Ocean salinity from satellite-derived temperature in the Antarctic Ocean

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Abstract

The aim of the MINERVE project (Mesures à l'INterface Eau-aiR de la Variabilité des Échanges de CO2) is to observe and understand the seasonal and inter-annual variability of the partial pressure of CO2 (pCO2) in surface waters using hydrological and biogeochemical data in the Southern Ocean south of Australia. Logistics routes of the R/V Astrolabe provide access to scarcely studied areas, thus allowing us to understand the different processes acting in this area of the Antarctic Ocean. The surface area covered by these cruises, however, is tiny compared with the total surface area of the Antarctic Ocean. We apply correlations between in situ surface temperature and salinity data to satellite images of sea surface temperature to map ocean surface salinity over a much wider area than under the cruise tracks. Comparing with salinity given by satellites which provide 100 km resolution and 0.1 accuracy, we are able to map salinity at 4 km resolution and almost the same accuracy of ±0.1.

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Key words: mapping, Southern Ocean, surface salinity, temperature fields.

1 Introduction

The Southern Ocean plays a significant role in the exchange of CO_2 between the global atmosphere and ocean (Lenton et al., 2013). The MINERVE project (Mesures à l'INterface Eau-aiR de la Variabilité des Échanges de CO2) was designed to observe and understand the seasonal and interannual variability of the partial pressure of CO_2 (pCO_2) in surface waters in the Southern Ocean south of Australia. The logistics routes of the RV Astrolabe between Hobart, Tasmania and the French Antarctic station at Dumont d'Urville provide an opportunity to collect hydrological and biogeochemical data in this remote area. However, the surface area sampled during these cruises is tiny compared with the surface area of the entire region of interest. Therefore, we seek ways to extrapolate the in situ data to a broader area using satellite images.

The exchange of CO_2 between the ocean and atmosphere is affected by both sea surface temperature (SST) and the stability of the surface mixed layer. The SST is routinely monitored by satellites. However, in cold high-latitude oceans, surface mixed layer stability is often controlled by salinity, which has only recently been mapped by satellite even though sea surface salinity (SSS) is one of the fundamental variables for which sustained global observations are required to improve our knowledge and prediction of the ocean circulation, global water cycle and climate (Lagerloef et al., 2010). Two satellite missions now provide estimates of SSS.

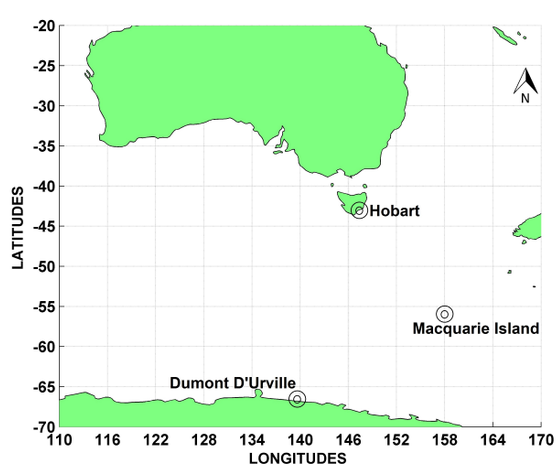

Figure 1: Regional map showing Hobart, Dumont D'Urville and Macquarie Island. Source: Google Earth.

The Aquarius satellite, a collaboration between NASA and the Space Agency of Argentina, was launched in June 2011 and operated until June 2015. Aquarius provided global maps of salinity with accuracy of ±0.2 and a spatial resolution of 150 km (Le Vine et al., 2007). Data are available from `http://oceandata.sci.gsfc.nasa.gov/Aquarius/`. The Soil Moisture and Ocean Salinity (SMOS) satellite was launched in November 2009 and continues to operate, providing maps of salinity with an accuracy of ±0.1 and a spatial resolution of 50–100 km (Michel, 2006). Data are available from `http://cp34-bec.cmima.csic.es/data/data-access/`.

In this paper, we report *in situ* measurements of the interannual variability of SSS in the southern Indian Ocean during the early spring of each year between 2002 and 2009. We then describe a technique for mapping SSS in the same period of the year, but from 2010–12 using satellite-based maps of SST. The technique is then assessed by comparisons between the *in situ* data and mapped values, and with direct SSS estimates from the two salinity satellites.

