nature portfolio

Peer Review File

The Southern Ocean carbon sink has been overestimated in the past three decades

Web links to the author’s journal account have been redacted from the decision letters as indicated to maintain confidentiality.

Decision letter and referee reports: first round

16th Jan 24

Dear Professor Li,

Your manuscript titled "Melting sea ice will weaken carbon sinks in the Southern Ocean" has now been seen by 2 reviewers, whose comments are appended below. You will see that they find your work of some potential interest. However, they have raised quite substantial concerns that must be addressed. In light of these comments, we cannot accept the manuscript for publication, but would be interested in considering a revised version that fully addresses these serious concerns.

In addition, we are including some editorial thresholds: i) please include and explain in-depth the use of predictors in the main text, ii) include a comparison to traditional approaches, and iii)consider including additional pCO2 datasets in their analysis (if available).

We hope you will find the reviewers' comments useful as you decide how to proceed. Should additional work allow you to address these criticisms, we would be happy to look at a substantially revised manuscript. If you choose to take up this option, please either highlight all changes in the manuscript text file, or provide a list of the changes to the manuscript with your responses to the reviewers.

Please bear in mind that we will be reluctant to approach the reviewers again in the absence of substantial revisions.

If the revision process takes significantly longer than three months, we will be happy to reconsider your paper at a later date, as long as nothing similar has been accepted for publication at Communications Earth & Environment or published elsewhere in the meantime.

We are committed to providing a fair and constructive peer-review process. Please do not hesitate to contact us if you wish to discuss the revision in more detail.

Please use the following link to submit your revised manuscript, point-by-point response to the reviewers’ comments with a list of your changes to the manuscript text (which should be in a separate document to any cover letter), a tracked-changes version of the manuscript (as a PDF file) and any completed checklist:

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Please do not hesitate to contact us if you have any questions or would like to discuss the required revisions further. Thank you for the opportunity to review your work.

Best regards,

Jose Luis Iriarte Machuca, PhD
Editorial Board Member

Communications Earth & Environment

Clare Davis, PhD
Senior Editor
Communications Earth & Environment

EDITORIAL POLICIES AND FORMAT

If you decide to resubmit your paper, please ensure that your manuscript complies with our editorial policies and complete and upload the checklist below as a Related Manuscript file type with the revised article:

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For your information, you can find some guidance regarding format requirements summarized on the following checklist:(https://www.nature.com/documents/commsj-phys-style-formatting-checklist-article.pdf) and formatting guide (https://www.nature.com/documents/commsj-phys-style-formatting-guide-accept.pdf).

REVIEWER COMMENTS:

Reviewer #3 (Remarks to the Author):

The manuscript describes an approach to reduce the uncertainty/discrepancy in data products and model outputs for surface ocean pCO2 in the Southern Ocean.
The authors state that this is mainly due to the lack of in situ observations during winter (compared to summer).

They have applied the boosting ensemble learning feed forward neural networks (BEL FFNNs) method using a gridded version of SOCAT data, and data from the Southern Ocean flux station (SOFS, 142.0°E, 46.8°S), south of Tasmania (Australia) for validation.

Question: Aren't there any other pCO2 observing time series in other sector of the S. Ocean? Or only for summer periods?

My main question for the methods section concerns the following (l. 76-78):
"The surface ocean pCO2 converted from the Surface Ocean CO2 Atlas version 2023 (SOCAT v2023) dataset was used for pCO2 mapping by fitting the non-linear relationship between pCO2 and environmental variables"

To which environmental variables?

Additionally, the list of predictors appears in the supplmentary material only, and it is hard for the reader to understand why the winter predictors were chosen for each latitude area.

In the conclusion section, my concern is about the statement on lines 502-506:
Is there an estimate for this in the future? In figure 9 we see the decrease in the S. Ocean carbon sink

in the scenarios where 50% or 100% of the sea ice melts - but within the period ~1992-2022 considered in this study. What are the modelled predictions (please cite the models, like in figure 7, for instance), despite the discrepancy in the ocean carbon sink?

How does the calculated uncertainty in sea-air CO_2 fluxes (section "uncertainty") affect the estimates of the decreasing C sink from this manuscript?

Melting sea ice will weaken carbon sinks in the Southern Ocean

Guorong Zhong[1,2,3,4], Xuegang Li[1,2,3,4]*, Jinming Song[1,2,3,4]*, Baoxiao Qu[1,3,4], Fan Wang[1,2,3,4], Yanjun Wang[1,4], Bin Zhang[1,4], Jun Ma[1,3,4], Huamao Yuan[1,2,3,4], Liqin Duan[1,2,3,4], Qidong Wang[1,3,4], Jianwei Xing[1,3,4], and Jiajia Dai[1,3,4]

(1. Institute of Oceanology, Chinese Academy of Sciences, Qingdao 266071, China;

2. University of Chinese Academy of Sciences, Beijing 101407, China;

3. Laoshan Laboratory, Qingdao 266237, China;

4. Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao 266071, China)

Correspondence to: Xuegang Li (lixuegang@qdio.ac.cn) and Jinming Song (jmsong@qdio.ac.cn)

Abstract: Employing machine learning methods for mapping surface ocean pCO_2 has reduced the uncertainty in estimating sea-air CO_2 flux. However, a general discrepancy exists between the Southern Ocean carbon sinks derived from pCO_2 products and those from biogeochemistry models. By performing a boosting ensemble learning feed-forward neural networks (BEL FFNNs) method, we have identified an underestimation of the surface Southern Ocean pCO_2 due to notably uneven density of pCO_2 measurements between summer and winter, which resulted in about 16% overestimating of Southern Ocean carbon sink over the past three decades. In particular, the Southern Ocean carbon sink since 2010 was notably overestimated by approximately 29%. This overestimation can be mitigated by a winter correction in algorithms, with the average Southern Ocean carbon sink during 1992-2021 corrected to -0.87 PgC yr^{-1} from the original -1.01 PgC yr^{-1}. Furthermore, the most notable underestimation of surface ocean pCO_2 mainly occurred in regions south of 60°S and was hiding under ice cover. If sea ice melts completely, there could be a further reduction of about 0.14 PgC yr^{-1} in the Southern Ocean carbon sink due to exposure of high pCO_2 seawater to the atmosphere in winter.

Keywords: Carbon sink, Southern Ocean, CO_2 flux, pCO_2, machine learning

1 Introduction

The increasing concentration of atmospheric CO_2 since the onset of the industrial era has been affecting the natural climate due to the greenhouse effect. This effect is partially mitigated by the global ocean CO_2 uptakes, which account for about one-quarter of the anthropogenic CO_2 emissions (Sabine et al., 2004). Natural climate variability and anthropogenic climate change also feedback to influence the sea-air CO_2 exchange (Rödenbeck et al., 2022). It is essential to quantify the global ocean carbon sink and its temporal variability to understand further the response of the carbon cycle to future global change. The surface ocean partial pressure of CO_2 (pCO_2) measurements from the SOCAT dataset were widely used and mapped into continuous gridded data to estimate the sea-air CO_2 flux (Bakker et al., 2016). Due to a lower spatial decorrelation length scale of hundreds of kilometers in the surface ocean than that of thousands of kilometers in the atmosphere (Wanninkhof et al., 2013), surface ocean pCO_2 has more notable spatial variability than atmospheric pCO_2. Considerable variability and sparse measurements of surface ocean pCO_2 indicate insufficient observations to estimate CO2 flux in most ocean areas directly. Significant uncertainty in carbon sink estimation arises from sparse and uneven pCO_2 measurements, the gas ~~transition~~ velocity, and the cool skin effect (Woolf et al., 2016; Woolf et al., 2019; Watson et al., 2020). Recent application of machine learning algorithms in pCO_2 mapping methods increased data availability and further reduced the uncertainty in pCO_2-based carbon sink estimates (Gregor et al., 2021; Chau et al., 2022; Gloege et al., 2022; Zhong et al., 2022). The average net global ocean carbon sink during the last three decades was documented as -1.40~-2.45 PgC yr^{-1} (Zeng et al., 2014; Landschützer et al., 2016; Watson et al., 2020; Iida et al., 2021; Rödenbeck et al., 2022). The differences between results were caused by differences in algorithms, division of global biogeochemical provinces, and selection of pCO_2 predictors. The accuracy of pCO_2 mapping based on machine learning methods remains to be improved, especially in polar regions with sparser pCO_2 measurements.

