed to ENSO). In contrast, spectral slopes are largely unaffected at mid and high latitudes (Fig. 11), implying that the frequency spectra of leading EOFs simply resemble that of ambient ζ responses to atmospheric disturbances.

Figure 9: Latitudinal contrasts in power density spectra of ζ , p_b and ζ_p . Left: normalized power density spectra averaged in 10° latitude bands for p_b (blue) and ζ_p (black). Middle: total power (variance, shown in log scale) at periods longer than 1 day. Right: spectral slopes between periods of 3 years and 3 months. Trend and seasonal cycle were removed before computing spectra.

Figure 10: Spectral slopes of the three dimensional hydrostatic pressure field. Values represent zonal averages (area and power weighted). Spectral slopes are computed as a best fit between periods of 3 years and 3 months.

Figure 11: Spectral slopes of ζ when including (blue curve) or excluding (red curve) the 20 leading EOFs (see Appendix Appendix E for algorithmic details). In both cases, trend and mean seasonal cycle are omitted. Spectral slopes are computed as a best fit between periods of 3 years and 3 months.

4.2. Meso-Scale Versus Large-Scale

Meso-scale ζ variance exceeds large-scale ζ variance for periods up to 3 years, except between 10°S and 10°N (cf. black curves in Fig. 12). Power levels are comparable even at periods longer than 3 years. The presence of considerable meso-scale energy at long periods may be surprising, but is consistent with the fact that simple annual mean anomaly maps calculated from altimetry contain strong meso-scale features of eddy origin (Wunsch, 2010). Our findings are also supported by the model results of Penduff et al. (2011).

Meso-scale variability has a flatter frequency spectrum (Fig. 12, top left) than large-scale variability does (bottom left). The spectral slope for meso-scale signals is near 0 at periods longer than a year, but becomes steeper at shorter time scales (top left) and at mid-latitudes (top right). In comparison to altimetry, the meso-scale spectrum in the state estimate (top panels, blue curves) generally shows very little power at all frequencies, as expected since the coarse resolution model is meant to filter out meso-scale eddies. Subtracting the state estimate from altimetry (leading to the red curves in Fig. 12) affects the meso-scale estimate but only at low latitudes.

In stark contrast with the meso-scale case, at large scales altimetry and state estimate show very similar power levels at all frequencies, with very similar spectral slopes (Fig. 12, bottom panels). Some additional large scale variance in ζ_a is expected due to the necessarily imperfect filtering of geophysical and instrumental noise. However, remaining large-scale misfits (bottom panels, red curves) are only a small fraction of the corresponding variability at all frequencies and latitudes. The spectral slope of large-scale misfits is flatter ($n = -1$) than that of ζ itself ($n = -1.6$), with largest differences occurring at low latitudes (-1 versus -2). The implication is that remaining large-scale misfits are more significant at higher frequencies.

Figure 12: Top : meso-scale variability in ζ_a (black; altimetry), ζ_e (blue; state estimate) and $\zeta_a - \zeta_e$ (red) diagnosed using the $\mathcal{E}$ filter (see Appendix Appendix C). Bottom: large scale variability in ζ_a , ζ_e and $\zeta_a - \zeta_e$ diagnosed using the $\mathcal{DB}$ filter (see section 2.2). Left: global (area-weighted) average of power density spectra. Middle: total power (variance, shown in log scale) at periods longer than 1 month. Right: spectral slope for periods between 3 months and 3 years. Trend and seasonal cycle are removed before computing spectra. This plot is restricted to latitudes between 65°S and 65°N , which have a dense altimeter sampling.

5. Partition Into Modes of Variability

This section addresses the partition of large-scale ζ variability in terms of its main spatio-temporal patterns. About 90% of the estimated monthly variance can be cast as a combination of trend, seasonal fluctuation and 20 leading empirical orthogonal functions (EOFs). Algorithmic details are reported in Appendix Appendix E. We start with an analysis of the EOFs geography and time series, and then compare their combined variance with the magnitude of the bi-decadal trend and mean seasonal cycle.

5.1. Empirical Orthogonal Functions

The two global modes with most (area weighted) variance are associated with ENSO (Fig. 13, top panels). Their temporal fluctuations (Fig. 14, top panels) are highly correlated with various ENSO indices (Niño3.4 and Southern Oscillation Index for mode 1, and El Niño Modoki Index for mode 2). They peak during the large ENSO event in 1997–98, and fluctuate predominantly at interannual and longer timescales. The global extent of these modes, beyond the tropical Pacific, reflects both ocean wave propagation and global shifts in atmospheric forcing during ENSO events. For example, ocean wave propagation plays a role in establishing the patterns along the Pacific eastern boundary (Enfield and Allen, 1980; Chelton and Davis, 1982). Patterns near the Gulf of Alaska and the Labrador Sea, however, emerge from atmospheric teleconnections associated with Pacific SST anomalies, such as the Pacific-North American teleconnection (Wallace and Gutzler, 1981; Ashok et al., 2007). The relative importance of ocean propagation vs. atmospheric teleconnections is further assessed in section 7.2.

Southern Hemisphere modes are identified separately for the Pacific (Fig. 13, bottom right) and the Indian (bottom left) between 30S and 65S. These modes are well documented in the literature (Fukumori et al., 1998; Webb and de Cuevas, 2002a,b; Fu, 2003; Vivier et al., 2005; Weijer, 2010, 2012; Ponte and Piecuch, 2014). Their single pole patterns are intimately related to ocean bathymetry features (abyssal plains and limiting ridges) and their fluctuations are excited by variable winds. The divergence (or convergence depending on phase) implied by these single pole modes must be compensated by small sea level changes over the global ocean. They predominantly fluctuate at high frequency (Fig. 14, bottom panels). Their fluctuations are weakly, but significantly, correlated with the Antarctic Oscillation Index.

The first North Pacific and North Atlantic modes (Fig. 13, second and third row) are associated with a spin up/spin down of subtropical or subpolar gyres. Their patterns are delineated by features of the time mean ocean state, rather than by ocean bathymetry contours. They predominantly fluctuate at low frequencies. The two North Pacific modes are significantly correlated with the Pacific Decadal Oscillation Index, and the second mode also correlates with other common atmospheric Northern Hemisphere indices (North Pacific Oscillation, Pacific North America Oscillation, Arctic Oscillation). The first Atlantic mode is significantly correlated with North Atlantic Oscillation and Arctic Oscillation indices, whereas the second Atlantic mode is significantly correlated with the Atlantic Multidecadal Oscillation index.