		From Hobart to Dumont D'Urville				From Dumont D'Urville to Hobart				
Part	Year	Start date	End date	Lowest L.	Highest L.	Start date	End date	Highest L.	Lowest L.	D.N.
1	2002	16/10	21/10	-43.96	-63.62	30/10	03/11	-61.81	-43.11	294
	2003	21/10	26/10	-45.14	-62.82	06/11	11/11	-62.15	-43.66	388
	2004	19/10	23/10	-43.47	-61.96	04/11	09/11	-62.14	-43.29	421
	2005	18/10	22/10	-44.92	-61.88	03/11	08/11	-62.82	-43.26	470
	2006	20/10	29/10	-43.64	-66.56	03/11	12/11	-66.66	-43.45	201
	2007	28/10	01/11	-43.20	-63.44	16/11	20/11	-63.42	-44.28	348
	2008	21/10	26/10	-42.84	-61.17	02/11	11/11	-65.84	-43.36	4410
	2009	22/10	25/10	-48.58	-62.05	11/11	16/11	-62.47	-43.47	7671
2	2010	21/10	27/10	-42.88	-63.53	31/10	07/11	-63.28	-43.51	11 045
	2011	25/10	26/10	-54.59	-57.97	06/12	10/12	-63.46	-43.31	4181
	2012	23/10	28/10	-42.84	-62.83	18/11	22/11	-61.70	-42.94	6169

Table 1: Details of the MINERVE database. Part 1 was used to establish the model. Part 2 was used to validate the model. L. = Latitude, D.N. = Data numbers

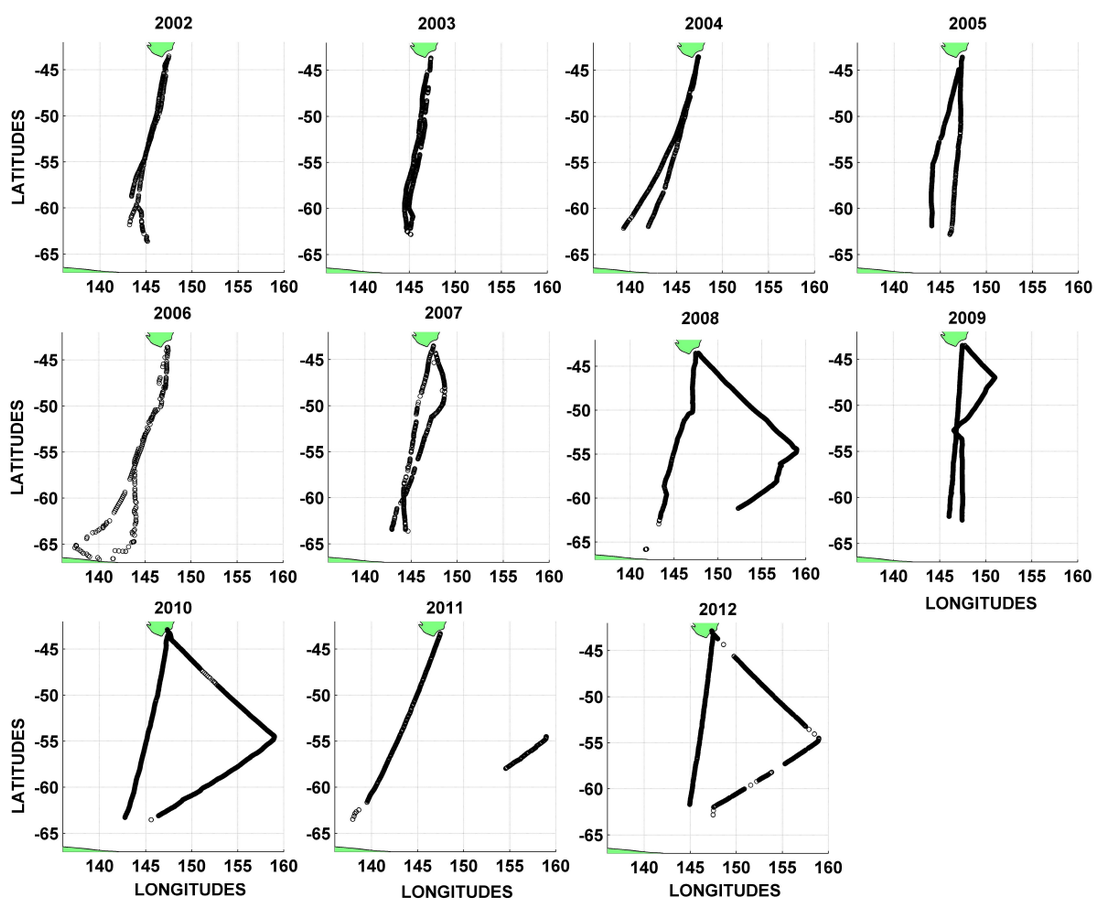

Figure 2: Cruise tracks of the MINERVE project where data are during the first cruise every year.