The Southern Ocean south of 35°S was a strong carbon sink and has contributed to about 40% of global ocean anthropogenic CO_2 uptakes (Sabine et al., 2004; Fletcher, S. E. M. et al., 2006; Frölicher et al., 2015; Landschützer et al., 2015). Changes in the Southern Ocean carbon sink strongly affect the global ocean CO_2 uptake. However, the Southern Ocean carbon sink estimated by pCO_2-based machine learning methods was about 0.4 PgC yr^{-1} stronger than the result from global ocean biogeochemical models since 2012 (Friedlingstein et al., 2022; Mayot et al., 2023). A notable seasonal variability of surface ocean pCO_2 was reported in the Southern Ocean, mainly south of 50°S, with high pCO_2 levels and carbon sources observed in winter (Takahashi et al., 2009; Landschützer et al., 2016). The strongly seasonally uneven surface ocean pCO_2 measurements with missing winter observations may result in an overestimation of the Southern Ocean carbon sink from pCO_2 products (Bushinsky et al., 2019; Hauck et al., 2020; Gloege et al., 2021; Friedlingstein et al., 2022). Besides supplying more measurements from sailboats or floats (Landschützer et al., 2023), whether this overestimation can be solved by improving algorithms is worth investigating. Thus, we reestimated the Southern Ocean carbon sink using a different machine learning method and investigated the influence of seasonally uneven SOCAT pCO_2 measurements on the pCO_2 mapping and carbon sink estimate.

2 Data and methods

2.1 pCO_2 mapping and winter correction

The surface ocean pCO_2 converted from the Surface Ocean CO_2 Atlas version 2023 (SOCAT v2023) dataset was used for pCO_2 mapping by fitting the non-linear relationship between pCO_2 and environmental variables (Bakker et al., 2016). The relationship fitting was based on a boosting ensemble learning feed-forward neural networks (BEL FFNNs) consisting of three FFNNs. The first FFNN (FFNN I in Figure 1) outputs will be used as a pCO_2 predictor in the second and the last FFNN (FFNN II and FFNN III in Figure 1). All FFNNs in this work used 10 neurons in each hidden layer, and the number of hidden layers was adjusted to achieve an optimal FFNN size based on a change in predictor errors. The average of several FFNN outputs with changing initial states was taken as the final pCO_2 prediction value. The pCO_2 predictors used in this work were selected by the stepwise FFNN algorithm based on the variation of pCO_2 predicting error caused by each predictor (Zhong et al., 2022). However, due to the lack of winter measurements, the pCO_2 predictors in the Southern Ocean selected by the stepwise FFNN algorithm were more relevant to the drivers of pCO_2 in summer than in winter. By increasing the weightings of winter measurements in calculating the predicting error (equation S1), the pCO_2 predictors in the Southern Ocean were corrected for the winter period (Table S1). Furthermore, another winter correction was also carried out by changing the temporal period of measurements used for training networks.

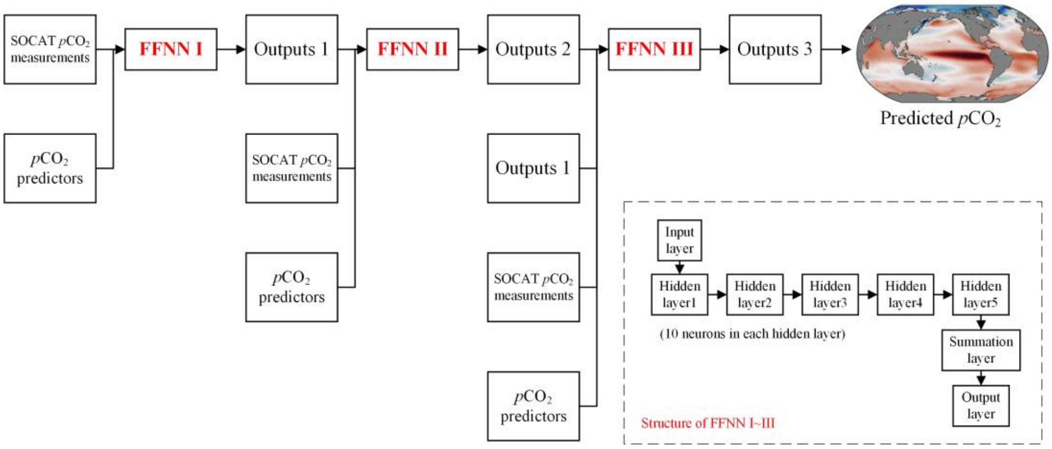

Figure 1. The procedure of the Boosting Ensemble Learning Method

To eliminate the influence of FFNN structure on correction validity, the performances of the individual FFNN and BEL FFNNs were compared under different training strategies: one based on SOCAT pCO_2 measurements of all months and others based on sectional winter measurements. The predicted pCO_2, root mean square error (RMSE), and bias with different training strategies and pCO_2 predictors were compared to evaluate the influence of seasonally uneven pCO_2 measurements and to determine which training strategy will be used. The predictor error was calculated using a K-fold cross validation method, where the pCO_2 measurements were divided into four groups by year, and each one was predicted by the other three groups (Gregor et al., 2019; Zhong et al., 2022). Then, the results were further compared to the observations from the Southern Ocean Flux station (SOFS) time series stations for validation (Sutton et al., 2019). The final pCO_2 product includes two types of data: 1) the pCO_2 from October to April based on SOCAT measurements of all seasons, and 2) the pCO_2 from May to September based on sectional SOCAT winter measurements and corrected predictors.

2.2 CO_2 flux estimate

The sea-air CO_2 flux was estimated based on the pCO_2 difference across the interface (Woolf et al., 2016; Watson et al., 2020):

$$F = k \cdot (a_{\mathrm{subskin}} \cdot p\mathrm{CO}_{2\mathrm{w}} - a_{\mathrm{skin}} \cdot p\mathrm{CO}_{2\mathrm{atm}}) \quad (1)$$

where pCO_{2w} represents surface ocean pCO_2 and pCO_{2atm} represents atmospheric pCO_2. The pCO_{2atm} was calculated from the xCO_2 of the NOAA Greenhouse Gas Marine Boundary Layer Reference product (Lan et al., 2023) and sea level pressure from the ERA5 monthly averaged data (Hersbach et al., 2019), with the water vapor correction (Dickson et al., 2007). a_{skin} and $a_{subskin}$ are the solubility of CO_2 at the skin and subskin layers (Woolf et al., 2016), calculated from temperature and salinity (Weiss, 1974). k is the CO_2 transfer velocity as a function of wind speed (Wanninkhof, 1992):

$$K = \Gamma(660/Sc)^{0.5}U^2 \tag{2}$$

where *Sc* is the Schmid number of CO_2 in seawater, and *U* is the average wind speed using the ERA5 product (Hersbach et al., 2020). The transfer velocity was scaled by the scale factor (Γ) 0.27 for ERA5 wind products to match the ^{14}C constraint (Sweeney et al., 2007).

2.3 uncertainty

The uncertainty of sea-air CO_2 flux estimate includes mainly three parts: the uncertainty of transfer velocity k, the cool skin impact, and the uncertainty in the surface ocean pCO_2 reconstruction. The uncertainty of transfer velocity k was related to the wind product and considered about 5-30% (Takahashi et al., 2009; Ho et al., 2011; Woolf et al., 2019), and here we used 10%. Recent research suggested an underestimate of 0.35 PgC yr^{-1} in the global ocean carbon sink caused by the cool skin impact (Woolf et al., 2019). The uncertainty caused by the temperature and salinity gradient was considered 3% and 1.7% after the subskin correction, respectively (Woolf et al., 2016; Watson et al., 2020). The last uncertainty term came from the reconstruction of gridded surface ocean pCO_2 data, including the uncertainty of the pCO_2 measurement, averaging to 1°×1° grids, and the pCO_2 interpolation. Thus, the total uncertainty in the pCO_2 reconstruction was calculated on average (Wang et al., 2014): where the measurement uncertainty σ(meas) was about 2-5 μatm (Pfeil et al., 2013; Wanninkhof et al., 2013b), which was lower than the others and can be neglected (Landschützer et al., 2014). The uncertainty of averaging to 1°×1° grids, σ(grid), used 5 μatm from the previous research (Sabine et al., 2013). For the pCO_2 interpolation uncertainty σ(map), we used the predicting error of 7-25 μatm in different regions (Zhong et al., 2022). The uncertainty in each area was calculated as the following (Landschützer et al., 2014):

$$\sigma(< pCO_2 >)^2 = \frac{\sigma(\mathrm{grid})^2}{N_{\mathrm{eff}}(\mathrm{grid})} + \frac{\sigma(\mathrm{map})^2}{N_{\mathrm{eff}}(\mathrm{map})} \tag{3}$$

The σ(<pCO_2>) calculated from the pCO_2 interpolation uncertainty ranges from 1.7 to 6.6 μatm in each region. Based on the average CO_2 transfer velocity of 0.07 mol C m^{-2} yr^{-1} in the Southern Ocean, the uncertainty σ(pCO_2) caused by the pCO_2 interpolation errors in different regions range from ±0.05 to ±0.10 PgC yr^{-1}. The total uncertainty of pCO_2 interpolation estimated by the sum of squares of σ(pCO_2) in each province was ±0.13 PgC yr^{-1}, corresponding to roughly 15% of the average Southern Ocean carbon sink estimated below. Thus, combining the uncertainties stemming from transfer velocity, cool skin influences, and pCO_2 interpolation, the final uncertainty was ±18.4% ($= \sqrt{10\%^2 + 3\%^2 + 1.7\%^2 + 15\%^2}$), using the square root of the sum squares propagation, corresponding to ± 0.16 PgC yr^{-1} (1σ).

