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RESEARCH ARTICLE

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Mapping error in Southern Ocean transport computed from satellite altimetry and argo

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Key Points:

- This study quantifies the uncertainty in mapping zonal geostrophic transport of the Antarctic Circumpolar Current
- We show there are significant correlations between the baroclinic and barotropic error contributions to the total transport error
- We show the increase in Argo floats in the Southern Ocean is effective in reducing mapping error

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Abstract In an effort to better estimate transport dynamics in response to wind forcing (primarily the Southern Annual Mode), this study quantifies the uncertainty in mapping zonal geostrophic transport of the Antarctic Circumpolar Current from sparse temperature, salinity and sea surface height observations. To do this, we sampled an ocean state estimate at the locations of both Argo floats and the Jason-1 altimeter groundtrack. These sampled values were then optimally interpolated to create SSH and temperature/salinity grids with 1° resolution. The temperature, salinity and SSH grids were then combined to compute the zonal geostrophic transport and compared to that estimated from the full state estimate. There are significant correlations between the baroclinic and barotropic error contributions to the total transport error. The increase in Argo floats in the Southern Ocean is effective in reducing mapping error. However, that error improvement is not uniform. By analyzing systematic errors in transport time series, we find the transects that are most appropriate for analyzing the dynamics of ACC transport using Argo and altimetric gridded fields. Based on our analysis, we conclude region south of Tasmania is most appropriate, with lowest uncertainty. Using real-world data, we calculated zonal transport variability at a transect south of Tasmania. There is an insignificant trend ($0.3 \pm 0.4 \text{ Sv yr}^{-1}$, 90% confidence) but significant low-frequency variability correlated with the Southern Annular Mode (0.53, $p < 0.05$). The barotropic component is most responsible for the low-frequency variability, and this would be unobservable from ship casts without velocity measurements at depth.

1. Introduction

Increasing winds associated with changes in the Southern Annular Mode are expected to force a response from the Antarctic Circumpolar Current (ACC). Coarse-resolution models have predicted a steepening of isopycnals with increased winds, resulting in an increase in ACC transport [Fyfe and Saenko, 2006; Gnanadesikan and Hallberg, 2000]. Eddy-permitting models, alternatively, predict an “eddy saturation” that steepening of isopycnals will release the potential energy contained therein as baroclinic eddies [Hallberg and Gnanadesikan, 2006, Meredith et al. 2012, Morrison and Hogg, 2013]. These baroclinic eddies act to reduce isopycnal steepening and retard transport increases. A recent study by Langlais et al. [2015] found partial eddy saturation (both transport and eddy energy respond) with increased wind over the ACC, with enhanced eddy kinetic energy lagging behind the wind. Their findings supported the partial eddy saturation predicted by Farneti et al. [2010]. A chapter by Rintoul and Garabato [2013] provides a review of both theories.

These predicted responses have yet to be unambiguously observed. Hogg et al. [2015] found an increase in regional eddy kinetic energy in altimetry data in addition to providing evidence of decreased ACC transport based on sea level around Antarctica. The evidence of transport decrease is supported by observations of decreases in depth-averaged transport computed from data from the Gravity Recovery and Climate Experiment (GRACE) [Makowski et al., 2015].

Kosempa and Chambers [2014] calculated zonal geostrophic velocity fields above 1975 dbar for the Southern Ocean from 2004 into 2011. Although other studies have performed similar calculations based on either sub-surface T/S from a state estimate or climatology [Cadden et al., 2009; Griesel et al., 2012] or from projections of surface data onto fixed empirical modes or regressions with historical data [Meijers et al., 2010; Mulet et al., 2012], Kosempa and Chambers [2014] used coincident mapped T/S profiles from Argo and coherent mapping functions for all data sets to reduce problems of using different resolutions. They also used the highest-resolution geoid in processing, unlike other studies [Cadden et al., 2009; Griesel et al., 2012; Meijers et al., 2010].

Kosempa and Chambers [2014] combined Argo-derived densities with surface velocity obtained from Jason-1 and -2 altimetry to estimate zonal geostrophic transport north of 60°S and integrated across much of the ACC. They found a significant correlation between transport variability in the south Indian Ocean and the Southern Annular Mode climate index (Antarctic Oscillation), consistent with correlations seen in the GRACE data [*Bergmann and Dobslaw*, 2012; *Makowski et al.*, 2015] and bottom pressure and sea level data in the Drake Passage [*Meredith et al.*, 2004]. However, *Kosempa and Chambers* [2014] did not find any significant trend in zonal transport above 2000 dbar in roughly the same region of the south Indian Ocean where *Makowski et al.* [2015] found a strong trend in GRACE-derived transport.

This study was designed to better quantify the error in the method used to derive transport variability in *Kosempa and Chambers* [2014]. Error arises primarily from sampling temperature (T), salinity (S), and sea surface height (SSH) discretely in time and space and objectively mapping in an eddy-rich environment. Their analysis assumed purely random errors and did not quantify potential systematic errors that may arise from mapping sampled data, especially in light of changing numbers of Argo floats in the region over time.

To quantify the error, we relied on output from a high-resolution ocean state estimate—the Southern Ocean State Estimate (SOSE) [*Mazloff et al.*, 2010]. We sampled the state estimate at locations and times of individual Argo floats and the along-track Jason-1 and Jason-2 altimetry data, and then optimally interpolated the sampled temperature, salinity, and 5 dbar pressure anomalies (as a proxy of SSH) into gridded fields that are then used to compute geostrophic velocity and transport fields as in *Kosempa and Chambers* [2014]. The optimally interpolated grids were compared to the monthly, 1° averaged values from the full SOSE estimate to quantify uncertainty.