5.2. Variance Contributions

Most variability at the scale of ocean basins is captured within 22 identified modes (trend and seasonal cycle, plus 5 global EOFs and 15 regional EOFs; see Appendix Appendix E for details). Thus, subtracting these modes reduces the standard deviation of the monthly state estimate ζ by a factor of 2, or more, at most latitudes (Fig. 15, left panel). The residual variability amplitude (red curve) shows very little latitudinal structure compared with the full variability amplitude (green curve). The few subtracted modes (most of them limited to individual basins) thus suffice to explain much of the regional contrasts in large scale ζ variance (i.e. in Fig. 3).

The mean seasonal cycle is a main contributor at all latitudes (Fig. 15, right panel). The trend amplitude is fairly homogeneous, and its associated variance is generally smaller than that due to seasonality. The variability associated with leading EOFs is often as large as that due to seasonality, although its relative importance depends on the region of interest and also on choices of EOF basis truncation. Robust conclusions are that seasonality is particularly important at mid northern latitudes and EOF modal structures particularly important at low latitudes.

The maxima seen in Fig. 15 near 70°N correspond to strong ζ fluctuations over the Siberian and Barents Sea shelves. In addition, there is considerable energy in spatially homogeneous ζ oscillations spanning the entire Arctic and the Greenland Sea at non-seasonal time scales. This energy is associated with the main Arctic modes of variability originally discussed by Hughes and Stepanov (2004) and recently observed by GRACE (Volkov and Landerer, 2013; Peralta-Ferriz et al., 2014; Fukumori et al., 2015). Our EOF decomposition confirms the presence of these main Arctic modes, which represent

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5 481 about 70% of the non-seasonal ζ variance in the region (not shown). They
6 482 account for the large variance reduction seen in Fig. 15 (left panel) north
7 483 of 60°N when EOFs are subtracted. The Antarctica shelf also shows much
8 484 variance reduction near 80°S due to the subtraction of the vigorous Southern
9 485 Ocean mode discussed by Hughes et al. (1999) and Hughes and Stepanov
10 486 (2004).
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Figure 13: Spatial patterns of ζ variability (in cm) identified by EOF analysis of ζ_e (see Appendix Appendix E for algorithmic details). Principal component time series are shown as black curves in Fig. 14, with identically laid out panels.

Figure 14: Principal component time series (black curves; unitless and of variance 1) associated with the spatial patterns in Fig. 13 (with identically laid out panels) for the state estimate. Corresponding time series for altimetry and model-data misfits are also shown as blue and red curves, respectively (see Appendix Appendix E for algorithmic details). Thin curves are monthly means, while thick curves are annual means.

Figure 15: Zonally averaged standard deviation of monthly ζ (left panel; green curve). The same quantity is also shown after subtracting, in sequence: 1) trend (blue curve); 2) mean seasonal cycle (black curve); 3) 20 leading EOFs (red curve; see Appendix Appendix E for algorithmic details). The corresponding standard deviations of subtracted signals are shown in the right panel.

6. Partition Into Physical Processes

This section focuses on hydrostatic pressure budgets of the ECCO v4 state estimate that provide information on the baroclinicity of interannual ζ variability (section 6.1) and the local impact of thermohaline processes (section 6.2). The various terms are obtained as part of a precise daily hydrostatic pressure budget of the state estimate (Appendix Appendix F). They are displayed after subtracting the bi-decadal trend and applying e.g. a one-year boxcar window filter to focus on interannual variability.

6.1. Mass and Steric Contributions

In accounting for interannual ζ variance (Fig. 16, top left), the neglect of either p_b variance (bottom left) or ζ_ρ variance (top right) would generally lead to sizable errors. However, one can distinguish between two types of dynamics, as hinted to in the frequency spectra discussion (section 4.1).

Figure 16: Logarithm of interannual variance (in m^2) for ζ (top left), p_b (bottom left), ζ_ρ (top right), and ζ_s (bottom right).

High latitudes show significant barotropic-like interannual variability, in which changes in ζ are primarily associated with changes in p_b . In the Arctic and GIN Seas, barotropic variability is thus the predominant mechanism of interannual ζ variability. As a result, given the limited availability of altimetric data in polar oceans, interannual ζ variability may in fact be best

observed by gravimetry in these regions (Volkov and Landerer, 2013; Peralta-Ferriz et al., 2014; Fukumori et al., 2015). In the Southern Ocean, interannual p_b variability (bottom left) is apparent both around Antarctica and over regions highlighted in section 5.1 (see also Piecuch et al., 2013; Ponte and Piecuch, 2014). Despite the predominance of interannual p_b variability at high latitudes, however, interannual ζ_ρ variability of leading order is also seen in the vicinity of the Antarctic Circumpolar Current and in the Arctic (top right). The latter are predominantly halo-steric in nature (bottom right), as one would expect in the presence of sea ice.

In stark contrast, interannual ζ variability at low and mid latitudes is almost exclusively baroclinic, since ζ_ρ contributions (top right) are much larger than p_b contributions (bottom left). This behavior is typical of forced baroclinic waves (e.g. Rossby and Kelvin waves) as well as of passive response to surface buoyancy fluxes. Low and mid latitude steric contributions largely result from temperature changes. However, sizable halo-steric effects (bottom right) occur in the vicinity of western boundary currents and in the ACC, as these regions are associated with large salinity gradients.

This predominance of baroclinic variability is characteristic of low frequencies (e.g., see Fig. 8). In contrast, for periods less than one month, variability in ζ and p_b is generally, and to a good approximation, barotropic (Fig. 17; see also Fukumori et al. 1998). Sizable steric contributions are only found near the Equator for periods less than a month (Fig. 17).

6.2. Mechanisms of Steric Variability

Interannual ζ_ρ variability involves contributions from advection, diffusion and surface forcing. Variable heat advection (ζ_T^a) plays a leading order role in interannual variability of thermo-steric sea level (ζ_T) virtually everywhere (Fig. 18, top left). A variance ratio $\frac{\mathcal{V}[\zeta_T^a]}{\mathcal{V}[\zeta_T]}$ of exactly one would follow from adiabatic fluctuations of the thermocline under variable wind forcing, which may be regarded as the null hypothesis in the present context.