3 Result and Discussion

3.1 Influence of uneven measurements on the Southern Ocean pCO_2 mapping

Various machine learning methods were applied in the surface ocean pCO_2 mapping and CO_2 flux estimating (Landschützer et al., 2016; Gregor et al., 2021; Iida et al., 2021; Wang et al., 2021; Chau et al., 2022; Zhong et al., 2022), where a majority of methods are based on non-linear relationship fitting between SOCAT fCO_2 measurements, or converted pCO_2, and environmental variables (Bakker et al., 2016). However, the number of SOCAT measurements is uneven between different seasons in the Southern Ocean. The SOCAT measurements in the Southern Ocean are concentrated in summer with low surface ocean pCO_2 ~~(Figure 2a). While in winter~~, the number of measurements with high surface ocean pCO_2 was only about one-fifth of that in summer. In most Southern Ocean areas, the SOCAT measurements covered less than four unique months from 1992 to 2021 (Figure 2b). Meanwhile, ~~the~~ high surface ocean pCO_2 was observed during the winter in the Southern Ocean, according to the research based on either pCO_2 measurements or gridded products. The lack of measurements during high surface ocean pCO_2 seasons in most Southern Ocean areas may notably influence the non-linear relationship fitting and pCO_2 mapping, particularly in the months from June to September with the sparsest measurements. The seasonally unbalanced distribution of measurements may be a potential reason for the higher pCO_2 predicting error of the Southern Ocean than the neighboring areas in previous research (Landschützer et al., 2016; Chau et al., 2022; Zhong et al., 2022).

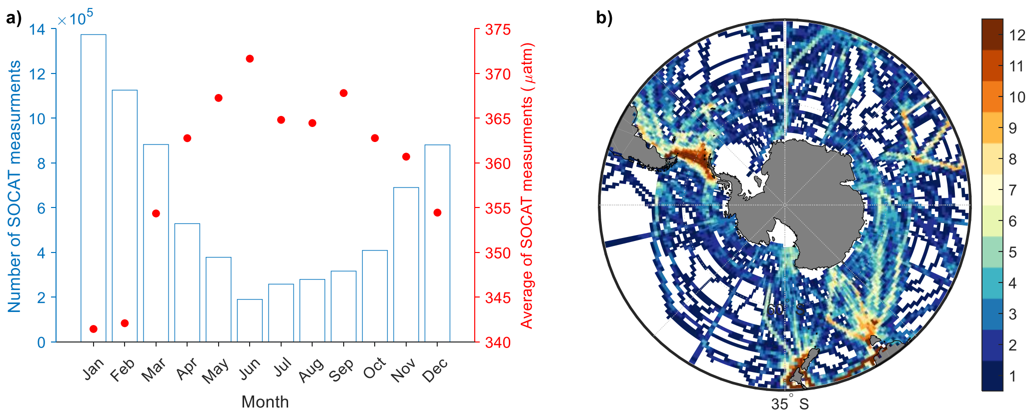

Figure 2. The number of a) SOCAT fCO_2 measurements in each month and b) unique months covered by SOCAT measurements in the Southern Ocean south of 35°S from 1992 to 2021. SOCAT: the Surface Ocean CO_2 Atlas dataset version 2023 (Bakker et al., 2016).

To evaluate the influence of seasonal-uneven SOCAT measurements on pCO_2 mapping, the RMSE and bias from May to September were compared between different validation groups, with the only difference in training strategy (Table 1). The comparison of pCO_2 predicting error between different training strategies reveals a substantial influence of uneven measurements on the accuracy of machine learning pCO_2 predicting method. Training neural networks with SOCAT measurements only from April to October instead of all months resulted in a notable decrease of 0.5~1.4 μatm in RMSE. This decrease in RMSE caused by the change of training strategies was even more effective than the decrease of less than 0.4 μatm caused by the improvement of the FFNN structure (BEL FFNNs in Table 1). In the areas south of 50°S, the BEL FFNNs and the individual FFNN trained with sectional winter measurements resulted in significantly lower RMSE during winter than those trained with all-month measurements. The bias during May-September between predicted pCO_2 and SOCAT measurements of more than -3 μatm was notably different from the range of -1~1 μatm in other months, indicating a significant underestimation of surface seawater pCO_2 in the areas south of 50°S. In particular, the pCO_2 from May to September in the area south of 60°S, as predicted by BEL FFNNs using measurements from all months, was underestimated by an average of 5.77 μatm. Meanwhile, the pCO_2 predicted by the individual FFNN in the Southern Ocean south of 60°S was also notably lower than SOCAT data in winter due to missing winter measurements. When training with measurements only from April to October, the BEL FFNNs reached the lowest RMSE in winter, and the bias was only -1.38 μatm. Similarly, the predicted pCO_2 by the individual FFNN was only 1.47 μatm lower than measurements on average, indicating a significant improvement in the underestimation of pCO_2 during winter. In the 50-60°S region, training BEL FFNNs and the individual FFNN with sectional winter measurements can also reduce the predicting bias. By training BEL FFNNs only with measurements from April to September, the winter RMSE in the 50-60°S area was the lowest among different training strategies, with a bias of only -0.36 μatm.

Table 1. Comparison of pCO_2 predicting error in the Southern Ocean during May-September among different training strategies

Validation group	Training period	35-50° S		50-60° S		S of 60° S	
		RMSE (μatm)	bias (μatm)	RMSE (μatm)	bias (μatm)	RMSE (μatm)	bias (μatm)
BEL FFNNs	May-Sep	12.01	+0.61	11.97	+0.22	14.76	+0.33
	Apr-Sep	10.70	+0.38	11.88	-0.36	14.87	-0.90
	May-Oct	11.39	-0.36	12.07	-0.66	14.50	-0.07
	Apr-Oct	11.10	-0.68	12.09	-1.16	14.20	-1.38

	Mar-Nov	11.32	-1.26	12.51	-2.13	15.50	-4.47
	All Months	**9.86**	**-0.39**	13.27	-3.13	16.09	-5.77
BEL FFNNs with corrected predictors	May-Sep	12.24	+0.74	11.93	+0.17	14.44	+1.17
	Apr-Sep	10.76	+0.30	11.26	+0.09	13.49	-0.06
	May-Oct	12.81	-0.28	11.44	+0.04	14.27	-0.20
	Apr-Oct	11.83	-0.79	**10.93**	**-0.25**	**13.29**	**-0.74**
	Mar-Nov	11.69	-1.49	13.07	-0.46	14.07	+0.02
	All Months	9.88	-0.29	11.49	-1.08	14.61	-0.90
Individual FFNN	May-Sep	12.05	+0.50	11.99	+0.07	15.15	0.36
	Apr-Sep	10.58	+0.30	12.02	-0.52	15.04	-1.14
	May-Oct	11.43	-0.59	12.21	-0.75	14.92	-0.32
	Apr-Oct	11.19	-0.83	12.29	-1.49	14.86	-1.47
	Mar-Nov	11.64	-1.43	12.82	-2.56	15.76	-3.95
	All Months	9.95	-0.34	13.31	-3.33	17.14	-5.38
Individual FFNN with corrected predictors	May-Sep	12.57	+0.50	12.30	+0.37	14.54	+0.83
	Apr-Sep	10.72	+0.27	11.45	+0.14	13.79	-0.27
	May-Oct	13.09	-0.45	11.52	-0.07	14.46	-0.23
	Apr-Oct	11.35	-0.92	11.06	-0.09	13.63	-0.27
	Mar-Nov	12.02	-1.55	11.55	-0.09	17.86	+0.50
	All Months	9.95	-0.28	12.06	-1.04	15.85	-0.05

(BEL FFNNs: boosting ensemble learning based on three FFNNs constructed in this work; Individual FFNN: one FFNN with the same structure used in the BEL; Training Period: a period of SOCAT samples used for training neural networks to predict pCO_2 during May-September; RMSE and bias: calculated from the difference between predicted pCO_2 and SOCAT measurements during May-September based on the K-fold cross validation method. Corrected predictors: pCO_2 predictors selected by a stepwise BEL FFNNs algorithm based on increasing weightings of winter measurements, see supplementary S1.)