2 methods

Cruise details

The database from the MINERVE project was utilized for this study. The database was divided into two parts: one to build a model (2002–09) and the second (2010–12) to provide a validation test. There are 14 203 *in situ* data points available to establish the model and 21 395 *in situ* data points for the validation process. The MINERVE project acquired data during three cruises each summer from October to March, between Hobart (Tasmania, Australia, ∼43°S) and Dumont D'Urville (Adélie Land, Antarctica, ∼67°S) (Fig. 1). Only data from early summer is considered here, mainly in October and November; see Table 1 for dates and latitudes of each cruise used to establish (part 1) and validate (part 2) the model. The cruise tracks (Fig. 2) every year cross all latitudes between Tasmania and Antarctica, although the presence of ice in the early summer prevents data collection south of ∼63°S. Changes of longitude are primarily due to weather conditions; however, in some years (2008,2010, 2011 and 2012), the ship had to go to Macquarie Island (55°S, 158°E) (Fig. 1).

Data and model

The MINERVE project provides data on surface water parameters from southern Australia to the sea ice edge north of Antarctica. The latitudinal distribution of SST and SSS (Fig. 3) shows cooling and freshening from roughly SST = 2°C and SSS = 35.1 near Hobart to ∼-1.9°C (the freezing point) and 33.9 near 63°S. There is a substantial range in both SST and SSS at each latitude, associated with both the differences in cruise tracks (Fig. 2) and interannual variability.

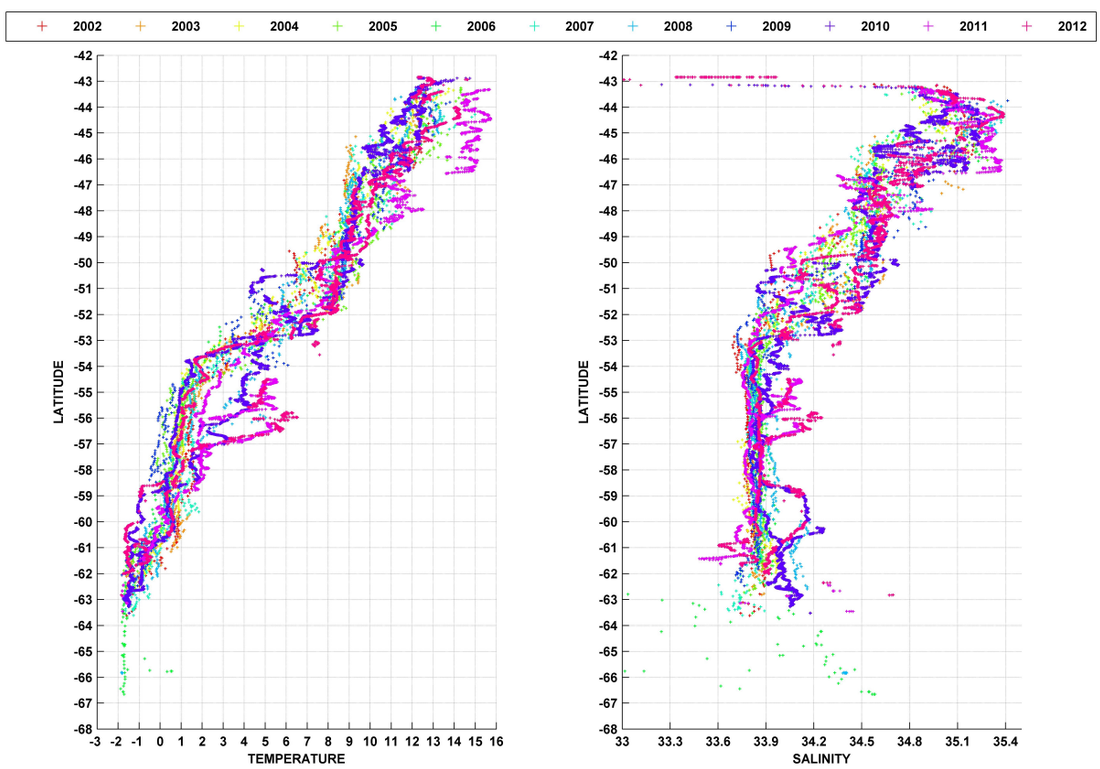

Figure 3: Latitudinal distribution of temperature and salinity in the Southern Ocean south of Australia during the 2002–12 MINERVE project.