The goals of the experiments are: (1) document the uncertainty for monthly estimates of transport both for 1° gridded and transect-integrated transport; (2) quantify potential systematic errors in transport computed from altimetry and Argo; and (3) identify the areas of the ACC that enable robust observation and analysis of transport dynamics obtained from Argo and satellite altimetry. Section 2 describes the data and methods used. Section 3 presents the results and analyzes the uncertainty. Section 4 discusses the implications of the results in terms of computing trends in integrated zonal geostrophic transport across the ACC.

2. Data and Methods

2.1. SOSE and Sampling

The Southern Ocean State Estimate (SOSE) is a general circulation model solution obtained from the MIT general circulation model (MITgcm) [<http://mitgcm.org/>]. SOSE assimilates available ocean observations (including altimetry and Argo data) using a least squares estimation technique, with a solution optimized from initial and boundary conditions [*Wunsch and Heimbach*, 2007]. The estimate agrees with observations collected from several platforms and produces a realistic mean zonal transport estimate [*Mazloff et al.*, 2010]. The model is eddy permitting at 1/6°, with temperature, salinity and hydrostatic pressure anomaly available at 5 day intervals from 2008 through 2010. SOSE's vertical grid cells spans the full column with 42 levels of varying thickness. The archived "iteration 60" is used throughout this study [http://sose.ucsd.edu/sose_stateestimation_data_08.html]. We restricted latitudinal coverage to between 78°S and 31°S. The pressure anomaly at 5 dbar was chosen as a proxy for altimeter observations of SSH in lieu of the sea surface height available from SOSE. While the products agree at the initial time step, SSH and pressure gradients diverge significantly at late time steps, with pressure gradient being closer with surface velocity obtained from integration of SOSE's internal temperature and salinity. We believe this is most likely due to the fact that the MITgcm uses a free-surface. Since the 5 dbar pressure anomalies should be very close to the geostrophic SSH, we utilize them as a proxy to avoid this significant disparity between the SSH and internal density structure.

A mean monthly climatology was estimated and removed from SOSE T/S prior to sampling, to be consistent with the optimal interpolation (OI) approach used with gridded Argo fields [*Roemmich and Gilson*, 2009]. Because of the SOSE 5 day resolution, months are defined here as 30 day periods, except for 35 days in August. To create climatologies, temperature and salinity state estimates in each 1/6° grid cell were first linearly interpolated to the depth levels used by *Roemmich and Gilson* [2009], except the shallowest layer of SOSE, which remains at 5 dbar. The depth-interpolated temperature, salinity, and pressure anomaly data from SOSE were then averaged over each month and at 1° and retained for comparison with products of

Figure 1. Argo sampling events in the study area (78°S–31°S) binned by month for both the “early” (2005–2007) and “late” (2008–2010) periods.

the optimal interpolation. To produce the final climatologies, a model with annual sinusoids and a linear trend was fit to the 36 month series in each 1° grid by linear least squares. The linear trend was removed from each 36 month series in order to reduce the influence of interannual changes. The resulting de-trended data were averaged for every month to produce the 12 month climatology for each 1° grid and depth level.

The full-resolution SOSE was also sampled to generate T/S profiles at the times and locations of each Argo float, based on historical Argo float sampling locations and times from 2005 through 2010 downloaded from http://www.usgoda.gov/cgi-bin/argo_select.pl. SOSE output is only 3 years and so was repeated for the 2005–2007 and 2008–2010 Argo sampling. Only delayed-mode data with a quality control flag of “good” were used. It was assumed T and S was available for all levels to 2000 dbar; although this is not strictly true for many early

Argo floats, it is true for late profiles. Thus our computations only consider changes in spatial sampling, not changes in depth sampling. Argo observations in the study area increase from about 1500 per month in early 2005 to over 3000 per month by early 2008, and then hold steady through 2010 (Figure 1).

Full resolution SOSE temperature and salinity fields were interpolated linearly to the geographic locations, standard pressures of Roemmich and Gilson [2009], and times of each Argo profile. The resulting sampled SOSE T/S profiles were then aggregated by month. The estimated climatology was then removed to obtain anomalies for use in the optimal interpolation. This was performed for two different periods: 2008 through 2010 (the “full-Argo period”) and 2005–2007 (the “transitional-Argo period”). The transitional-Argo period simply sampled the corresponding months of SOSE for 2008–2010.

The altimetry locations and times were derived from a single Jason-1 repeat cycle starting in January 2008 based on the Geophysical Data Records (https://podaac.jpl.nasa.gov/dataset/JASON-1_GDR_NETCDF). To reduce computations in the objective mapping, the times, longitudes, and latitude values were averaged to a 0.5° spacing along-track. The times for the ground track were then repeated every 9.9156 days for 3 years to generate pseudo-SSH locations and times for the period 2008–2010. The full-resolution SOSE pressure anomalies at 5 dbar were then interpolated to these locations/times, and aggregated by month. Colocated values were averaged within each month to save computation. Since the SOSE output is only 3 years and was repeated for the 2005–2007 Argo sampling, we assumed the 2005–2007 SSH sampling was identical to the 2008–2010 sampling. This saved considerable computation time, since we only had to interpolate and map 3 years of pseudo-SSH data.