In contrast, there is no significant underestimation of winter surface ocean pCO_2 in the Southern Ocean 35-50°S. The RMSE by training BEL FFNNs with sectional winter measurements was larger than that by training with all measurements, and the improvement of bias was also not observed when using sectional winter measurements. On the other hand, corrected pCO_2 predictors may better reflect the drivers of surface ocean pCO_2 in the Southern Ocean during winter. By using the month as a predictor, the correction of pCO_2 predictors can also effectively mitigate the underestimation of winter pCO_2 in the Southern Ocean. Simply changing pCO_2 predictors without correcting the training period, the RMSE of BEL FFNNs with weighted predictors during winter in the 50-60°S region decreases to 11.49 μatm, and the bias reduces to -

1.08 μatm compared to BEL FFNNs with original predictors (see predictors listed in Table S1). The same decrease in RMSE was also observed in the areas south of 60°S. Using both correction methods simultaneously, the RMSE can be minimized to 10.93 μatm and 13.29 μatm in the 50-60°S and regions south of 60°S, respectively. The bias also fell within an acceptable range of -1 to 1 μatm, close to the bias level in other months without notable underestimation or overestimation.

The BEL FFNNs and individual FFNN both showed an underestimated surface seawater pCO_2 in the Southern Ocean south of 50°S in winter, indicating that the underestimation of surface seawater pCO_2 was not caused by the structure of FFNN but rather by the seasonally uneven pCO_2 measurements. Training networks with sectional winter measurements and correction of pCO_2 predictors can mitigate the underestimation of surface Southern Ocean pCO_2 in winter. Considering that the BEL FFNNs have a lower RMSE compared to the individual FFNN, the BEL FFNNs using corrected pCO_2 predictors and training with measurements only from April to October have better accuracy of the pCO_2 mapping in the Southern Ocean during winter.

With the correction of the training period and pCO_2 predictors, the bias of predicted pCO_2 from May to September was notably smaller than the uncorrected result (Figure 3a). In July, the pCO_2 predicted by the BEL FFNNs was notably lower than SOCAT measurements, with a considerable bias of 6.6 μatm. In contrast, the bias from October to April was generally within the range of -1 to 1 μatm, indicating a non-significant overestimation or underestimation of surface seawater pCO_2 in the Southern Ocean. With the winter correction, the bias from May to September decreased notably to near zero. Even in the most biased July, the bias of corrected BEL FFNNs fell to only -0.3 μatm, significantly mitigating the underestimation of winter surface ocean pCO_2 in the Southern Ocean. The bias at different latitudes reveals that the underestimation of surface seawater pCO_2 in the Southern Ocean due to seasonally uneven measurements becomes more significant at higher latitudes (Figure 3b). In the region south of 50°S, the uncorrected average deviation is negative, reaching approximately -20.92 μatm at around 68.5°S. The difference in the effect of the winter correction may be related to the density of measurements, as the decrease in bias was more notable in sparsely sampled high-latitude areas.

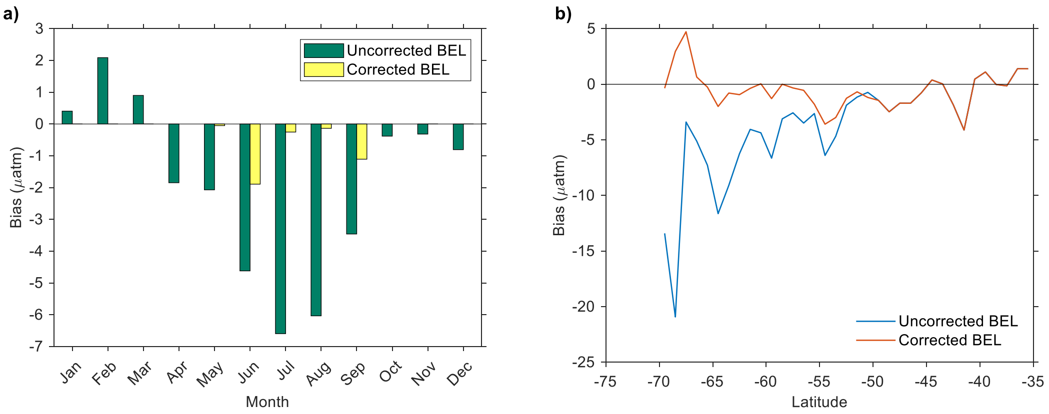

Figure 3. Distribution of bias between predicted $p\mathrm{CO_2}$ and SOCAT measurements in the Southern Ocean south of 35°S. a): monthly bias in the Southern Ocean south of 50°S (predicted $p\mathrm{CO_2}$ minus SOCAT measurements); b): zonal bias during May-Sep; Uncorrected BEL: based on training sample of all seasons; Corrected BEL: based on training sample only from April to October. BEL: Boosting ensemble learning FFNNs used in this study.

Compared to the observation from the SOFS time series station (Sutton et al., 2019), the $p\mathrm{CO_2}$ values from May to September from different methods were lower due to the lack of SOCAT winter data for training (Figure 4). During years that winter SOCAT data are available, such as 2012, 2013, and 2018, the $p\mathrm{CO_2}$ values from different methods were close to the observations from the SOFS time series station (Landschützer et al., 2016; Gregor et al., 2021; Iida et al., 2021; Chau et al., 2022;). The surface ocean $p\mathrm{CO_2}$ of BEL FFNNs product after correction in winter was about 10 µatm higher than the uncorrected BEL FFNNs results. It was much closer to the time series observation, suggesting a better accuracy of corrected BEL FFNNs $p\mathrm{CO_2}$ than the uncorrected results. Both the validation based on the SOCAT dataset and the validation based on time-series observations from the SOFS station suggest that correction of the training period and $p\mathrm{CO_2}$ predictors can effectively mitigate the underestimation due to seasonally uneven measurements. Therefore, the final $p\mathrm{CO_2}$ product constructed in this study consists of $p\mathrm{CO_2}$ data from October to April based on all measurements and $p\mathrm{CO_2}$ data from May to September based on corrected $p\mathrm{CO_2}$ predictors and measurements only from April to October.

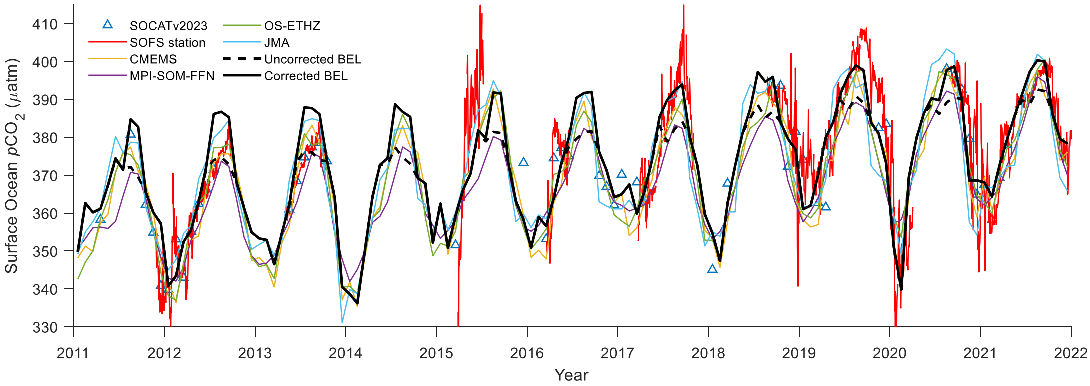

Figure 4. Comparison between corrected and uncorrected ensemble learning pCO_2 product in the SOFS station. CMEMS: Chau et al., 2022; MPI-SOM-FFNN: Landschützer et al., 2016; OS-ETHZ: Gregor et al., 2021; JMA: Iida et al., 2021; Uncorrected BEL: boosting ensemble learning FFNNs based on training sample of all seasons; Corrected BEL: pCO_2 during May-September were predicted based on corrected predictors and training samples only from April to October.