However, variable air-sea heat flux (ζ_T^f) also plays a leading order role in many locations, at all latitudes (Fig. 18, bottom left). Furthermore, variable heat diffusion (ζ_T^d) seems responsible for sizable interannual ζ_ρ variability (top right) as noted by Piecuch and Ponte (2011). Finally, halo-steric effects (ζ_s) also become important at high latitudes (bottom right). While the null hypothesis is of broad value as a qualitative first order depiction, quantitative analyses of interannual fluctuations in ζ_ρ require taking into account all of the terms shown in Fig. 18 (see also Köhl, 2014).

Figure 17: Logarithm of submonthly variance (for periods less than one month; in m^2) for ζ (top) and p_b (bottom).

Regions of ‘excess variable advection’ (i.e., such that $\frac{\mathcal{V}[\zeta_T^f]}{\mathcal{V}[\zeta_T]} > 1$) are found where variable air-sea heat flux is generally also large (i.e., $\frac{\mathcal{V}[\zeta_T^f]}{\mathcal{V}[\zeta_T]}$ is of order 1). These regions often correspond to locations of water mass transformations (e.g. in the vicinity of the Gulf Stream and ACC). An interesting question, which remains to be elucidated, is the extent to which advection might drive interannual variability in ζ_T while air-sea fluxes provide a feedback mechanism, or vice versa. An analysis of this point is presented for upper-ocean heat content variability in the North Atlantic by Buckley et al. (2014).

Variable diffusion affects interannual ζ_ρ variability mostly at the grid scale. This is demonstrated by spatially smoothing the daily hydrostatic budget to remove scales below 12 grid points, before computing the variance of the various terms (Fig. 19). By this procedure the ‘local’ scale is reset to be representative of the atmospheric synoptic scale rather than the ocean grid scale. Thus, interannual effects of variable diffusion become negligible

Figure 18: Interannual ζ_p variance contributions diagnosed from the state estimate hydrostatic pressure budget (see Appendix Appendix F for details and notations). Top left: $\log(\frac{\mathcal{V}[\zeta_T^a]}{\mathcal{V}[\zeta_T]})$ where $\mathcal{V}$ denotes interannual variance. Top right: $\log(\frac{\mathcal{V}[\zeta_T^d]}{\mathcal{V}[\zeta_T]})$. Bottom left: $\log(\frac{\mathcal{V}[\zeta_T^f]}{\mathcal{V}[\zeta_T]})$. Bottom right: $\log(\frac{\mathcal{V}[\zeta_S]}{\mathcal{V}[\zeta_T]})$.

almost everywhere (Fig. 19, top right). Only notable exceptions are in the Arctic and near Antarctica continental margins.

The relative importance and geography of interannual halo-steric variability is generally robust to the change in ‘local’ scale definition (Figs. 18-19, bottom right). However, subtle but important changes in the interplay of variable heat advection (ζ_T^a ; top left) and air-sea heat fluxes (ζ_T^f ; bottom left) appear upon spatial smoothing. Hence, the 25th and 50th percentiles of $\frac{\mathcal{V}[\zeta_T^a]}{\mathcal{V}[\zeta_T]}$ decrease from 0.98 and 1.4 in Fig. 18 to only 0.62 and 0.87 in Fig. 19, which shows virtually no trace of excess variable advection. In general ζ_T^a thus becomes less predominant in the ocean interior at increasingly large spatial scales, consistent with simple scaling arguments (Gill and Niler, 1973).

Figure 19: Same as Fig. 18 but only for scales larger than 12×12 grid points.

7. Partition into Forcing and Response Mechanisms.

This section focuses on the forcing and propagation mechanisms of interannual ζ variability. The contribution of anomalous wind stress is diagnosed by removing it from the state estimate forcing and computing the difference that results in ζ interannual variability. Appendix G provides technical details regarding these perturbations experiments that use the state estimate as the baseline. Their results shed light on the integrated ζ response to surface forcing disturbances (section 7.1) and the role played by propagating, nonlocal effects in interannual ζ variability (section 7.2).

7.1. Various Forcing Contributions

Interannual ζ variability is predominantly forced by surface wind stress anomalies (Fig. 20, top panel), as reviewed by Stammer et al. (2013). Regional sea level responses typically emerge from the integration of local wind forcing along Rossby wave characteristics (e.g., see Qiu, 2002) and along characteristics of the global ocean dynamics more generally. The remainder variability (Fig. 20, bottom panel) is forced by anomalous surface fluxes of buoyancy and mass. Its geography mostly results from surface buoyancy fluxes, as the dynamical impact of surface mass loading is expectedly small (Ponte, 2006b). While wind stress can be regarded as the null hypothesis for the origin of interannual ζ variability, there are wide regions where buoyancy-driven interannual variability (Fig. 20, bottom panel) is as large as, or larger than, the wind-driven¹ contribution (Fig. 20, top panel).

In the North Atlantic, in particular, our findings confirm the analysis of Cabanes et al. (2006). The mid latitude North Pacific (particularly in the eastern basin) is a second region where interannual ζ variability seems to be substantially buoyancy-driven, in general agreement with results of Thompson and Ladd (2004). Sizable buoyancy-driven interannual ζ variability is also seen in the vicinity of the ACC and Kuroshio, as well as in the Arctic, South Atlantic, and tropical Pacific. The importance of buoyancy forcing and related dynamical ζ response at interannual timescales in the tropics has also been highlighted by Piecuch and Ponte (2012, 2013).

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¹Only features generated by the action of wind stress are referred to as ‘wind-driven’, which is conventional terminology. Note, however, that air-sea fluxes of buoyancy and mass also vary with wind speed.

598 The estimated 1993–2010 trend in ζ driven jointly by surface fluxes of
 599 mass and buoyancy is generally positive (Fig. 21, bottom panel). Global
 600 mean ζ rises due to both mass gain and heat uptake in approximate agree-
 601 ment with previous estimates. Note, however, that the associated trends
 602 tend to be larger in the Atlantic as compared to the Pacific (Fig. 21, bottom
 603 panel). There is also substantial spatial structure within each basin (e.g.,
 604 additional trends in subtropical gyres, and in the North Atlantic subpolar
 605 gyre). In the tropical Pacific, buoyancy forcing seems to also contribute to
 606 the east-west asymmetry in trends. The ability to separate and explore such
 607 regional features in the state estimate can help reveal long term shifts in
 608 regional hydrological and radiational balances.