2.2. Optimal Interpolation and Estimating Geostrophic Currents and Transport

Sampled anomalies of temperature, salinity, and pressure (SSH) were mapped to 1° grids using the same optimal interpolation method and covariance function ($C(\text{dist})$) as Roemmich and Gilson [2009],

$$C(\text{dist}) = 0.77 \exp \left(- \left(\frac{\text{dist}}{140.0} \right)^2 \right) + 0.23 \exp \left(- \frac{\text{dist}}{1111.0} \right), \quad (1)$$

where $\text{dist} = \sqrt{dx^2 + dy^2}$, dx is the zonal distance in km between the grid center and observation, and dy is the meridional distance. A noise-to-signal variance ratio of 0.15 was used on the diagonal to account for random noise. The monthly temperature, salinity and pressure anomaly maps were added to their respective climatology to obtain grids of full T, S and SSH.

For analysis of uncertainty, we consider baroclinic, barotropic, and total velocities, where the total is the sum of the barotropic and baroclinic components. We compute these velocities from the 1°, monthly gridding of the full-resolution SOSE data (denoted with the subscript *truth*), and the sampled and mapped data

(denoted with the subscript *mapped*). Thus, the difference between the two (*mapped* – *truth*) indicates the error due to both sampling and mapping.

We use the convention that: baroclinic velocities ($u(z)$) are those derived from the subsurface density assuming a level of no motion at the deepest common level (in this case, 1975 dbar), while the barotropic velocity is the velocity at the deepest level ($u(1975 \text{ dbar})$). The total velocity at any depth ($u_{total}(z)$) will therefore be $u(z) + u(1975 \text{ dbar})$. There are several different ways to compute the baroclinic velocities given density derived from an equation of state [McDougall and Barker, 2011]. We use the method of computing dynamic topography relative to 1975 dbar (assuming a level of no motion) for each depth, z , and then computing the velocity from the gradient of the relative dynamic topography. See Wunsch and Gaposchkin [1980] or Kosempa and Chambers [2014] for a full derivation.

Barotropic velocity ($u(1975 \text{ dbar})$) was derived following the method described in Kosempa and Chambers [2014], based on comparing the absolute dynamic topography (η_{abs} , measured by mapped altimetry) with the relative topography obtained from mapped Argo data (η_{rel} (1975), integrated from 1975 dbar to 5 dbar). In our experiment, the absolute dynamic topography is simply the mapped surface pressure anomaly scaled by $(1/g)$, where g is acceleration due to gravity. Once the mapped absolute dynamic topography and relative topography are known, the barotropic current can be computed as:

$$u(1975 \text{ dbar}) = -\frac{g}{f} \left(\frac{d\eta_{abs}}{dy} - \frac{d\eta(1975 \text{ dbar})_{rel}}{dy} \right). \quad (2)$$

where f is the Coriolis parameter. Errors in the mapped barotropic velocity will arise from errors in both the mapped altimetry and Argo data.

Integrating the velocity data between available levels results in the total volume transport at any location (x, y) and time (t) and its components:

$$\begin{aligned} T(x, y, t)_{baroclinic} &= \int_H^{5 \text{ dbar}} u(x, y, z, t)_{baroclinic} dz \\ T(x, y, t)_{barotropic} &= \int_H^{5 \text{ dbar}} u(x, y, t, H) dz. \\ T(x, y, t)_{total} &= T(x, y, t)_{baroclinic} + T(x, y, t)_{barotropic}. \end{aligned} \quad (3)$$

H refers to the deepest level available at x, y in SOSE. In some cases, this will be shallower than 1975 dbar. Transport (and velocities) will be computed from both the “truth” cases and “mapped” cases and differenced to quantify uncertainty.

2.3. ACC Mask

A persistence measurement [Kosempa and Chambers, 2014] was adopted to isolate the ACC region of the Southern Ocean. Persistence is defined as the number of cells in depth and time where the total velocity flowed eastward at each latitude and longitude. For example, a single coordinate (x, y) will have $36 \times 58 = 2088$ cells in which there could be eastward flow over the course of 36 months since there are 58 depth levels. ACC persistence was obtained at each latitude and longitude from the 1° averaged SOSE total velocities, and all coordinates with persistence above 94.5% were identified. The ACC was then defined as all cells between the southern and northernmost cells with persistence of at least 94.5% for every longitude (Figure 2).

2.4. ACC Transects

Our definition based on persistence enabled isolation of the ACC for the “mapped” and “truth” grids. However, we also wanted to evaluate transport mapping error across specific transects that are based on those historically sampled by ship casts [http://cchdo.ucsd.edu/]. We identified transects from the database which had been occupied by ships collecting temperature and salinity data after the dawn of altimetry (circa 1993). These transects run roughly perpendicular to the ACC and span its entire breadth as defined by our mask (Figure 2). The collection of temperature and salinity data perpendicular to the ACC allows for computation of baroclinic currents across each transect, which conceivably could be combined with altimetry to add total velocity data points to the time series afforded by Argo. The chosen transects are along the prime

Figure 2. Mask of the ACC, the ACC is shown in yellow. Prime Meridian, Africa, Australia, Tasmania and Pacific transects are indicated in red from left to right.

meridian in the eastern Atlantic Basin, along the 30°E meridian in the western Indian Basin, along the 115°E meridian in the eastern Indian Basin, along the 141°E meridian south of Tasmania and along the 210°E meridian in the Pacific. These transects will be referred to later as Prime Meridian, Africa, Australia, Tasmania, Pacific, respectively.