3.2 Overestimated Southern Ocean carbon sink due to biased *p*CO₂ mapping

The validation based on SOCAT measurements and SOFS time series observations reveals that the pCO_2 products constructed using FFNN with the entire monthly pCO_2 measurements from the SOCAT dataset may significantly underestimate the winter surface ocean pCO_2 in the Southern Ocean south of 50°S. Due to upwelling derived from the wind driving a strong surface divergence through the Ekman transport (Gruber et al., 2019)， the surface seawater pCO_2 in the winter of the Southern Ocean is significantly higher than in the summer, with strong carbon source regions in winter (Landschützer et al., 2016; Gruber et al., 2019; Wang et al., 2021). The previous studies may have underestimated the strength of carbon sources in the winter of the Southern Ocean, leading to an overestimation of the overall carbon sink intensity in the Southern Ocean. Our results demonstrate that the variations in surface seawater pCO_2 before and after the winter correction significantly impact the pCO_2 difference and CO_2 flux across the air-sea interface (Figure 5). The surface seawater pCO_2 in the Southern Ocean south of 50°S is higher than atmospheric pCO_2 from May to September, and the pCO_2 difference after correction became larger, particularly in the region south of 60°S. However, due to the influence of sea ice coverage, the pCO_2 flux in the area south of 60°S is nearly zero from May to September, and the difference in CO_2 flux between uncorrected and corrected BEL FFNNs was not significant. In the 35-50S area with relatively more measurements, the seasonal variation pattern of pCO_2 differs from that south of 50S, and there is almost no change in the pCO_2 difference and CO_2 flux between uncorrected and corrected BEL FFNNs. Overall, although the south of 60S shows the most considerable change in winter ΔpCO_2 before and after correction, the underestimation of surface seawater pCO_2 in the 50-60 area unaffected by sea ice coverage is the main reason for the overestimation of the carbon sink intensity in the Southern Ocean. The corrected average Southern Ocean carbon sink from May to September is -0.58 PgC yr^{-1}, decreasing by 0.34 PgC compared to the uncorrected results.

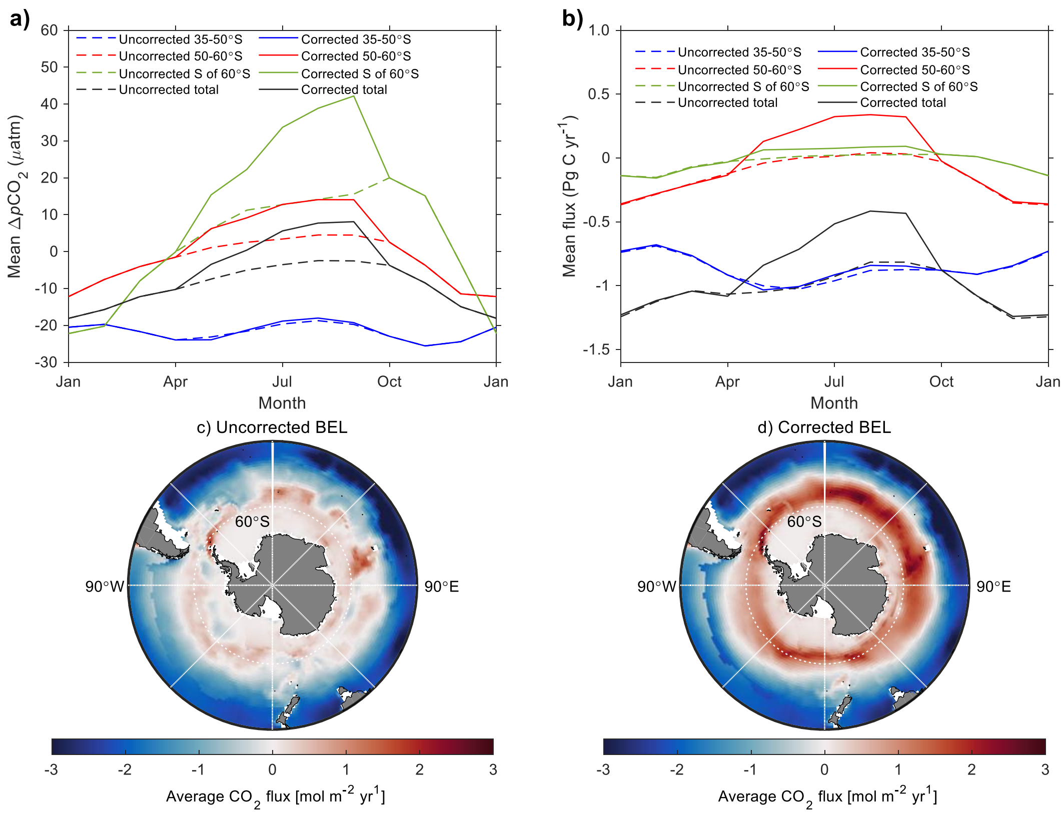

Figure 5. Distribution of average sea-air pCO_2 difference and CO_2 flux from May to September during 1992-2021. a) sea-air ΔpCO_2 in different regions: surface ocean pCO_2 minus atmospheric pCO_2; b) sea-air CO_2 flux in different regions; c) distribution of CO_2 flux from uncorrected BEL FFNNs product; d) distribution of CO_2 flux from corrected BEL FFNNs product; uncorrected BEL FFNNs: constructed from SOCAT measurements of all month, corrected BEL FFNNs: data from May to September constructed based on corrected predictors and only SOCAT measurements during Apr-Oct.

Over the past 30 years, the corrected average Southern Ocean carbon sink was -0.87 ± 0.16 PgC yr^{-1}, which is approximately 0.14 PgC yr^{-1} lower than before the correction, suggesting an overestimation of about 16%. The overestimation of the carbon sink intensity in the Southern Ocean is mainly observed after 2010, with a decrease in the decadal average carbon sink from -1.20 PgC yr^{-1} to -0.93 PgC yr^{-1} after correction. This indicates that the seasonally uneven measurements led to an overestimation of the Southern Ocean carbon sink by approximately 29% compared to the corrected intensity during this period (Figure 6). Although the corrected Southern Ocean carbon sink was lower than uncorrected results in the 1990s, the variability pattern was similar before and after correction. Since 2001, the Southern Ocean carbon sink has generally strengthened, but the strengthening rate is relatively slower after the winter correction. The variability of the Southern Ocean carbon sink from our corrected BEL product was highly consistent with previous research based on models or observations, in which the Southern Ocean carbon sink receded significantly in the 1990s, reaching a trough at the beginning of the 21st century (Le Quere et al., 2007; Lovenduski et al., 2008), and subsequently restrengthened to full intensity (Gregor et al., 2018; Landschützer et al., 2015; Munro et al., 2015). Compared to previous products, our estimation of the corrected Southern Ocean carbon sink shows a similar intensity in the 1990s and the lowest intensity since 2003. However, research based on SOCCOM buoy data also suggested a significantly weaker Southern Ocean carbon sink, challenging existing results from pCO_2 products (Bushinsky et al., 2019), although the float pCO_2 data calculated indirectly from pH and alkalinity seems to be overestimated in organic-rich freshwaters (Abril et al., 2015). Notably, there was almost no difference between the uncorrected and corrected carbon sink from 1999 to 2001, when the Southern Ocean carbon sink was at its weakest point in the past three decades. The relatively denser measurements in the SH winter than in other decades may be one important reason. Around 2000, the SOCAT winter measurements were close to half of the measurements in summer. Therefore, the influence of seasonally uneven measurements is relatively minor.

Both carbon sinks before and after the winter correction consistently show a rapid weakening of the Southern Ocean carbon sink during the 1990s. The corrected Southern Ocean carbon sink in this work weakened from -0.99±0.15 Pg C yr^{-1} in 1992 to -0.68±0.13 Pg C yr^{-1} in 2001, and then strengthened back to -1.13±0.14 Pg C yr^{-1} until 2021. Such notable interannual changes were also found in other research based on observations covering the past two decades (Landschützer et al., 2016; Rödenbeck et al., 2014; Ritter et al., 2017; Gregor et al., 2021; Chau et al., 2022). The contribution of the Southern Ocean south of 35% on the global ocean CO_2 uptakes decreased from approximately 63% in 1992 to 45% in 2021. The weakening of the Southern Ocean carbon sink in the 1990s was thought to be caused by the strengthening of the upper-ocean overturning circulation and CO_2 release in source areas and the weakening of CO_2 uptake in sink areas due to a southward shift of westerlies (Gillett et al., 2003; Gruber et al., 2019; Landschützer et al., 2015; Miller et al., 2006; Rödenbeck et al., 2015). The upwelling of the Southern Ocean increased by approximately 40% due to enhanced wind-driven circulation. (DeVries et al., 2017). However, the weakening of the upwelling since the beginning of the 21st century led to the reinvigoration of carbon sink (Landschützer et al., 2015). Research based on an idealized upper ocean box model also suggested that the slowed growth rate of atmospheric pCO_2 and the global sea surface temperature response to the 1991 eruption of Mt Pinatubo volcanic were two external forces to explain the global-scale reduction in the ocean carbon sink, and the reinvigoration of carbon sink was drived by the acceleration of atmospheric pCO_2 growth after 2001 (McKinley et al., 2020).