609 The geography in the estimated 1993–2010 trend in ζ is also largely im-
 610 printed by evolutions in the wind stress forcing (Fig. 21, top panel). Wind
 611 driven ζ trend patterns are suggestive of particular phases of common spatio-
 612 temporal modes of variability (see Fig. 13). This is most distinctly the case
 613 in the tropical Pacific, where large wind-driven ζ trends predominate in the
 614 west, in a pattern that has been associated with increasing zonal winds over
 615 the basin (Merrifield, 2011; McGregor et al., 2012; Qiu and Chen, 2012;
 616 Moon and Song, 2013). A general implication of Fig. 21 is that the patterns
 617 of altimetric ζ trends may have little to do with a shifting global hydrologi-
 618 cal cycle or heat balance, and may rather reflect low frequency wind-driven
 619 redistributions of mass and heat.

Figure 20: Interannual variability in ζ (log of variance is displayed) due to wind stress (top) and to mass and buoyancy forcing (bottom). Trends are not included in interannual variability but displayed in Fig. 21.

Figure 21: Change in ζ between 1993 and 2010 (in cm) obtained by fitting a linear trend. Top : contribution due to wind stress; bottom : contribution due to mass and buoyancy forcing (bottom).

7.2. Local vs. Nonlocal Response to Forcing

The response to anomalous wind stress occurring in one basin or a latitude band is diagnosed by removing it selectively from the state estimate forcing (see Appendix Appendix G for details). Regional sea level variability in one basin or over a latitude band is, to first order, driven locally. Within the 20-year altimetric period, the practical value of this null hypothesis is illustrated in Fig. 22 by comparing a hypothetical, purely local response (green contours) with the actual response obtained through model experiments with perturbed wind stress (color shading).

Departures from the null hypothesis are expected to originate from slowly-propagating planetary waves and advected anomalies, which have been identified in altimetric data, at least in certain specific regions (e.g. Fu and Qiu, 2002; Qiu, 2002). Kelvin waves and other equatorial and coastal-trapped waves allow for faster propagation, and play a major role in ENSO events (Wyrtki, 1975). Here we focus on possible pathways for ζ variability propagation, within 20 years, between different ocean basins as well as between low, mid and high latitude bands.

The propagation of high latitude wind-driven variability (poleward of 65°) to the subtropics is most significant in the North Atlantic and eastern South Pacific (Fig. 22, top right). The northward extension of elevated variance seen in the eastern South Pacific (dark color shading) can be linked to ocean topography effects, through the excitation of a barotropic mode (Fig. 13, bottom right) by wind stress variations south of 65°S .

The North Atlantic seems to support a uniquely efficient western boundary path for the southward propagation of coastally-trapped signals originating in the Arctic or the Nordic seas, which may be detectable as far south as 40°N . Similarly, mid-latitude wind stress variability south of 65°N can also generate large ζ fluctuations over the entire Arctic basin (Fig. 13, middle right). A refined analysis of this behavior is presented by Fukumori et al. (2015).

Variability driven at mid-latitudes appears to be of little influence in the tropics over 20 years (Fig. 22, middle right), with no significant activity visible along the western boundary and the equator. In contrast, variability driven at low-latitudes extends to mid latitudes (Fig. 22, bottom right), particularly along the eastern boundaries (South and North Pacific) and the eastern and southern coast of Australia. Variability from tropical Pacific origin, in fact, appears to enter the Arctic through Bering Strait and may be detectable along East Greenland according to Fig. 22 (bottom right).

Variability generated in one basin carries over to the others mostly through their Southern Ocean connections (Fig. 22, left panels). Coastal Kelvin waves can propagate around Antarctica. In the open ocean, variability generated in the Indian (middle left) or Pacific (top left) Oceans is seen to extend both westward and eastward into contiguous basins. Baroclinic Rossby waves provide a mechanism for westward propagation, while advection is predominantly eastward in the Southern Ocean. However, Atlantic variability does not seem to extend westward from Drake Passage (bottom left), apart from very near the Antarctica coast. It is possible that both the predominant eastward mean flows and the topography limit interior westward wave propagation there. Other noticeable variability routes are the straits towards the Arctic Ocean and the East Indian Archipelago, with a marked asymmetry in the way Indian Ocean variability mainly affects the equatorial Pacific while effects of Pacific winds on the Indian Ocean are strongest over 10°S–30°S band.

Figure 22: Propagation of wind-driven sea level variability between basins (left column) and latitude bands (right column), based on perturbation experiments conducted with variable wind forcing suppressed region by region (see Appendix Appendix G for details). Color shading denotes $\log(\mathcal{V}[\delta\zeta]/\sigma_a^2)$ where $\delta\zeta$ is the monthly ζ response to a given wind stress perturbation $\delta\tau$, $\mathcal{V}$ denotes the variance operator, and σ_a^2 is the estimated large scale noise variance. Black color denotes signal variance larger than the noise variance. Green contours denote the same signal-to-noise ratios but computed based on the hypothetical, purely local response defined in Appendix Appendix G. Color shading outside the green contours thus denotes non-local responses originating from the region, within green contours, where variable forcing was perturbed. In contrast, color shading inside the green contours primarily reflects local responses.

8. Summary and Perspectives

This study is an assessment of the composite nature of regional ζ variability. Much of the daily ζ variability at scales of 1° and larger is associated with signals from surface pressure loading, tides and meso-scale eddies. Meso-scale altimetric variability shows considerable power even at interannual time scales, consistent with earlier inferences from numerical models (Penduff et al., 2011). Common assumptions about the lack of eddy energy at sufficiently low frequencies thus need to be cautiously weighted in the interpretation of ζ records (see also Wunsch, 2010; Vinogradov and Ponte, 2011).