3. Results

3.1. Velocity Mapping Error (2008–2010)

We first consider the uncertainty in the mapped velocities for the best Argo sampling period (2008–2010) at several levels. For this analysis, we consider the 1° box-averaged data from the full SOSE grids to be the “truth” (or the closest to the truth one can expect), and compute geostrophic velocities at all levels using the surface pressure and T/S data. Likewise, ours is based on the same procedure, but using the mapped surface pressure and T/S from the sampled SOSE data. The impact of aliasing eddies on the optimal interpolation is evident when comparing “mapped” velocities to “truth” at 1975 dbar for a single month (Figure 3). The true barotropic velocities are smoother, with a spatial standard deviation of 2 cm s^{−1}. Despite some high values near bathymetry, extreme values are ± 5 cm s^{−1} in the “truth” data. The velocities in the mapped data are nearly double this, with a standard deviation of 4 cm s^{−1}.

The mapping error is defined as the standard deviation of the difference between the zonal velocities obtained from the mapped data and those from the “truth” from the averaged full-resolution SOSE data. At 5 dbar, error is due only to mapping of the Jason altimetry data (Figure 4a). The largest errors are located in regions of high mesoscale eddy activity, as expected. Errors are up to 5 cm s^{−1} in the Agulhas and 2–3 cm s^{−1} farther east near 60°E. The mean error over the entire grid shown in Figure 4a is 0.7 cm s^{−1}. Over the area of the ACC defined by our mask (Figure 2) errors are between 2 and 3 cm s^{−1}.

Velocity at depth requires combining the pressure anomaly with subsurface temperature and salinity data from Argo floats. Hence, we expect the mapping error to increase with depth and display geographically similar error patterns as found at the surface (Figure 4b). The average of the zonal velocity mapping error at 1000 dbar grid is double the 5 dbar value, at 1.4 cm s^{−1}. Within the ACC region the errors are between 0.1 and 7.5 cm s^{−1} with an average value of 1.4 cm s^{−1}.

Figure 3. Zonal geostrophic velocity for a single representative month (January 2010) at 1975 dbar using (a) 1° SOSE T/S and pressure anomaly. (b) Argo and Jason-1 and -2 sampling and OI mapped.

Figure 4. Mapping error in zonal geostrophic velocity at (a) 5 dbar, (b) 1000 dbar, (c) 1975 dbar defined as standard deviation of residuals 2008–2010.

Kosempa and Chambers [2014] estimated the error in the mapped velocity at 1000 dbar by comparing to Argo drifts. Their average error over the entire grid was 2.5 cm s^{-1} , based on an estimate of error in the Argo drift and assuming the errors were uncorrelated. That estimate is considerably higher than what we estimate here. There are several possible explanations for this: (1) the Argo drift velocity error was underestimated, (2) errors in Argo temperature, salinity, and/or depth are significant (they are not considered here), or (3) a combination. Other studies find the errors in temperature, salinity, and/or depth are much smaller than the mapping error [Roemmich and Gilson, 2009] which suggests the source of the difference is an underestimation of Argo drift velocity error in Kosempa and Chambers [2014].

The mapping error continues to increase with depth to the 1975 dbar level, as shown in Figure 4c). The majority of cells display errors below 4 cm s^{-1} and within the ACC the average error is 2.1 cm s^{-1} . The ACC error is slightly lower than the average of the entire grid (2.2 cm s^{-1}).

3.2. Baroclinic Transport Mapping Error

Mapping errors attributed to baroclinic transport (equation (3)) are routinely less than the barotropic contributions (Figure 5a). The mean uncertainty over the entire grid is 2.0 Sv ($1 \text{ Sv} = 10^6 \text{ m}^3 \text{ s}^{-1}$). There are values of 7 Sv along the Tasmanian chokepoint, and from 7 to 10 Sv within the Brazil Malvinas confluence. The Indian Basin, particularly close to Australia, displays relatively high baroclinic transport errors ($4+$ Sv) when compared to the Atlantic (2 – 3 Sv) and Pacific basins (2 Sv). The average over the ACC is 2.0 Sv . Low values of 1 – 2 Sv are typical south of the ACC, with the exception of large errors around topographic features.

3.3. Barotropic Transport Mapping Error

Barotropic mapping errors are the dominant source of error (Figure 5b) due to the fact errors in barotropic velocity are high (Figure 4c). These velocity errors are added together at each level without the possibility of cancellation [Kosempa and Chambers, 2014]. The mean uncertainty over the entire grid is 4.2 Sv . South of the African continent and east of Australia mapping error exceeds 20 Sv . The area of the Agulhas return has the highest barotropic transport mapping error in the ACC, with values between 20 and 25 Sv . Areas along the Tasmanian and South American chokepoints again demonstrate areas of mapping error between 10 and 15 Sv . These values are again relatively high for the ACC. Most of the ACC, away from the regions south of Africa, have values between 5 and 10 Sv . Barotropic transport error exceeds 7 Sv in the ACC between Africa and New Zealand. For the Atlantic ACC, and areas downstream of New Zealand and upstream of the Drake Passage, the barotropic transport errors are between 3 and 5 Sv . The mean error within the ACC is 4.3 Sv .

Figure 5. (a) Baroclinic-, (b) barotropic-, (c) total-integrated from depth geostrophic transport mapping error defined as standard deviation of residuals 2008–2010.

3.4. Depth-Integrated Total Transport Mapping Error

The depth-integrated total transport mapping error is shown in Figure 5c. The mean error in the ACC region is 2.7 Sv. The mean mapping error for total transport over the entire grid is 2.6 Sv. A comparison of the total transport error to the means of the baroclinic (2.0 Sv) and barotropic (4.2 Sv) errors suggests significant anti-correlation of errors between the estimated barotropic current and the baroclinic currents, which is what we find (Figure 6). Assuming no correlation from errors (i.e., as done by *Kosempa and Chambers [2014]*), one would assume the error would be 4.7 Sv.