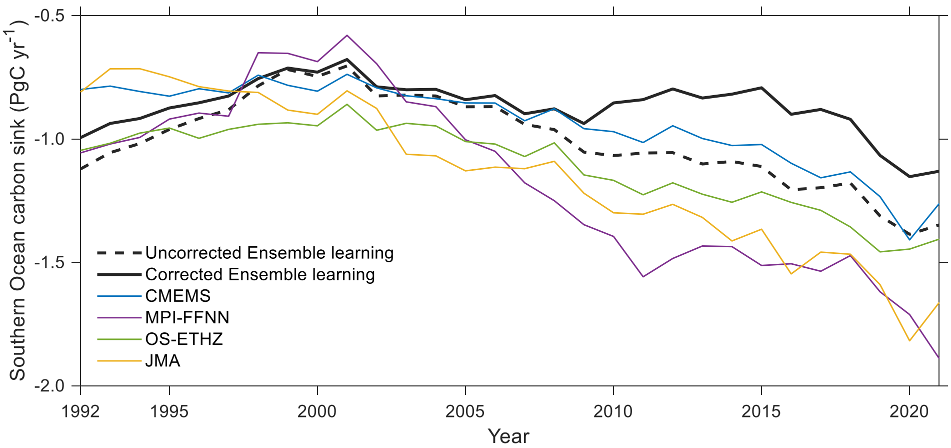

Figure 6. Interannual variability of the Southern Ocean carbon sink from uncorrected and corrected ensemble learning method and other products. CMEMS: Chau et al., 2022; MPI-SOM-FFNN: Landschützer et al., 2016; OS-ETHZ: Gregor et al., 2021; JMA: Iida et al., 2021; Uncorrected BEL: boosting ensemble learning based on training sample of all seasons; Corrected BEL: pCO_2 during May-September were predicted based on training sample only from April to September.

After the winter correction for seasonally uneven measurements in the Southern Ocean, the global ocean carbon sink estimated from the Stepwise FFNN product and corrected Southern Ocean pCO_2 data was relatively lower than other pCO_2 products (Figure 7). However, our estimates are more consistent with the average results from the Global Carbon Budget study, based on 10 global ocean biogeochemistry models and 7 pCO_2 products (Friedlingstein et al. 2022). The global ocean carbon sink estimated from previous pCO_2 products was notably stronger than the result from biogeochemical models, and the discrepancy mainly occurred in the Southern Ocean carbon sinks (Friedlingstein et al. 2022). The corrected Southern Ocean carbon sink decreased the discrepancy with model results, indicating that previous pCO_2 products using the SOCAT dataset may also experience an overestimation of the Southern Ocean carbon sink due to seasonally uneven measurements.

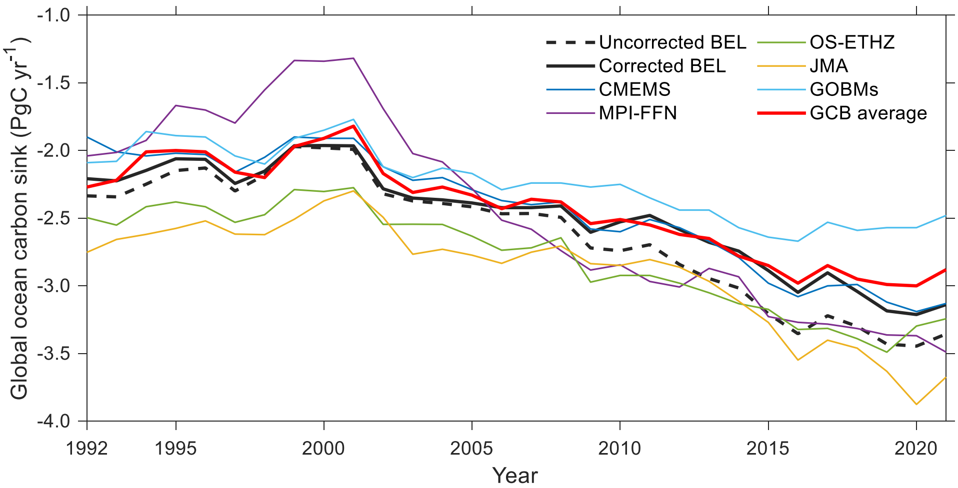

Figure 7. Global ocean carbon sink over the past three decades after the Southern Ocean correction. GOBMs: average results of global ocean biogeochemical models (Friedlingstein et al. 2022); GCB average: average results of 10 global ocean biogeochemical models and 7 pCO_2 products in the Global Carbon Budget 2022 (Friedlingstein et al. 2022); CMEMS: Chau et al., 2022; MPI-SOM-FFNN: Landschützer et al., 2016; OS-ETHZ: Gregor et al., 2021; JMA: Iida et al., 2021; Uncorrected BEL: boosting ensemble learning FFNNs based on training sample of all seasons; Corrected BEL: Southern Ocean pCO_2 during May-September were corrected for uneven measurements.

3.3 Influence of sea ice cover on the Southern Ocean carbon sink

The significant differences in the Southern Ocean carbon sink before and after correction were only observed in the last decade. However, the pCO_2 difference across the interface after the winter correction was much more notable, particularly in the Southern Ocean south of 60°S, where the surface seawater pCO_2 is much higher than atmospheric pCO_2 (Figure 8). The vertical mixing and biological activity were reported as primary controlling factors of surface ocean pCO_2 in continent shelf areas, leading to more considerable uncertainty in CO_2 flux estimate compared to the open ocean (Qu et al., 2014; Laruelle et al., 2017; Song et al., 2018). However, CO_2 exchange between the seawater and the atmosphere in the Antarctic shelf is impeded due to the extensive sea ice coverage in most areas south of 60°S. As a result, despite the high surface seawater pCO_2 in this region, the CO_2 release to the atmosphere is limited, and the carbon source intensity is close to zero. The sea ice coverage in the Southern Ocean south of 60°S also eliminates the influence of seasonally uneven pCO_2 measurements. Therefore, although the pCO_2 difference across the interface was more significant after the winter correction in areas south of 60°S, the carbon source intensity and its difference before and after correction remain close to zero. Recent research has reported that the melting of sea ice in the Arctic Ocean exposes more sea surface, serving as one of the essential factors of rapid acidification in the Arctic Ocean (Qi et al., 2022). Similarly, in the Amundsen and Bellingshausen Seas of the Southern Ocean, which are characterized by warm water intrusion from the open ocean, the highest basal ice shelf melting rates have been observed (Jacobs et al. 2011; Nakayama et al. 2013; Hellmer et al., 2017). The Antarctic shelf ocean warming accelerated by increasing El Niño variability was hastening the ice shelf/sheet melt (Cai et al., 2023). Unlike the Arctic Ocean, the surface ocean pCO_2 under sea ice coverage in the winter Southern Ocean was much higher than in the atmosphere. If the sea ice completely melts, a significant amount of CO_2 will be directly released into the atmosphere through the exposed sea surface. Furthermore, sea ice melting can indirectly impact the surface ocean pCO_2 and carbon sink intensity in the Southern Ocean through various pathways, such as reducing sea surface temperature and altering convective overturning rates (Merino et al., 2016).