The surface fitting toolbox of MATLABTM was used to develop a model based on the MINERVE database of SST, SSS and latitude, φ. This toolbox performs multiple linear regressions between these three variables. This method provides good results for our purpose (Moussa et al., 2015). We carried out the analysis for Part 1 of the database (2002–09), setting the degree of φ at 1 and the degree of SST at 2, resulting in the following function:

$$\begin{aligned} SSS_{mod} &= a + b \times \varphi + c \times SST \\ &+ d \times Lat \times SST + e \times SST^2 \end{aligned} \quad (1)$$

where the optimized values of coefficients were a = 33.10000, b = -0.01257, c = 0.103600, d = 0.001929 and e = 0.008504. The fitting surface and the residual plot are shown in Fig. 4.

Three statistical measures were calculated to evaluate the model. Model error at each point in parameter space is defined as $e_i = P_i - O_i$ where e_i is the error, P_i $(i = 1..n)$ is the model-predicted value and $O_i(i = 1..n)$ is the observed value. The root-mean-square error (RMSE; Willmott and Matsuura (2005)) is defined as:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n} e_i^2\right]^{\frac{1}{2}} \quad (2)$$

The mean absolute error (MAE) is based on the absolute value of each error estimate (Willmott and Matsuura, 2005),i.e.

$$MAE = \left[\frac{1}{n}\sum_{i=1}^{n} |e_i|\right] \quad (3)$$

The mean bias error (MBE) is the simple average of individual error estimates:

$$MBE = \left[\frac{1}{n}\sum_{i=1}^{n} e_i\right] \quad (4)$$

The MBE indicates whether the average estimate is less than or greater than the observed values. The following measures were obtained for the modelled error in salinity: MBE = -3.01×10^{-14}, MAE = 0.0706, and RMSE = 0.0958. The values for MBE and RMSE indicate that the model, in general, has a salinity accuracy that is comparable with satellite-derived SSS accuracy. However, some large values of ei are found in the far southern portion of the domain (Fig. 4b).