3.5. Mapping Error 2005–2007

The previous analysis was also done for the 2005–2007 sampling period, but we only show the total transport mapping error (Figure 7). The mean over the ACC region is 2.7 Sv. Although the increasing Argo sampling results in improvement in some areas (comparing Figure 5c to Figure 7), that improvement is not uniform. The area with greatest reduction in mapping error is in regions of high eddy kinetic energy, such as the Brazil Malvinas confluence (~ 1 Sv improvement) and southeast of the African continent (~ 3 Sv improvement). Improvement from increased Argo sampling is also seen along the ACC within the Atlantic and western Indian basins, and at Tasmanian and South American chokepoints. Areas that fail to improve significantly are found along the northern edge of the ACC in the Indian basin, south of Australia within the ACC, and also south of the African continent, which includes the Agulhas retroflexion region.

3.6. Transect-Integrated Transport

The ultimate goal of this work is not to measure the transport averaged over a 1° grid, but to integrate it from the south to north across the ACC in order to obtain time-variable transport for any longitude (x) and time:

Figure 6. Covariance of barotropic and baroclinic mapping errors.

Figure 7. Total integrated transport mapping error for the 2005–2007 Argo sampling period.

$$T(x, t)_{total} = \int_{y_S}^{y_N} T(x, y, t)_{total} dy. \quad (4)$$

where y_S and y_N are the south and north boundaries of the ACC as defined by our mask (Figure 2), and vary by longitude.

The longitude-specific transport time-series can also be averaged across meridians to further reduce uncertainty. *Kosempa and Chambers [2014]* estimated that such an averaging would reduce transport errors considerably (by up to 70% in some areas), but they assumed no correlation between local barotropic and baroclinic transport errors, and no correlation between one grid to the next. Here, we can estimate the actual error accounting for correlations, by comparing the transport calculated from the “truth” data with that computed from the “mapped” data. This was done for every 1° of longitude, and after averaging over 11° and 21° of longitude centered on each transect (as suggested by *Kosempa and Chambers [2014]* to reduce uncertainty). Results are shown in Figure 8 for the transect-integrated transport that have 1° , 11° , and 21° averages in longitude centered at every meridian. Correlations between the “truth” and “mapped” transport time-series are high enough to be significant ($p < 0.01$) at every longitude and for every area averaging (Figure 8a).

Mapping error varies with longitude for the three area averages (Figure 8b). Wider area averaging reduces the error at most longitudes. The error is highest south of and down-stream from the African transect, until approximately 70°E when it is 5–10 Sv for a 1° transect and 3–5 Sv for a 21° -average. Away from the African transect, the remainder of the ACC has similar mapping error between basins. The characteristic error for 1° transect is approximately 5 Sv, while it is about 3 Sv for 11° and 21° area averaging.

Evolving Argo sampling during 2008–2010 and 2005–2007 periods impacts the mapping error (Figure 8c). For 1° transects, the mapping error is reduced with the 2008–2010 sampling in much of the Atlantic basin

Figure 8. (a) Correlations of mapped and truth total transport time series for the 2008–2010 Argo sampling period (b) total transport mapping error for 2008–2010 mapping period and (c) change in total transport mapping error from 2008–2010 minus 2005–2007 mapping period, i.e., negative values represent an improvement in mapping error. Area averaging was performed after isolating the Antarctic Circumpolar Current based on persistence in each plot.

Table 1. Transect-Integrated Total Transport Mapping Error for Early and Late Argo Sampling Periods at the Prime Meridian, African, Australian, Tasmanian, and Pacific Transects^a

	Mapping Error 2008–2010 (2005–2007)		
	1 Meridian	11 Meridians	21 Meridians
Prime Meridian	3.51(3.37)	1.54(2.83)	1.53(2.47)
Africa	18.15(19.04)	8.19(7.14)	6.45(7.10)
Australia	4.89(5.45)	3.75(3.60)	3.02(3.23)
Tasmania	4.61(4.36)	3.27(3.34)	2.49(2.69)
Pacific	2.39(2.46)	2.67(2.65)	2.9(3.08)

^aResults are shown for 1-, 11- and 21- meridian averages for the ACC isolated by persistence.

and that improvement extends until 90° E. The increased sampling after 2008 reduces mapping error most downstream of Africa. A similar improvement is found in the 11° area average. The 21° area average, alternatively, shows little to no improvement for most longitudes, and in some regions, mapping error with the 2008–2010 sampling is worse than with the 2005–2007 sampling, likely indicating more regional degradations in the Argo sampling for these regions as

early floats have moved out of the region and not been replaced.

For the 2008–2010 sampling period, the transport error at Africa is 18.2 Sv, but the error at all others is below 5 Sv (Table 1). The lowest transport error is at the Pacific transect (2.4 Sv). After averaging over 11° of longitude, the error at the Prime Meridian transect drops to 1.5 Sv. The Pacific transect error increases slightly to 2.7 Sv. The Australian and Pacific transects errors are 3.8 and 3.3 Sv, respectively. Averaging over 21° of longitude does not significantly reduce error at Africa. Even after averaging over 21°, transport error at Africa is no better than 4.6 Sv.

3.7. Systematic Errors in Transport Variability

This experiment also allows us to estimate systematic errors introduced by the mapping, by examining the transport residuals ($T_{mapped} - T_{truth}$). Because the 11° averaging appears optimal in terms of reducing the mean standard deviation (section 3.6), we only examine those residuals for the 5 historical transects (Figure 9).