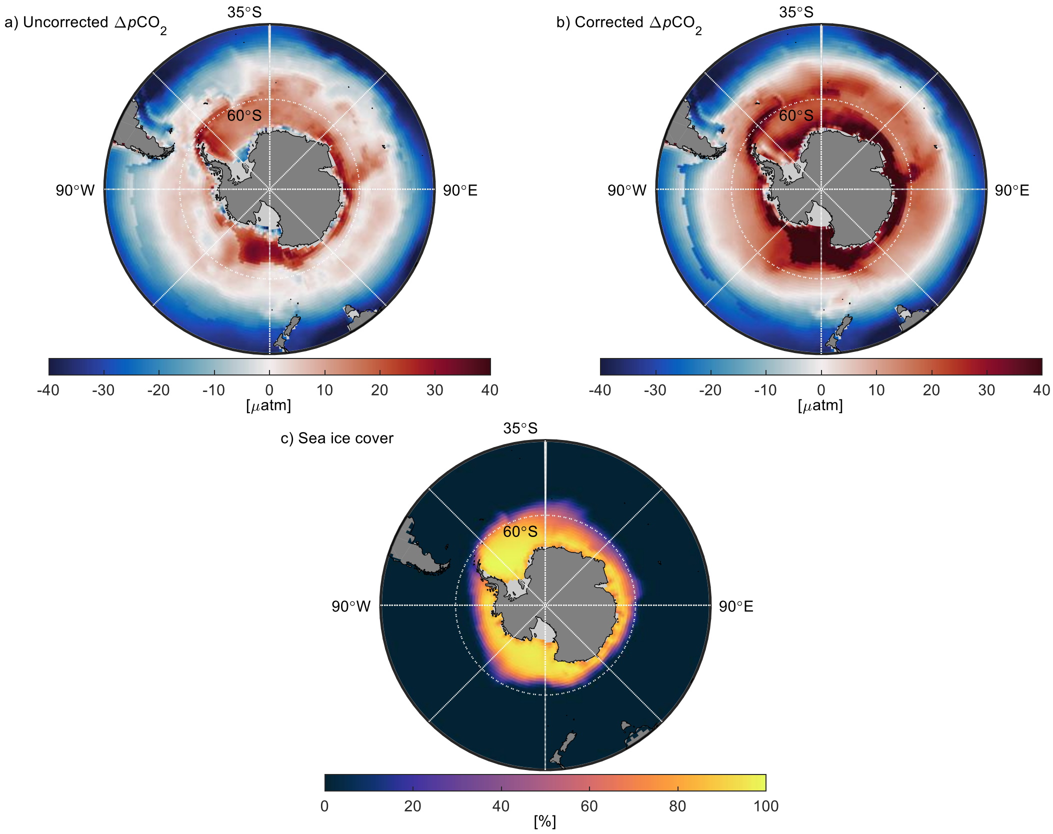

Figure 8. Distribution of average sea-air ΔpCO_2 and sea ice coverage during May-Sep in the

Southern Ocean. a) $\Delta p CO_2$ calculated from uncorrected BEL product, b) $\Delta p CO_2$ calculated from corrected BEL product, c) sea ice coverage from ERA5 product (Hersbach et al., 2020). $\Delta p CO_2$: surface ocean pCO_2 minus atmospheric pCO_2.

Figure 9 shows the simulated carbon sink intensity in the Southern Ocean under different sea ice coverage without considering indirect factors based on the recent sea-air pCO_2 difference. During the summer period in the Southern Ocean, when sea ice coverage is limited, and the surface seawater pCO_2 in the covered areas is lower than atmospheric pCO_2, it is assumed that the complete melting of the currently covered sea ice would have little impact on the summer carbon sink intensity. However, during the winter, when sea ice coverage is extensive, and the surface seawater pCO_2 in the covered areas is much higher than atmospheric pCO_2, the complete melting of the currently covered sea ice would result in the release of CO_2 from the exposed surface Southern Ocean at an average rate of 0.28 PgC yr^{-1} during winter. This would weaken the role of the Southern Ocean in the global ocean CO_2 uptakes and the role of the global ocean in buffering the rise in atmospheric CO_2 concentration. Additionally, unlike the relatively stable increasing trend in carbon sink intensity during summer over the past 20 years, the winter carbon sink intensity in the Southern Ocean has shown significant fluctuations in the last decade but with no significant long-term trend. Based on the current data, considering the presence of sea ice-covered carbon sink areas in spring and autumn, the complete disappearance of sea ice coverage would lead to an average reduction of 0.14 PgC yr^{-1} in the overall annual CO_2 absorption in the Southern Ocean. The magnitude of this reduction depends on the pCO_2 values of seawater covered by sea ice, and it is still uncertain how this will change in the future. However, it can be anticipated that sea ice melting will slow down the rate of carbon sink enhancement in the Southern Ocean for a considerable period until the continuously rising atmospheric pCO_2 exceeds the surface ocean pCO_2 beneath the winter sea ice.

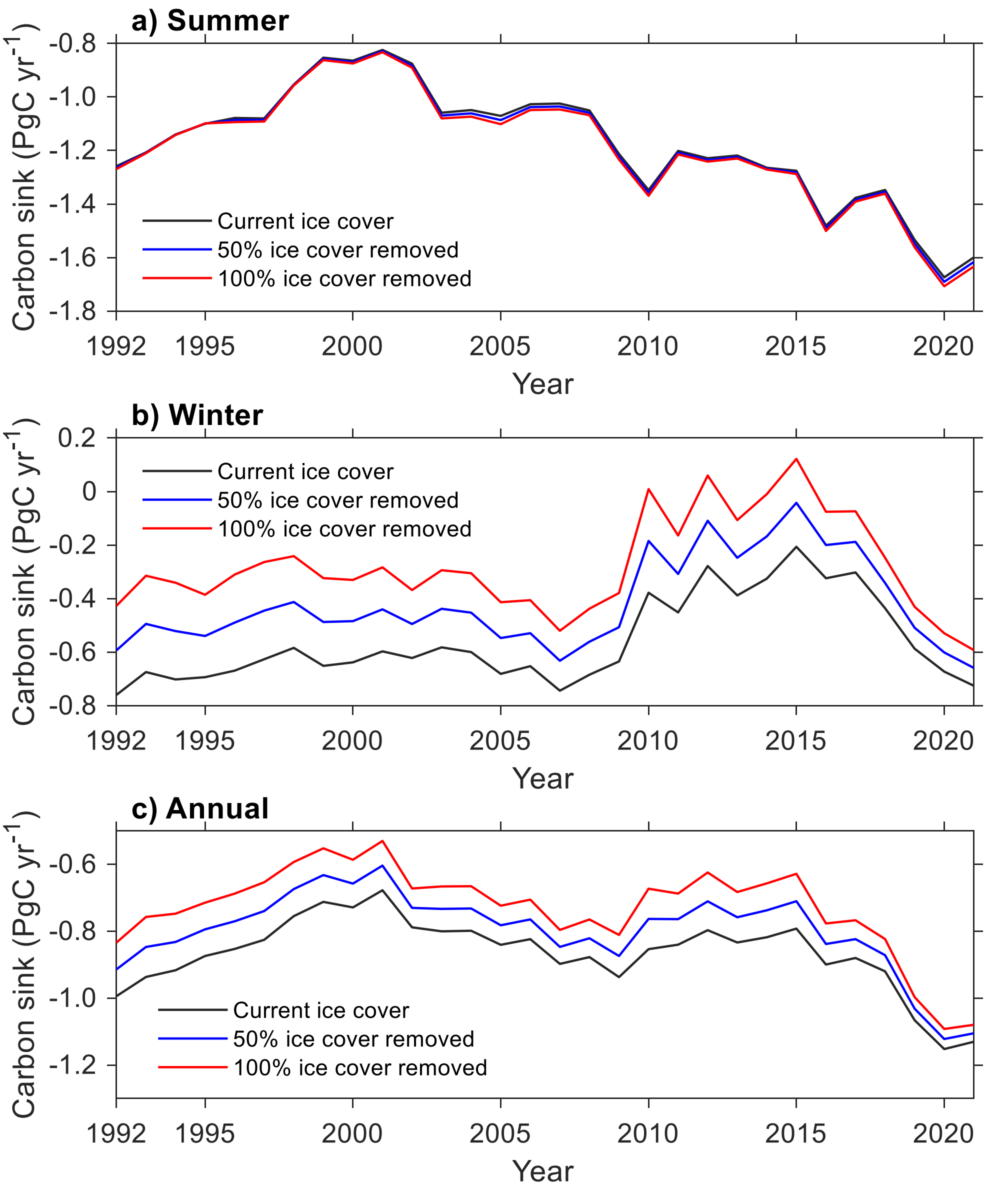

Figure 9. Southern Ocean carbon sink on different scenarios of sea ice melt. a) CO_2 flux from December to February in each year; b) CO_2 flux from June to August in each year; c) annual CO_2 flux. Current ice cover: ice coverage data from the ERA5 product (Hersbach et al., 2020); 50% ice cover removed: assuming that 50% of current ice cover melts; 100% ice cover removed: assuming that all ice cover melts.