Large scale ζ variability forced by variable surface wind stress, buoyancy and mass fluxes is, nevertheless, often highly significant at time scales longer than one month and spatial scales of 3° and larger. The estimated signal-to-noise ratio in the altimetric record is between 1 and 10 at those scales. Monthly large scale errors are rather homogeneous and generally below 1cm in amplitude. This is in clear contrast with daily pointwise errors where heterogeneous eddy representation error predominates (see also Ponte et al., 2007) and the instrumental error floor as estimated over the quieter parts of the ocean exceeds 2.7 cm (the corresponding monthly large-scale value is 0.8 cm). A large scale model-data distance can thus be formed that yields a highly sensitive altimetric constraint for use in ocean state estimation.

About 90% of the monthly large scale ζ variability forced by variable surface wind stress, buoyancy and mass fluxes can be cast as a combination of trend, seasonal fluctuation and 20 leading EOFs (most of them restricted to individual basins). Both global and basin modes analyzed represent the ζ signature of major climate patterns (ENSO, PDO, AAO, AMO, etc.). Global modal expressions tend to reflect global forcing patterns rather than ocean long-range propagation mechanisms. Non-modal monthly large scale ζ variability (i.e., the remainder) shows a rather homogeneous amplitude of about 2 cm. The ECCO v4 ocean state estimate captures most of the modal variability seen in altimetry, and generally explains about 80% of monthly altimetric variance at scales of 3° and larger.

Nearly universal shapes characterize the frequency spectra in both baroclinic (ζ_ρ) and barotropic (p_b) large scale responses to atmospheric disturbances (surface pressure load being omitted). Spectra of ζ_ρ are red for periods between 3 months and 3 years and flatten out at longer periods, whereas p_b spectra are essentially white for periods longer than 3 months. The known

latitudinal contrast in sea level frequency spectrum slope emerges from the relative power associated with ζ_ρ (largest at low latitudes) or p_b (largest at high latitudes). Mid- and high-latitude ζ modes generally show frequency dependences similar to those of the ambient ζ frequency spectra. Modes associated with ENSO, however, show predominant variability at low frequencies and stand out in comparison with the pink spectra of non-modal ζ variability in the tropics.

The composite nature of forced interannual ζ variability is further explored using the ECCO v4 estimate. The null hypothesis is that thermocline changes associated with the adiabatic ocean response to wind stress predominate. A canonical example is thermocline heaving under variable winds, associated with ocean buoyancy and mass redistribution. While this first order qualitative depiction has some practical value, quantitative analyses of interannual variability need to consider numerous departures from the null hypothesis. Firstly, the Arctic and the Southern Ocean show considerable p_b contributions, as well as halo-steric contributions, at interannual time scales. Secondly, buoyancy and mass surface forcing are found to play a leading order role in subtropical and subpolar regions, in the Northern Hemisphere in particular.

The effects of buoyancy forcing on ζ are far from being spatially homogeneous, both in interannual ζ fluctuations and in 20-year trends. The local impact of variable air-sea heat flux on interannual ζ_ρ variability tends to balance out, at least in part, the local impact of advection, both at the grid scale and at the basin scale. This interplay of diabatic and adiabatic processes may reflect air-sea fluxes reacting to damp wind-driven anomalies. The impact of diffusion on interannual ζ_ρ variability is generally found to be negligible, except at the grid scale and in the Arctic.

Furthermore, many instances of sizable non-local responses are found within the 20-year record. Energy transmission commonly occurs through gates that connect oceanic basins, following coastal and equatorial waves guides, and by virtue of high latitude barotropic modes. Marked asymmetries are present in zonal and meridional propagation. Thus, Drake Passage allows information to filter through eastward more than westward. Atlantic influences are broadly felt in the Arctic but Arctic influences tend to be confined to the western North Atlantic. Highlighted pathways and mechanisms for energy propagation imply a limited influence of oceanic propagation on establishing truly global variability patterns on interannual time scales.

In this work, many of the inferences from the 20-year altimetric record are

made possible to a large extent by the use of the ECCO v4 state estimate. As we have tried to highlight, apart from being a basic record of large-scale, low-frequency ζ variability, much more information can be extracted from the solution using budget diagnostics, forcing experiments, and other tools of choice. The capability of re-running the solution (Forget et al., 2015a) will allow users of the state estimate to further extend analyses of altimetric variability forced by variable surface wind stress, buoyancy and mass fluxes. In this study, we have been able to explore only a few aspects, while many other related topics (e.g., mean surface dynamic topography, ENSO ζ dynamics, global mean sea level, etc.) can be assessed using the current ECCO solution and its future extensions. The publicly available ECCO v4 ζ time series can also serve as an 'altimetric correction' for the oceanic response to variable surface wind stress, buoyancy and mass fluxes — in analogy with IB and tide altimetric corrections. From that point of view, the state estimate provides a means to further subtract non-eddy signals from altimetry and refine estimates of intrinsic ζ variability at the meso-scale and below, which remains a major goal of altimetry (Fu and Ubelmann, 2014).

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Appendix A. RADS Basic Processing

Relevant corrections provided by RADS, accounting for the effects of sea state bias, wet and dry tropospheric path delays, inverted barometer (IB) and tides, are first applied to the along track data. In particular, IB and tide corrections based on NCEP GFS pressure fields and GOT4.8, respectively, are subtracted from the data. Uncertainties in those corrections are accounted for in section 3 and come from both the underlying models (Ponte, 1993; Ponte and Gaspar, 1999) and atmospheric pressure fields (Ponte, 2006a; Salstein et al., 2008).

Each along-track altimeter data set (TPJ, EE, GFO) is then bin-averaged daily to the global ECCO v4 grid of 1° nominal resolution (see Appendix Appendix B). Between 65°S and 65°N the combined data base amounts to ≈ 8 daily bin averages per month and grid cell, for a total of ≈ 77 million daily bin averages over 20 years.

The RADS pre-processing software involves sophisticated quality checks on effects of the atmospheric state, IB, tides, sea state bias, significant wave height, backscatter coefficient, and ice concentration. Noteworthy is the option to remove ice-flagged data points, since ice cover is responsible for most outliers found in polar regions (see Fig. 1).

While the RADS quality checks are very helpful, they cannot be perfect. One of the reasons is that not all data outliers result from a readily identified problem or physical context. Another is that such elaborate checks require atmospheric retrievals and satellite estimates that are themselves uncertain. A generic outlier filter is therefore applied in addition to the RADS quality checks (see section 2.1).