Residuals for the two sampling periods at each of the transects described in section 2.4 indicate systematic problems in observation (Figure 9). The Prime Meridian transect's transport residuals show a disparate linear trend at the sampling periods (trends were fit without periodicities by linear least squares). The sampling period 2005–2007 has a trend of 2.18 ± 0.68 (90% confidence) compared to 0.65 ± 0.47 Sv yr⁻¹ for the 2008–2010 sampling period. While this indicates the sampling increase is effective in reducing mapping error from early to late sampling periods, the early sampling period would be expected to introduce spurious trends in real-world data. This change could be expected, given the relatively large improvement in mapping error between sampling periods seen in Table 1. The residuals for the African transect are quite noisy, which means any estimated trends are not significant. The residuals for the Australian and Tasmanian transects do not have any significant trends. The residuals for the Pacific transect have large and significant linear trends for both sampling periods (1.48 ± 0.76 Sv yr⁻¹ and 1.51 ± 0.76 Sv yr⁻¹ at 90% confidence for the early and late sampling periods, respectively). This suggests that transport trends computed from the Pacific transects would likely be overestimated in real world data.

Autocorrelation of the residuals can negatively impact ability to observe transport dynamics (Figure 9). For example, the transport residual at the Australian transect is shown to have a strong, repeating signal. This half-year periodicity in transport error at this location complicates the ability to estimate trends in real-world data and also implies the error estimation in the previous paragraph is too low, as that fitting uncertainty assumes uncorrelated error.

4. Transport Variability From Altimetry/Argo and Evaluation of Trends

Based on the analysis of transect-integrated transport error (section 3.6), and the analysis of the transport residuals (section 3.7), we concluded that the optimal location to study zonal geostrophic transport variability with a combination of altimetry and mapped Argo data is for the Tasmanian transect employing area averaging. Unlike other areas, the area south of Tasmania exhibited no evidence of systematic trends, and nearly random error in addition to the favorably low mapping errors. In addition, the estimated standard error is low (3.3 Sv for an 11-meridian average) and correlation is significant between T_{mapped} and T_{truth} (Figure 8a for 1°, 11° and 21° averages).

Figure 9. (a–e) Integrated total transport residuals of mapped minus truth 11° averaged transports for the two sampling periods (blue is early (2005–2007), red is late (2008–2010)) and (f–j) Autocorrelation of transport residual at each transect.

Figure 10. (a) Transport anomaly from real-world observations at the Tasmanian transect and the Southern Annular Mode index (SAM) computed from pressure anomalies at stations [Marshall, 2003]. The data were downloaded from <http://www.nerc-bas.ac.uk/icd/gjma/sam.html> on 26 April 2016. The Tasmania transect's error bars are the mapping errors listed in Table 1. (b) Transport anomaly at Tasmania and SAM after a 13 month low pass filter. Error bars of the 13 month low pass filtered transport time series assume uncorrelated error (that is, $3.3/\sqrt{13}$ Sv).

We calculated the transport anomaly time series for the Tasmanian transect using the mapped Argo data of Roemmich and Gilson [2009], and Jason-1 and Jason-2 altimetry data mapped with the same OI function, as outlined in Kosempa and Chambers [2014] (Figure 10). The transport was integrated across the ACC based on the persistence measurement in Kosempa and Chambers [2014]. An 11° averaging of 1° transects was used. Kosempa and Chambers [2014] compared transects near Africa and Tasmania, but found insignificant correlation. That can now be explained by high mapping error in the region south of Africa. The time-series indicates a slight trend over the 10 year time period that is not statistically significant (0.3 ± 0.4 Sv yr^{-1} , 90% confidence). Uncertainty was computed using a Monte Carlo simulation and an AR(1) noise model to represent the serial correlation in the residuals.

Much of the small trend can be explained by the positive transport anomalies throughout 2010–2012 when the Southern Annular Mode (SAM) was also anomalously positive (Figure 10a). It has been demonstrated in several studies that the interannual transport of the ACC is highly correlated with the SAM [e.g., Meredith

Figure 11. (a) Total, barotropic, and baroclinic transport. (b) Low pass filtered total, barotropic, baroclinic transport.

et al., 2004; Makowski *et al.*, 2015]. Although the monthly time series are not significantly correlated (0.1), this is primarily due to different high-frequency signals. If a low-pass filter (13 month boxcar) is applied to both, the correlation improves to 0.53 ($p < 0.05$, accounting for reduced degrees of freedom because of smoothing) (Figure 10b).

Deconstructing the total transport observed at Tasmania into barotropic and baroclinic contributions shows the barotropic contribution is the dominant source of variability (Figure 11). The dominance of barotropic variability in response to SAM verifies findings found in Makowski *et al.* [2015]. The total transport and the barotropic contributions are significantly correlated at 0.92, while the total transport and baroclinic contribution are not significantly correlated (Figure 11a). The barotropic and baroclinic contributions display opposing significant trends ($0.5 \pm 0.4 \text{ Sv yr}^{-1}$ versus $-0.2 \pm 0.1 \text{ Sv yr}^{-1}$, 90% confidence)

5. Conclusions

This study offers a comprehensive uncertainty analysis of volume transport mapped from sparse temperature, salinity, and sea surface height data. We showed the error in the deep current estimated from a combination of altimetry and Argo data is correlated with the baroclinic currents estimated from only Argo, unlike what was assumed by Kosempa and Chambers [2014]. The errors are negatively correlated, so combining the deep current and baroclinic currents results in a lower total transport error than considering the barotropic and baroclinic transport errors separately.