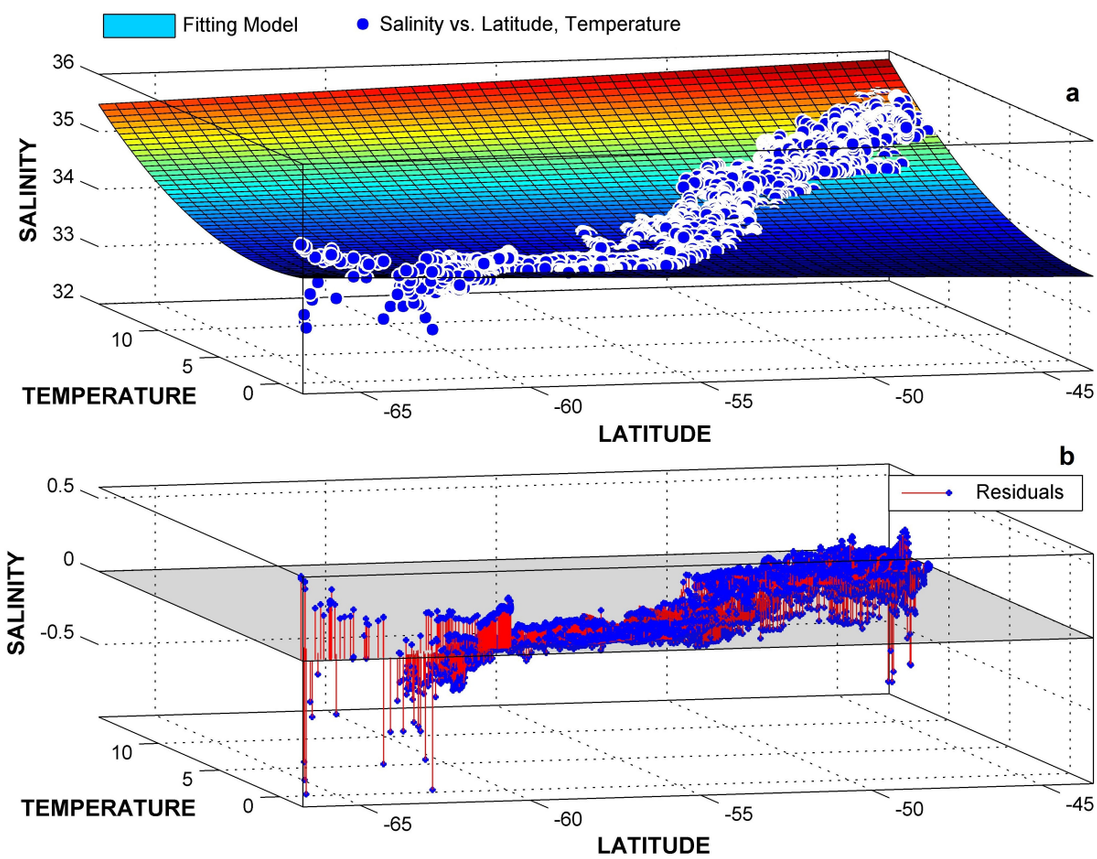

Figure 4: Model suggested by the surface fitting toolbox. a. Dataset points and fitting surface. b. Residuals plot.

3 Results

Satellite-derived maps of SST were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) on the NASA Aqua satellite. Data are provided as daily averages with a spatial resolution of 4×4 km (`http://oceancolor.gsfc.nasa.gov`). For comparison with the MINERVE database, MODIS SST points corresponding as closely as possible in space and time to our *in situ* datapoints were selected. Our statistical fit model (Eq. 1) was then applied to the satellite-derived SST and latitude φ to estimate SSS, and compare these values with in situ SSS data for part 2 data (2010–12) that were not included in the development of the model fit. The loss of satellite-derived SST data due to weather substantially reduces the number of points for comparison, from 21 395 to 4672 points. There is a mismatch between satellite and *in situ* SST around 48°S and 51°S (Fig. 5a). These errors are probably due to the calibration of the satellite instruments, which is rather complex. At the moment, there are four main calibration methodologies. The aim of these methodologies is to have a good accuracy over the globe; however, calibration can cause significant errors when satellite data are compared with specific local *in situ* data. Note that these errors appear in two fronts(explained in the following paragraph) which increase the difficulty for modelling for the satellite algorithms.

The errors as functions of latitude (Fig. 5) are usually small but with some regions of large outliers. The study area was divided into three regions (Laika et al.,

2009) representing five different hydrographic zones of the Southern Ocean (Rintoul et al., 1997):

1. The Sub-Antarctic Region (SAR) which it is composed of three zones:
   - The Sub-Tropical Zone (STZ) from -43.5°S to -47.5°S.
   - The Sub-Antarctic Zone (SAZ) from -47.5°S to -51.5°S.
   - The Polar Frontal Zone (PFZ) from -51.5°S to -54.5°S.
2. The Permanent Open Ocean Zone (POOZ) from -54.5°S to -60°S.
3. The Seasonal Ice Zone (SIZ) from -60.5°S to -65°S.

Table 2 shows all residuals by zone and for the whole study area. Model errors are larger in the SAZ and STZ than in the other zones. However, the error in the estimation of salinity is correlated with the difference between the *in situ* and the satellite temperature (Fig. 5a). That is, the large errors in SSS for some latitude ranges are caused by errors in satellite-derived temperature rather than in our regression model (Eq. 1).

There is large mean bias between satellite and *in situ* temperature (Fig 5a), with MBE = -0.6952 (Table 2). When outliers are removed, keeping only points where residuals are between +1 and -1.5, the new MBE is -0.2974. This bias is applied to satellite temperature data so that the MBE becomes zero. After testing the model, new residuals for salinity and temperature are smaller; compare Fig. 6 with Fig. 5, and Table 3 with Table 2.