Appendix B. ECCO v4 Estimation Settings

Like previous ECCO products (see Wunsch and Heimbach, 2013, for a review), the current estimate is a solution of the MITgcm fitted iteratively to the observations using the adjoint method. Through the state estimation procedure, the GCM yields a dynamically consistent filtering of data noise. The reader is referred to Forget et al. (2015a) for a general presentation of ECCO v4 and the state estimate.

Several novel features of ECCO v4 are of direct relevance to the synthesis and analysis of altimetric variability. The model grid is fully global (including the Arctic), comprising 50 levels in the vertical and a nominal resolution of

1°, with refinement in latitude to 44 km at the equator and a resolution of 41 km at the North Pole. Large scale misfits between model and altimetry are penalized more specifically (section 3). Surface mass fluxes are allowed to change sea level (including its global mean). To this end, a non-linear free surface and a z^* coordinate are used, along with a full seaice model (Campin et al., 2008; Losch et al., 2010).

Furthermore, mixing and eddy transport parameters are now optimized as part of the state estimation procedure (Forget et al., 2015a). As a result (see also Stammer, 2005; Ferreira et al., 2005), the fit to observations in the ocean interior is improved, which affects ζ_ρ most directly and the other terms in Eq. 1 indirectly. More generally, the optimization of surface forcing fields and parameterized physics, along with the short 1992–2011 period of analysis, partly alleviates the issue of slow model drifts and accumulating biases evident in long model runs (Danabasoglu et al., 2014; Forget et al., 2015b).

The ECCO v4 solution resolves the large scale mass-, buoyancy- and wind-driven sea level variability. Tidal and atmospheric pressure forcing are omitted, consistent with the subtraction of IB and tide corrections from RADS (Appendix Appendix A). First guess forcing is based on ERA-Interim 6-hourly fields from ECMWF (Dee et al., 2011). Mass and buoyancy forcing over the coupled ocean-ice model is computed from the 10m surface atmospheric state using a bulk formulae algorithm (Large and Yeager, 2004) and the re-analyzed wind stress estimate is used in the momentum equations. Forcing adjustments are applied on the basis of 2-week averaged fields, in order to allow for optimization of monthly and longer sea level variability. It is by virtue of these forcing and internal model parameter adjustments that the ECCO v4 solution qualifies as a state estimate.

Appendix C. Daily Pointwise Error Terms

The level of geophysical *noise* due to meso-scale eddies must be specified as part of the estimation problem of section 3.1. Many maps of meso-scale eddy variance can be found in the literature (e.g. Fu, 1983; Stammer, 1997a). In fact one of the most distinctive advances due to altimetry was to establish the geography of meso-scale activity.

Here a first estimate of meso-scale variance is derived by applying the $\mathcal{D}$ and $\mathcal{B}$ smoothing filters (defined in section 2.2) to the daily bin averaged observations ζ_a (RADS, all altimeters included). The approximate time scale

partition is simply set to 35 days by $\mathcal{B}$. This operation averages out high frequency noise. The spatial scale cutoff is set to $O(3^\circ)$ by $\mathcal{D}$ and thus $\mathcal{E}(\zeta_a) = \mathcal{B}(\zeta_a) - \mathcal{D}\mathcal{B}(\zeta_a)$ is an estimate of meso-scale eddies at approximately monthly and longer time scales.

This estimate can be refined using a model solution to subtract large scale mass-, buoyancy- and wind-driven sea level variability that can leak through the $\mathcal{E}$ filter. The model solution used here is similar to the ECCO v4 estimate but it includes only seasonal mean adjustments to the ERA forcing fields. It is subsampled in accord with altimetry. The resulting ζ_{ERA} is virtually independent of ζ_a . Filtering ζ_{ERA} accordingly yields an estimate $\mathcal{E}(\zeta_{ERA})$ of the contamination of $\mathcal{E}(\zeta_a)$ by "non-eddy" signals. It can be used to correct the time series of monthly meso-scale signals as

$$\zeta_{mms} = \mathcal{E}(\zeta_a - \zeta_{ERA})$$

and its variance σ_{mms} is displayed in Fig. 4 (bottom left).

The estimate ζ_{mms} shows reduced variance in the tropics compared with $\mathcal{E}(\zeta_a)$ (not shown), while variance is virtually unchanged at higher latitudes. This nontrivial result reflects the skill of ERA fields and MITgcm jointly in simulating observed "non-eddy" signals. An illustration, albeit using the state estimate ζ_e rather than ζ_{ERA} , is provided in section 4.2 (Fig. 12, top middle panel). Our working hypothesis is that the variance reduction in the tropics is associated with relatively fast baroclinic waves, which the model can resolve, and which are not commonly regarded as meso-scale features.

The variance of the differences between TPJ and EE for the period from 1993 to 2010 is shown in Fig. 4 (top left). In Eq. 4, σ_{tme}^2 denotes half the $\zeta_{TPJ} - \zeta_{EE}$ variance, assuming an even split of error variance between TPJ and EE for simplicity. This provides a simple measure of the effective level of instrumental errors within RADS, along with some contribution of eddy representation error. Most of the ocean shows a rather uniform σ_{tme} . The basic level of instrumental error can be gauged over the quieter parts of the ocean. As a practical, although somewhat subjective, definition we select the 15th percentile of σ_{tme}^2 , which corresponds to 2.7 cm for the error standard deviation per altimeter. Relative noise levels of different instruments are discussed in section 3.3.

In regions of high eddy activity the difference between TPJ and EE is rather indicative of meso-scale signals that are sampled differently by different altimeters (Fig. 4, top left). The 85th percentile of σ_{tme}^2 thus pro-

vides an approximate measure of this geophysical noise, to be compared with the 85th percentile of σ_{mms}^2 . This yields a ratio of 47% between daily small-scale geophysical noise and monthly meso-scale variance. The physical implication would be that σ_{mms}^2 amounts to about 2/3 of the full eddy variance². A more explicit partition between instrumental noise and geophysical noise, which is not a central goal of our study, can thus be written as $\sigma_{tme}^2 + \sigma_{mms}^2 \approx 0.027^2 + 1.5 \sigma_{mms}^2$.