This study was also able to quantify the change in mapping error as the Argo program evolved and more floats were put into the Southern Ocean. The change in Argo sampling leads to temporally and regionally dependent errors in several areas (primarily around Africa and in the Pacific). Some of these errors will likely cause significant biases in the transport trends for those regions.

This regional mapping error points to the fact that some areas are better suited for using this technique to analyze transport dynamics than others. The African transect was immediately eliminated from considerations because its error is much higher than the other transects. The Prime Meridian and Pacific transects both indicate significant trend errors within the different Argo sampling periods, and the mapping errors at the Pacific transect are likely nonrandom. That leaves the area south of Tasmanian has having reasonable errors, no evidence of systematic trends, and nearly random error. The Tasmanian transect has the additional benefit of being historically well sampled as a WOCE choke point and has relatively modest eddy kinetic energy as observed by altimetry [Ducet *et al.*, 2000].

Our transport time-series captures much of the interannual SAM variability after 2006, but there is a substantial difference in 2008 and 2009, when the estimated transport anomaly is zero or negative but the SAM is positive (Figure 10b). Estimates of transport anomalies from satellite gravity measurements do show increased transport between 2008 and 2009 in this area [Makowski *et al.*, 2015], consistent with the SAM. Our analysis indicates the discrepancy between transport and the SAM is not explained by baroclinic transport compensation. The discrepancy could be due to a problem in our transport estimate that has not been captured in our mapping experiment, as no signs of this error are apparent in the residual analysis (Figure 8). The relatively short time series presents another weakness, as there are only 4 cycles of the SAM during the Argo period, and our time series may simply not represent the relationship between low frequency transport anomaly and the SAM. However, more analysis will be needed to quantify the reason. The discrepancy between our transport estimates and the SAM during 2008 and 2009 are directly contributing to disagreement between our trends and those from Makowski *et al.* [2015]. Caveats on SAM disagreement notwithstanding, the response pattern seen in our low frequency time series agrees with the eddy saturation paradigm. While the total transport shows no change in total, the barotropic and baroclinic transport contributions exhibit opposing, significant trends. The increase in barotropic transport results from an increase in dynamic ocean topography gradient at the deepest level of 1975 dbar. Conversely, above 1975 dbar, there is a relaxation of dynamic ocean topography that directly translates into a reduction in depth-dependent transport. If eddies compensating the increased northward Ekman transport are restricted to the upper ocean, the only way for total transport to remain insensitive is a depth-independent response. Therefore, the lack of trend in total transport suggests an ACC transport insensitive to wind increases and also provides evidence for an increase in eddy activity of the upper ocean decreasing dynamic ocean

topography gradients across ACC. A depth-independent response compensates the upper-ocean changes. Further modeling studies could quantitatively test this hypothesis.

Finally, we have also demonstrated that the barotropic variability (i.e., the component due to the reference velocity at depth) is the dominant source of variability, explaining well over 85% of the low-frequency variance that is most correlated with SAM. Using only the density information and assuming a zero velocity at depth (as is typically done with hydrographic sections) would have severely underestimated the transport variability. Thus, understanding and measuring the currents at the deepest common level is critical to measuring the full geostrophic transport variability. Although the method we have investigated as some uncertainty associated with it, as quantified in this study, it is still more accurate than assuming zero velocity at the reference depth. A caveat to this interpretation is the velocity at 2km depth may not be exclusively depth independent and the sensitivity of the definitions presented here require further quantification.

The relatively short instrument record creates another significant drawback of this work. That drawback is the problem of a well-defined climatology, which is crucial for the optimal interpolation and is known to be a concern for the mapping of Argo data in this region [Roemmich and Gilson, 2009]. Our experiment assumed a perfect climatology from SOSE. Therefore, our estimates may be slightly optimistic, especially in the early part of the record when the effect of the climatology choice is more pronounced. It is not clear how one would address this problem in the experiment, and with continued Argo observations in the Southern Ocean, this will become less of a problem. A longer instrument record will not only help the climatology but also increase confidence in our trend and correlation analyses.

Another issue is the choice of the southern boundary for mapping of Argo data. Roemmich and Gilson [2009], for example, only map data to 60°S. Our ACC mask, however, extends below 60°S in many regions. Our experiments show that the mapping error poleward of 60°S is not higher than areas equatorward (Figure 5). In fact, the errors are smaller, because the largest contribution to the error is sampling of mesoscale eddies. Thus, future mapping of Argo data should extend farther to better encompass the entire ACC.

Even with these caveats, this study verifies that a combination of surface geostrophic currents from altimetry and subsurface density from mapped Argo data can be used to estimate transport variability in the Southern Ocean above 2000 dbar with reasonable accuracy, especially after 2008. These monthly and long-term measurements will supplement in situ estimates made intermittently primarily at the Drake Passage and shed better light on the interannual and decadal variability of the integrated ACC transport.