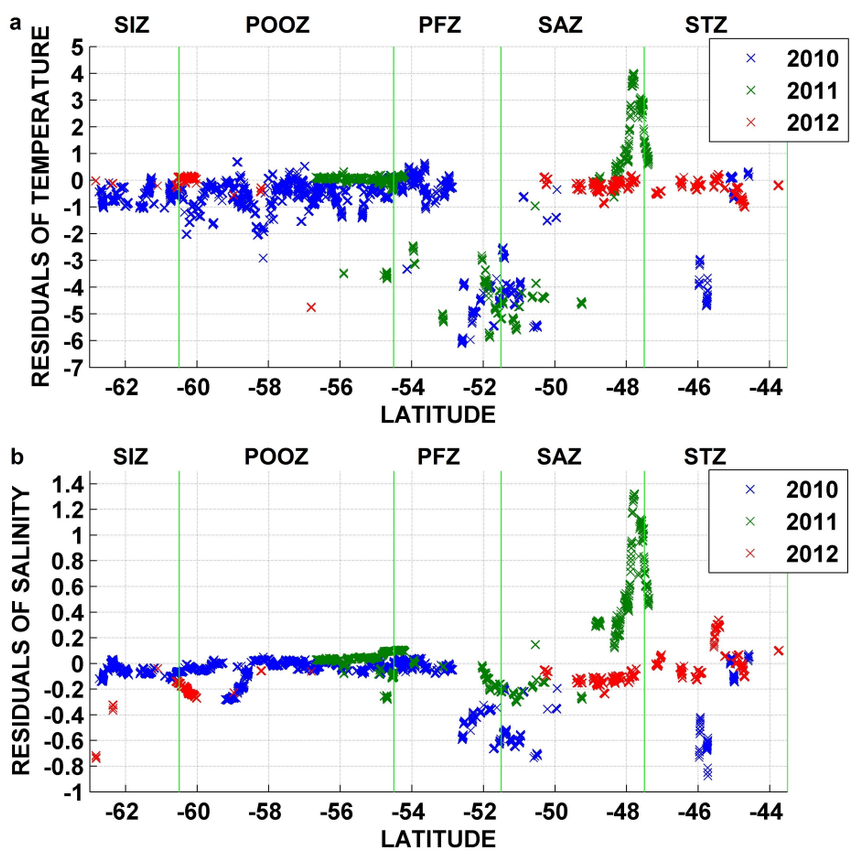

Figure 5: Salinity and temperature residuals (satellite to *in situ* data comparison). Residuals between a. satellite and observed temperature, and b. estimated and observed salinity.

		Estimated salinity vs *in situ* salinity			Satellite temperature vs *in situ* temperature		
Area	Numbers	MBE	MAE	RMSE	MBE	MAE	RMSE
STZ	354	0.0001	0.1763	0.2776	-0.4812	0.6958	1.3225
SAZ	678	-0.0223	0.3183	0.4296	-1.0521	1.7228	2.5537
PFZ	614	-0.1092	0.1387	0.2270	-1.7291	1.8288	2.7897
POOZ	2505	-0.0383	0.0577	0.0881	-0.4094	0.4611	0.6962
SIZ	521	-0.0758	0.0781	0.1102	-0.5322	0.5390	0.6064
Whole area	4672	-0.0466	0.1174	0.2119	-0.6952	0.8504	1.5500

Table 2: Model testing results (2010–12). MAE = mean absolute error, MBE = mean bias error, PFZ = Polar Frontal Zone, POOZ = Permanent Open Ocean Zone, RMSE = root-mean-square error, SAR = Sub-Antarctic Region, SAZ = Sub-Antarctic Zone, SIZ = Seasonal Ice Zone, STZ = Sub-Tropical Zone.