The error variance of IB correction (σ_{IB}^2 in Eq. 4) is taken as half of the variance in the difference between NCEP- and ECMWF-derived IB corrections ($2 \times \sigma_{IB}^2$ is shown in Fig. 4, top right), where surface atmospheric pressure errors in the two reanalyses are assumed to have equal variance. The dynamical response to surface pressure load (DP) is omitted in altimetric IB corrections. Its variance (σ_{DP}^2 in Eq. 4) is estimated by applying ECMWF pressure fields as a forcing onto ECCO v4 and subtracting the IB response (Fig. 4, middle left). Tide error variance (σ_{tide}^2 in Eq. 4) is taken as half the variance of the difference between GOT4.8 and FES2004 tide corrections ($2 \times \sigma_{tide}^2$ is shown in Fig. 4, middle right).

Appendix D. Monthly Large Scale Error Terms

Large scale errors due to IB (μ_{IB}), tides (μ_{tide}) and DP (μ_{DP}) are simply estimated by applying the $\mathcal{DB}$ smoother to the differenced IB and tide correction fields and to the DP estimates and calculating the respective variances. The instrument error term μ_{tme} is computed by applying a boxcar filter (35 days, 7×7 grid points) to each altimeter data set separately and the variance of the difference between altimeters is then computed at the overlapping points (i.e., as done in Fig. 4). The reason for using a boxcar filter rather than the $\mathcal{DB}$ smoother is that one altimeter is not sufficient to produce dense maps every 35 days. The spatial window was set to approximately match the variance reduction by the $\mathcal{D}$ smoother in the case of white noise. The basic level of large-scale instrumental error, gauged using the 15th percentile of μ_{tme}^2 , corresponds to 0.8 cm for the error standard deviation per altimeter.

The contribution of meso-scale eddies to large scale errors (bottom left) would be zero if the spatio-temporal filter was perfect (i.e., did not allow

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²Neglecting for the sake of the argument any joint contributions from eddies to the short-scale variance estimates from Fig. 4 (top left) and to the monthly meso-scale variance estimate in Fig. 4 (bottom left).

any leakage of eddy variance) and if altimeters provided a full eddy resolving map every day. In practice, residual noise due to the imperfect filtering of meso-scale variability (μ_{mms}) is estimated by applying the $\mathcal{D}$ smoother to ζ_{mms} . The rationale for this method is as follows.

Let z denote a spatially variable field of ζ anomalies, $\bar{z}$ its true large scale part, and $z' = z - \bar{z}$ its true small scale part. Specifying the separation scale is not necessary here. A perfect low pass filter f would be such that $f(z) = \bar{z}$, $f(\bar{z}) = \bar{z}$, and $f(z') = 0$. An imperfect filter g shows leakage between large and small scales. Here we seek a practical method for estimating such leakage that does not require detailed knowledge of the small scale noise spectrum.

It is assumed that $\bar{z}$ and z' are of similar magnitudes. While z' can be larger than $\bar{z}$ in altimetry, the following holds for $\|z'\| \gg \|\bar{z}\|$ as well. Filter g is assumed to be linear (the $\mathcal{DB}$ smoother is linear). Finally, leakage of filter g is assumed to be relatively weak so that

$$g(\bar{z}) = \bar{z} + \epsilon \|\bar{z}\|$$

$$g(z') = \epsilon' \|z'\|$$

where $\|\epsilon\| \ll 1$ and $\|\epsilon'\| \ll 1$ and may vary in space. From the linearity of g it follows that

$$z - g(z) = (\bar{z} + z') - (\bar{z} + \epsilon \|\bar{z}\| + \epsilon' \|z'\|) \approx z'$$

Hence a practical way to estimate leakage from small to large scales $g(z')$ is to compute $g(z - g(z))$.

The interest of this method is that it requires no further assumption about the spectral characteristics or the precise amplitude of the small scale noise z' in altimetry. The working assumptions are simply that (1) small scale signal is relatively strong and (2) leakage is relatively weak. In filtering out meso-scale eddies, these assumptions are supported by the fact that $\mathcal{V}[g(z - g(z))] \ll \mathcal{V}[g(z)] \ll \mathcal{V}[z]$ where $\mathcal{V}$ denotes the variance operator.

A similar argument holds for high pass filters and leads to a practical method for estimating leakage from large to small scales. However, such leakage is not a major concern in the error budget of section 3.2.

Appendix E. Frequency Spectra and EOFs

Frequency spectra (section 4) and empirical orthogonal functions (EOFs; section 5.1) are computed from detrended time series for 1993–2010 omitting

the mean seasonal cycle. The first year (1992) of the state estimate is omitted since initial condition estimates are known to lack in dynamical balance (e.g. see Forget et al. (2008)). The last year (2011) is omitted due to a suspicious increase in global mean sea level at the end of 2011, which adjoint optimization has not yet removed. The subtracted linear trend is computed using a least squares fit. The subtracted seasonal cycle is defined in terms of mean weekly averages.

All power density spectra depicted in section 4 are computed (after removing trend and seasonal cycle) using Matlab’s implementation of the multitaper method. Spectral slope is defined as the order n in $1/f^n$ (where f is frequency) and estimated as a best fit between periods of 3 years and 3 months. Area-weighted averages of individual spectra computed at each grid point are displayed (not to be confused with spectra of global averages).

The EOFs presented in section 5.1 are obtained using a sequence of global and regional (area-weighted) computations. Global EOFs tend to emphasize tropical variability since the tropics span much of the global ocean area and exhibit strong large-scale signals (Fig. 3). The first two global modes with most (area weighted) variance are displayed in Figs. 13-14 (top 2 panels). To further reveal extra-tropical variability, EOFs are then computed for each ocean basin separately and those of most variance are displayed in Figs. 13-14 (other 6 panels). The full sequence of EOF computations is as follows.

Global EOFs are computed first and the five leading modes are subtracted from the time series. The focus is then put on mid- and high-latitude modes (outside 25°N - 25°S) that can dominate over individual oceanic basins. Leading mid-latitude modes are selected as follows: 1 in the South Indian, 1 in the South Pacific, 2 in the South Atlantic, 2 in the North Pacific, and 5 in the North Atlantic. Leading high-latitude modes are selected as follows: 2 in the Southern Ocean (southward of 55°S), and 2 in the Arctic Ocean (northward of 60°N).