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References

- Bergmann, I., and H. Dobslaw (2012), Short-term transport variability of the Antarctic Circumpolar Current from satellite gravity observations, *J. Geophys. Res.*, **117**, C05044, doi:10.1029/2012JC007872.
- Cadden, D., B. Subrahmanyam, D. Chambers, and V. S. N. Murty (2009), Surface and subsurface geostrophic current variability in the Indian Ocean from Altimetry, *Marine Geodesy*, **32**(1), 19–29.
- Ducet, N., P. Y. Le Traon, and G. Reverdin (2000), Global high-resolution mapping of ocean circulation from TOPEX/Poseidon and ERS-1 and 552 22, *J. Geophys. Res.*, **105**(C8), 19,477–19,498, doi:10.1029/2000JC900063.
- Farneti, R., T. Delworth, A. Rosati, S. Griffies, and F. Zeng (2010), The role of mesoscale eddies in the rectification of the southern ocean response to climate change, *J. Phys. Oceanogr.*, **40**, 1539–1557, doi:10.1175/2010JPO4353.1.
- Fyfe, J. C., and O. A. Saenko (2006), Simulated changes in the extratropical Southern Hemisphere winds and currents, *Geophys. Res. Lett.*, **33**, L06701, doi:10.1029/2005GL025332.
- Gnanadesikan, A., and R. W. Hallberg (2000), On the relationship of the circumpolar current to southern hemisphere winds in coarse-resolution ocean models, *J. Phys. Oceanogr.*, **30**, 2013–2034, doi:10.1175/1520-0485(2000)030<2013:OTROT>2.0.CO;2.
- Griesel, A., M. R. Mazloff, and S. T. Gille (2012), Mean dynamic topography in the Southern Ocean: Evaluating Antarctic Circumpolar Current transport, *J. Geophys. Res.*, **117**, C01020, doi:10.1029/2011JC007573.
- Hallberg, R., and A. Gnanadesikan (2006), The role of eddies in determining the structure and response of the wind-driven Southern Hemisphere overturning: Results from the modeling eddies in the Southern Ocean (MESO) project, *J. Phys. Oceanogr.*, **36**, 2233.
- Hogg, A. M., M. P. Meredith, D. P. Chambers, E. P. Abrahamson, C. W. Hughes, and A. K. Morrison (2015), Recent trends in the Southern Ocean eddy field, *J. Geophys. Res. Oceans*, **120**, 257–267, doi:10.1002/2014JC010470.
- Kosempa, M., and D. P. Chambers (2014), Southern Ocean velocity and geostrophic transport fields estimated by combining Jason altimetry and Argo data, *J. Geophys. Res. Oceans*, **119**, 4761–4776, doi:10.1002/2014JC009853.
- Langlais C. E., S. R. Rintoul, and J. D. Zika (2015), Sensitivity of Antarctic Circumpolar Current Transport and eddy activity to wind patterns in the Southern Ocean, *J. Phys. Oceanogr.*, **45**, 1051–1067, doi:10.1175/JPO-D-14-0053.1.
- Makowski, J. K., D. P. Chambers, and J. A. Bonin (2015), Using ocean bottom pressure from the Gravity Recovery and Climate Experiment (GRACE) to estimate transport variability in the southern Indian Ocean, *J. Geophys. Res. Oceans*, **120**, 4245–4259, doi:10.1002/2014JC010575.
- Marshall G. J. (2003), Trends in the southern annular mode from observations and reanalyses, *J. Clim.*, **16**, 4134–4143, doi:10.1175/1520-0442(2003)016<4134:TITSAM>2.0.CO;2.

- Mazloff, M. R., P. Heimbach, and C. Wunsch (2010), An eddy-permitting Southern Ocean State Estimate, *J. Phys. Oceanogr.*, *40*, 880–899, doi:10.1175/2009JPO4236.1.
- McDougall, T. J., and P. M. Barker (2011), Getting started with TEOS-10 and the Gibbs Seawater (GSW) Oceanographic Toolbox, Version 3.0 (R2010a), *SCOR/IAPSO WG127 28*. [Available at www.TEOS-10.org.]
- Meijers, A., N. L. Bindoff, and S. R. Rintoul (2011), Estimating the four-dimensional structure of the southern ocean using satellite altimetry, *J. Atmos. Oceanic Technol.*, *28*, 548–568, doi:10.1175/2010JTECHO790.1.
- Meredith, M. P., P. L. Woodworth, C. W. Hughes, and V. Stepanov (2004), Changes in the ocean transport through Drake Passage during the 1980s and 1990s, forced by changes in the Southern Annular Mode, *Geophys. Res. Lett.*, *31*, L21305, doi:10.1029/2004GL021169.
- Meredith, M. P., A. C. Naveira Garabato, A. C. McHogg, and R. Farneti (2012), Sensitivity of the overturning circulation in the Southern Ocean to decadal changes in wind forcing, *J. Clim.*, *25*, 99–110, doi:10.1175/2011JCLI4204.1.
- Morrison, A. K., and A. McC. McHogg (2013), On the relationship between Southern Ocean overturning and ACC transport, *J. Phys. Oceanogr.*, *43*, 140–148, doi:10.1175/JPO-D-12-057.1.
- Mulet, S., M. -H. Rio, A. Mignot, S. Guinehut, and R. Morrow (2012), A new estimate of the global 3D geostrophic ocean circulation based on satellite data and in-situ measurements, *Deep-Sea Research II*, *77–80*, 70–81.
- Rintoul, S. R., and A. C. N. Garabato (2013), Dynamics of the Southern Ocean, in *Ocean Circulation and Climate: A 21st Century Perspective*, Int. Geophys. Ser., vol. 103, edited by G. Siedler et al., pp. 471–492, Academic Press, Cambridge, Mass.
- Roemmich, D., and J. Gilson (2009), The 2004–2008 mean and annual cycle of temperature, salinity, and steric height in the global ocean from the Argo Program, *Prog. Oceanogr.*, *82*, 81–100, doi:10.1016/j.pocean.2009.03.004.
- Wunsch, C., and E. M. Gaposchkin (1980), On using satellite altimetry to determine the general circulation of the oceans with application to geoid improvement, *Rev. Geophys.*, *18*(4), 725–745.
- Wunsch, C., and P. Heimbach (2007), Practical global oceanic state estimation, *Physica D*, *230*(1–2), 197–208.