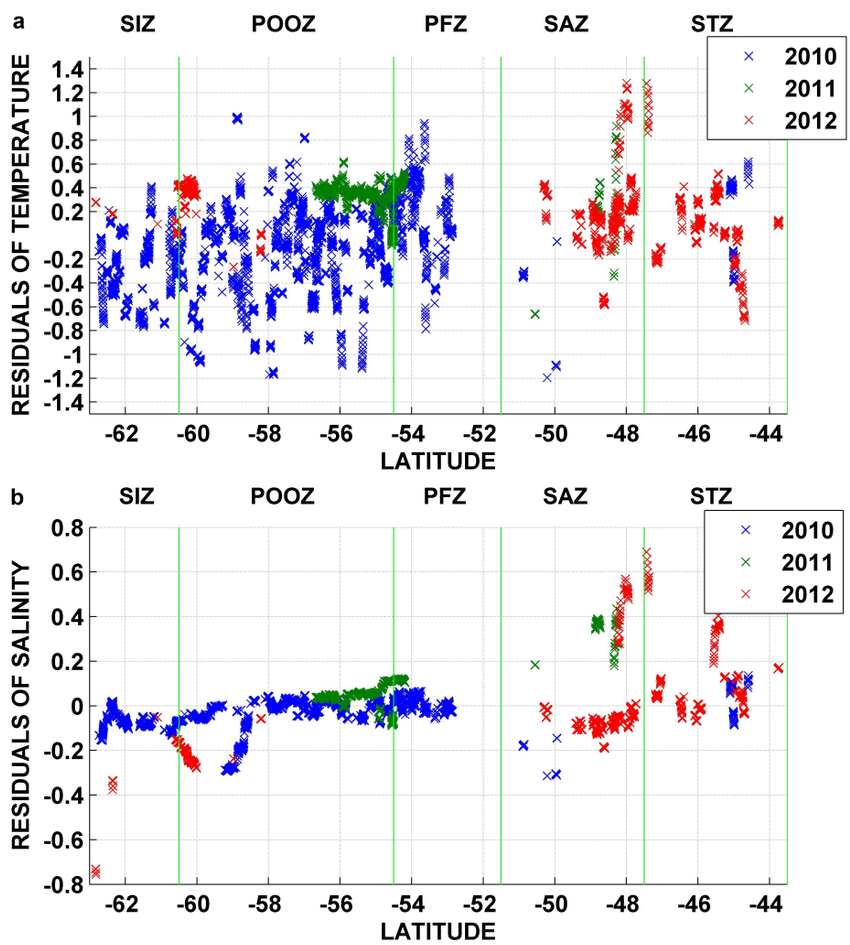

Figure 6: Salinity and temperature residuals after selecting process. Residuals between a. satellite and observed temperature, and b. estimated and observed salinity.

		Estimated salinity vs *in situ* salinity			Satellite temperature vs *in situ* temperature		
Area	Numbers	MBE	MAE	RMSE	MBE	MAE	RMSE
STZ	305	0.0969	0.1193	0.1805	0.1089	0.2923	0.3701
SAZ	401	0.0200	0.1480	0.2023	0.1457	0.2901	0.4001
PFZ	381	0.0268	0.0435	0.0567	0.2168	0.3197	0.3745
POOZ	2376	-0.0314	0.0578	0.0890	0.0218	0.3077	0.3837
SIZ	521	-0.0863	0.0872	0.1187	0.2348	0.3054	0.3735
Whole area	3984	-0.0180	0.0741	0.1160	0	0.3058	0.3822

Table 3: Model testing results after the selection process. L = Latitude. MAE =mean absolute error, MBE =mean bias error, PFZ =Polar Frontal Zone, POOZ =Permanent Open Ocean Zone, RMSE =root-mean-square error, SAR =Sub-Antarctic Region, SAZ =Sub-Antarctic Zone, SIZ =Seasonal Ice Zone, STZ =Sub-Tropical Zone.

4 Discussion

Satellite SST maps are available every day (with more or less points provided depending on the climatic conditions), at 4 km spatial resolution. The model we have established (Eq. 1) allows us to map SSS at the same resolution in the early summer in the Southern Ocean south of Australia.

This spatial resolution is much finer than we can obtain from existing satellite salinity sensors on the Aquarius and SMOS satellites (∼150 km and 50–100 km, respectively). The daily sampling of SST by satellites is much more frequent that either salinity satellite provides. The accuracy of our model, in salinity units (RMSE = 0.116 for the entire region from 43oS to the ice edge near 63°S), is comparable to the cited accuracy of the satellite-derived values; therefore, our model may provide valuable information on SSS for temporal and spatial scales that cannot be resolved by the satellite-based salinity records. An additional source of error, when modelling SSS based on satellite-derived SST, is that the RMSE for satellite vs in situ SST is ∼0.38°C (Table 3); based on Eq. (1), this converts to ∼0.1 in SSS.

As an example of the potential value of our model, Fig. 7 compares a one day modelled SSS (Eq. (1) applied to satellite-derived SST data) with coarser estimates from SMOS and Aquarius. The differences between resolutions are clear. Note that SMOS data are provided as an average of at a minimum of three days. Table 4 shows a pairwise comparison of modelled SSS with SMOS data and with Aquarius data using *in situ* data from 2011 to 2012 (Table I, part 2). The RMSE of our modelled SSS is much smaller than both SMOS and Aquarius data.