In section 5.1, EOFs are computed starting from $\mathcal{DB}(\zeta_e)$ between 65°S and 65°N , where altimetric sampling is dense. High latitude modes are not computed due to lack of altimeter data. Corresponding time series for altimetry alone (blue curves in Fig. 14) and model-data misfits (red curves in Fig. 14) are computed by regressing EOF patterns obtained from $\mathcal{DB}(\zeta_e)$ onto $\mathcal{DB}(\zeta_a)$ and $\mathcal{DB}(\zeta_e - \zeta_a)$, respectively. Although the $\mathcal{DB}$ smoother reduces the EOF patterns spatial resolution, the chosen methodology facilitates direct comparison of the ζ_e , ζ_a and $\zeta_e - \zeta_a$ time series. In section 5.2, however, EOFs are computed starting from full state estimate fields (ζ_e) to

extend the analysis of variance contributions to polar oceans.

To extend the model-data misfit assessment of sections 3 and 4, we shall stress the very close agreement between state estimate time series (black curves) and purely altimetric time series (blue curves) in Fig. 14, with values of $R^2 \geq 0.78$ in general and ~ 1 for the 2 global modes. Interannual variability is equally robust, with $R^2 \geq 0.75$ for low pass filtered time series. Thus, projections of the EOF patterns on model-data misfits are relatively small (Fig. 14, red curves). Agreement for monthly time series tends to be slightly weaker, particularly for the 2 North Atlantic modes (interannual: $0.87 < R^2 < 0.92$; monthly: $0.67 < R^2 < 0.71$). However, the 2 Southern Hemisphere modes show improved agreement at shorter time scales (interannual: $0.75 < R^2 < 0.78$; monthly: $0.82 < R^2 < 0.84$). Figure 14 thus provides an assessment of the ECCO fit to altimeter data, which complements sections 3.3 and 4.2.

Appendix F. Hydrostatic Pressure Budgets

Section 6 discusses hydrostatic pressure budgets. They are diagnosed from the state estimate according to Eq. 1 with the steric height term given by

$$\zeta_\rho = \zeta_T + \zeta_S \quad (\text{F.1})$$

$$\zeta_T = \zeta_T^a + \zeta_T^f + \zeta_T^d \quad (\text{F.2})$$

$$\zeta_S = \zeta_S^a + \zeta_S^f + \zeta_S^d \quad (\text{F.3})$$

where subscripts T and S denote thermo-steric and halo-steric effects, while superscripts a , d , and f denote advection, diffusion and surface buoyancy forcing, respectively. A detailed formulation of steric height contributions is provided e.g. by Piecuch and Ponte (2011). Parameterized adiabatic transports by meso-scale eddies are counted as an advective term, whereas ‘diffusion’ here refers to diapycnal, isopycnal, and convective mixing collectively.

Surface fresh water forcing adds and subtracts not only buoyancy but also volume, which is accounted for in ζ and p_b directly (see Forget et al., 2015a, and references therein). Furthermore the so-called global mean steric correction (see Griffies and Greatbatch, 2012, and references therein) is generally applied to the Boussinesq model output to allow for direct comparison with

observations (sections 3, 4, 5 and 7). Since it is not an explicitly resolved budget term however, it is omitted in section 6.

The tendency terms for Eqs. 1-F.1-F.2-F.3 are diagnosed at every time step as the model runs, using a centered second order scheme for thermal expansion and haline contraction coefficients. Their daily averaged output yields hydrostatic pressure budgets that are closed to a precision of eight digits. Their cumulative time integral (leading to ζ_ρ , ζ_T , ζ_S , etc.) is then computed starting from 0 in 1992. The mean, seasonal cycle and trend of ζ_ρ , ζ_T , ζ_S , etc. are subtracted. Frequency spectra are then computed and integrated over periods longer than one year to budget interannual variability (Fig. 16) or shorter than one month to budget submonthly variability (Fig. 17).

Appendix G. Wind Stress Perturbations

For the purpose of section 7, a suite of perturbed wind stress time series are prepared and applied in sensitivity experiments using the general circulation model. This is a relatively easy operation for the ECCO v4 setup since the surface momentum forcing is prescribed directly as stress. The other forcing contributions (mass and buoyancy forcing prescribed through bulk formulae) are more intricately intertwined and thus only considered collectively.

Within the suite of sensitivity experiments, one end member is forced with weekly averages (τ_1) of the optimized wind stress fields (i.e. those that drive the state estimate itself). The other end member is forced with the mean seasonal cycle (τ_0 , incl. the time mean). Let $\Delta\tau = \tau_1 - \tau_0$ denote the difference between these two wind stress time series, and $\Delta\zeta$ the resulting difference in ζ computed using the numerical model. Once wind-driven variability has thus been isolated, it can be subtracted from the full state estimate to reveal buoyancy- and mass-driven variability (section 7.1).

Each model sensitivity experiment used in section 7.2 is forced with a weekly wind stress time series that can be written as $\tau_0 + \delta\tau$ where $\delta\tau = m \times \Delta\tau$ and m denotes a regional mask. Each mask m goes from 1 to 0 gradually over $\approx 1000km$ at the edge of the region where forcing is perturbed. This approach was favored over a sharp forcing discontinuity to avoid introducing strong wind stress curl perturbations at the edges.

Masks m are generated for the Pacific, Indian and Atlantic Ocean, as well as for select latitude bands (poleward of $65^\circ N/S$, equatorward of $30^\circ N/S$,

and in between). If the ocean response $\delta\zeta$ to a wind stress perturbation was strictly local, it could simply be obtained by computing $m \times \Delta\zeta$. Since that is not the case, model sensitivity experiments are carried out to diagnose the $\delta\zeta$ response to wind stress perturbations.

Figure 22 (color shading) thus shows monthly variances of $\delta\zeta$ within the suite of experiments, normalized by the large scale error variance estimate (σ_a^2). For reference the purely local prediction, namely the variance of $m \times \Delta\zeta/\sigma_a$, is overlaid (green contours in Fig. 22). Areas within green contours are those where wind stress perturbations are applied. The response in these regions is usually above the large scale noise level (estimated in section 3.2). The result of most interest (discussed in section 7.2) is the response outside of the green contours, which denotes propagation of sea level variability away from the area where wind is perturbed.

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