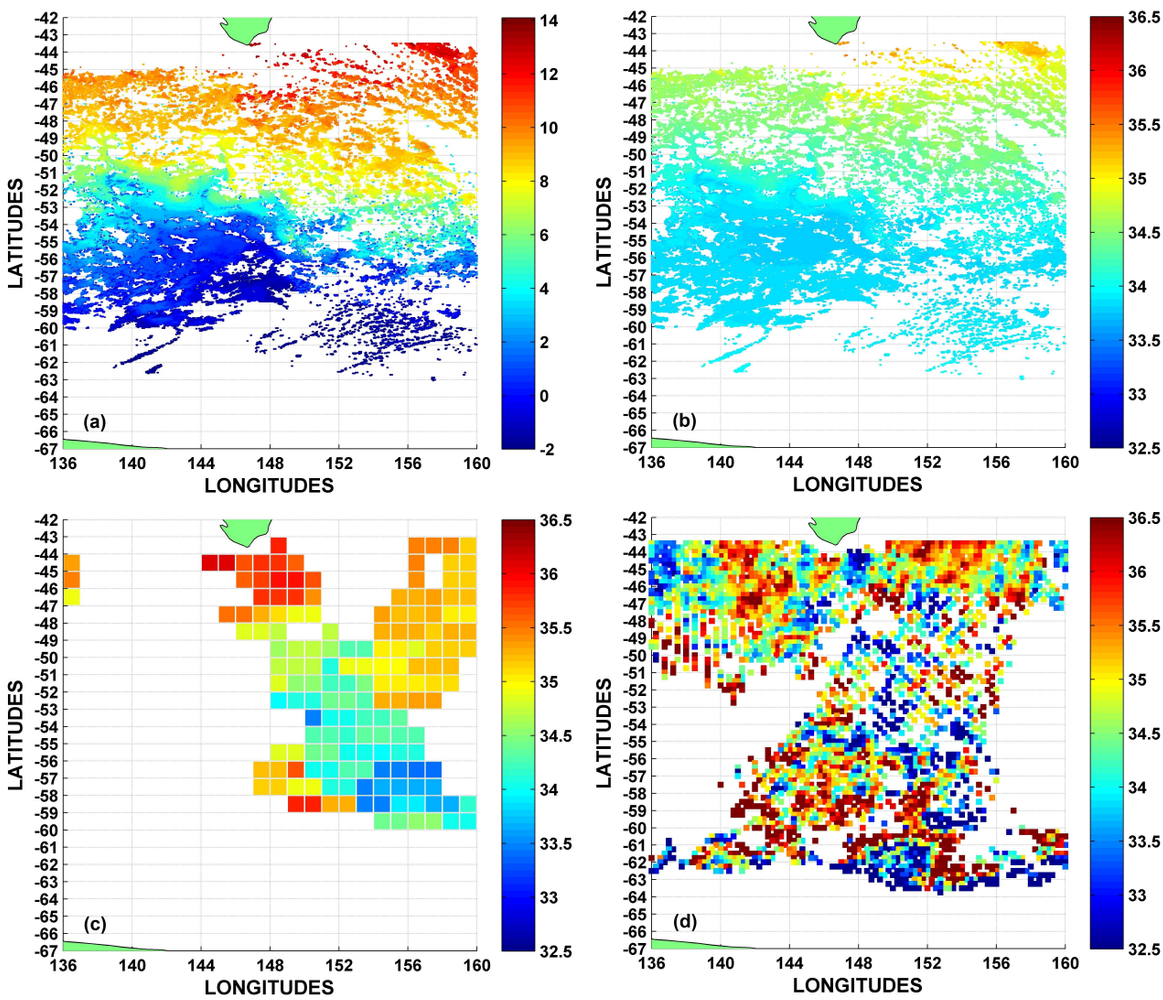

Figure 7: Comparison of modelled sea surface salinity (SSS) using sea surface temperature (SST) with SMOS and Aquarius satellite data. a. Satellite SST in the Antarctic Ocean south of Australia on 25 October 2011. b. Modelled estimated salinity from a. c. Aquarius satellite image from 25 October 2011. d. SMOS three-day average satellite image from 25 October 2011 to 27 October 2011.

	Modelled SSS vs SMOS data	Modelled SSS vs Aquarius data
Numbers	1083	696
RMSE of modelled SSS	0.1841	0.0755
RMSE of corresponding satellite data	1.9781	0.4989

Table 4: Comparison between modelled sea surface salinity (SSS) and two satellite products (SMOS and Aquarius). RMSE = root-mean-square error.

5 Conclusions

We have demonstrated the value of developing algorithms to relate SSS to satellite-derived SST, by providing the ability to map SSS at much finer spatial and temporal scales that can be resolved by existing salinity satellites, Aquarius (stopped on 17 June 2015) and SMOS. Furthermore, as these satellites have only been operating for a few years, the algorithm allows the extension of maps of SSS into time ranges for which no satellite maps of SSS are available. This approach can be further developed to determine SSS throughout the year, and to contribute to a broader range of applications including determination of surface density, air-sea exchanges, and estimation and analysis of air-sea CO2 fluxes.

Collecting more in situ data is the best way to improve our models; therefore, it is important that the MINERVE project remains active.

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7 Authors contributions

Mrs H. Moussa was involved in the conception and writing of the programs for the study. Dr F. Touratier supervised this PhD research and assisted with writing and revising this paper. Professor C. Goyet assisted with analysis of the data and provided ideas for the selection process which enabled the achievement of better results, and also participated in revising the article. Professor A. Poisson participated on the MINERVE project where we found our data, and also assisted with revising the article.

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