4 Summary and conclusions

As one of the most important carbon sink regions, the Southern Ocean experienced higher uncertainties of carbon sink estimation than other adjacent regions due to the sparse and seasonally uneven measurements. By comparing the performance of the

BEL FFNNs with different training strategies in the Southern Ocean from May to September, it was found that using data from all months for training the neural network resulted in higher RMSE and bias than using only sectional winter measurements for training. The predicted pCO_2 from May to September was significantly lower than the observed values when measurements of all months were used due to missing winter data, which was less than a fifth of summer measurements. As a result, the neural network significantly underestimated the surface seawater pCO_2 in the Southern Ocean during winter. However, training the neural network using sectional winter measurements and correcting the pCO2 predictors could effectively alleviate the underestimation of winter Southern Ocean pCO2. The underestimation of winter Southern Ocean pCO_2 further led to an overestimation of the carbon sink intensity by about 16%. This may be a key factor contributing to the general discrepancy between carbon sink intensity estimated from pCO_2 products and biogeochemical models. Especially in the last decade, the corrected average Southern Ocean carbon sink was only -0.93 PgC yr^{-1}, significantly lower than the original intensity of -1.20 PgC yr^{-1}, indicating an overestimation of the Southern Ocean carbon sink by about 29% in the last decade. The winter correction in the Southern Ocean carbon sink has reduced the discrepancy between pCO_2 products and biogeochemical models and brought the estimated global ocean carbon sink intensity closer to the average results obtained from the Global Carbon Budget 2022.

Furthermore, although the pCO_2 difference after correction was more notable in the Southern Ocean south of 60°S, the extensive sea ice coverage almost eliminates the CO_2 flux and mitigates the underestimation of winter surface ocean pCO_2. Therefore, the difference in carbon sink intensity before and after correction in the Southern Ocean was mainly observed in the 50-60°S region. If sea ice melts and exposes all currently covered surface Southern Oceans, the high pCO_2 seawater will release an additional 0.28 PgC yr^{-1} of CO_2 to the atmosphere in winter of each year, leading to an average reduction of 0.14 PgC yr^{-1} in the overall annual Southern Ocean carbon sink. Over a considerable period, sea ice melting will lead to CO_2 release from the sea ice-covered regions, slowing down the enhancement rate of the Southern Ocean carbon sink until the continuously rising atmospheric pCO_2 surpasses the surface ocean pCO_2 in the winter sea ice areas.

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This article describes the impact of melting sea ice on carbon sink. The paper addresses boosting ensemble learning feed-forward neural networks to underestimation of the surface Southern Ocean pCO_2 . The main issue regards sparse measurements of surface ocean pCO_2 . The sea-air CO_2 flux was estimated based on the pCO_2 difference across the interface. The major claim of the article regards the fact that when using all months for training the neural network resulted in higher RMSE and bias than using only sectional winter measurements for training. Also the winter correction in the Southern Ocean carbon sink has reduced the bias in the pCO_2 estimation with notable difference South of 60S.

Even if promising the author should add additional analysis to the results and correct the following:

-The github link to the code is missing, that is necessary

-The author in the method should highlight more why they choose feedforward neural network with 10 layers. Can the author provide a plot of their loss function?

-The paper is missing a comparison with a classic regression approach which would highlight why choosing the feedforward neural network can be a good choice. I highly recommend adding it.

-In line 99 the author has used the SOCAT pCO_2 measurements, the authors should talk more about the dataset including the time range of it.

-In line 104 the author mentioned K-fold cross validation with a number of folds equal 4. Is the number 4 arbitrary?

-In line 188 the authors train a neural network with SOCAT measurements only from April to October. The resulting RMS is lower in this case. The author should emphasize more why it should be the case. This section 188-200 needs further confirmation.

The predictors used for the neural network have been put in supplemental materials. I would encourage to talk more in the text about these predictors and why they are important.

In the conclusion part the authors should emphasize more about the broader impacts of their findings and how these methods can be beneficial to the scientific community.

Given the interested topic covered by the article I would recommend major revision to the editor in order to address the changes written above.

(**Bold black: Reviewer comments**; thick red: Response to comments; thick black: changes in manuscript)

Reviewer #1:

This article describes the impact of melting sea ice on carbon sink. The paper addresses boosting ensemble learning feed-forward neural networks to underestimation of the surface Southern Ocean *p*CO_2. The main issue regards sparse measurements of surface ocean *p*CO_2. The sea-air CO_2 flux was estimated based on the *p*CO_2 difference across the interface. The major claim of the article regards the fact that when using all months for training the neural network resulted in higher RMSE and bias than using only sectional winter measurements for training. Also the winter correction in the Southern Ocean carbon sink has reduced the bias in the *p*CO_2 estimation with notable difference South of 60S.

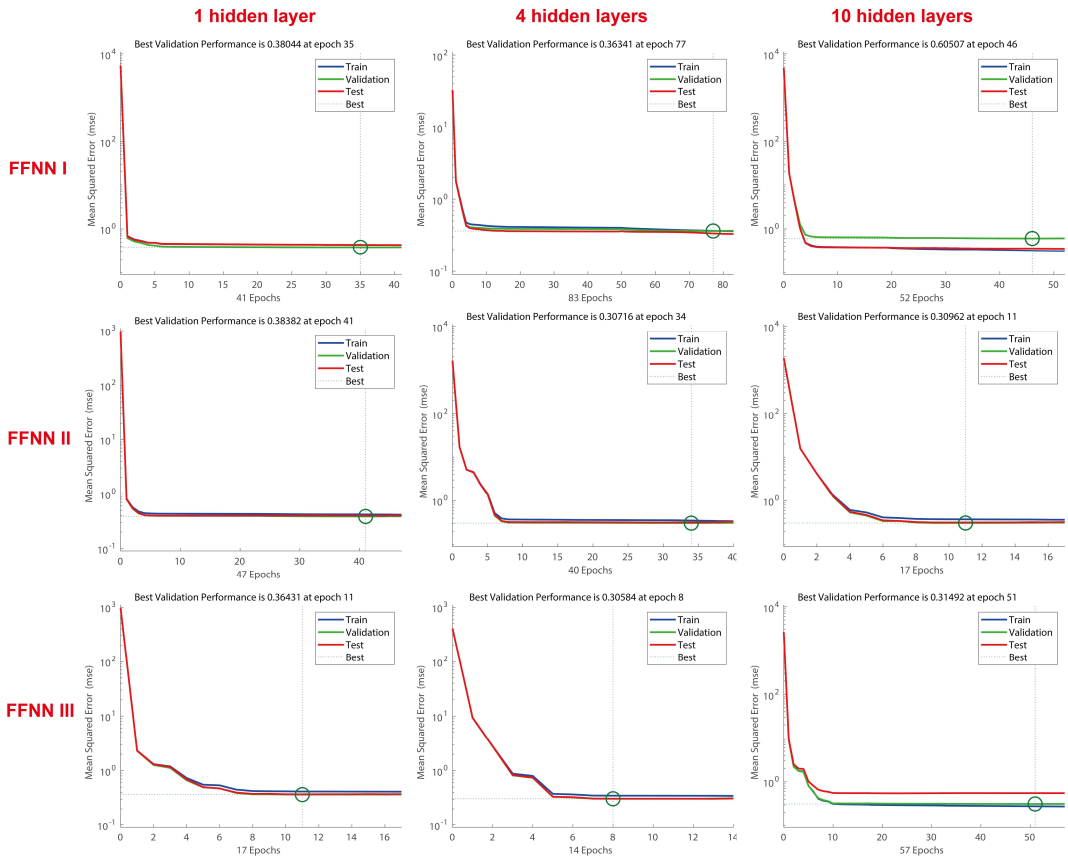
Even if promising the author should add additional analysis to the results and correct the following:

1) The github link to the code is missing, that is necessary

Response: The MATLAB codes have been uploaded to the GitHub repository at https://github.com/GuorongZhong/Stepwise-BEL-FFNN-code-for-MATLAB.git, and the link has been added in a Data Availability section.

2) The author in the method should highlight more why they choose feedforward neural network with 10 layers. Can the author provide a plot of their loss function?

Response: We used a few hidden layers with 10 neurons in each layer, and the number of hidden layers was adjusted based on *p*CO_2 predicting errors to avoid underfitting caused by too less neurons and overfitting caused by too many neurons. One another way is using only one hidden layer and adjusting the number of inner neurons. These two structures were commonly used in previous research. However, to achieve the same predicting error, neural networks with more hidden layers require far fewer neurons compared to shallower neural networks. Therefore, we used a deeper structure and changed the number of hidden layers instead of directly changing the number of neurons in each layer. We used the mean squared error as the loss function and compared the performance of FFNNs with different numbers of hidden layers, to determine how many layers should be used. Although we evaluated the performance based on RMSE rather than the loss function, the RMSE and loss function both suggested the best performance when we used a proper number of hidden layers. For example, we used FFNNs with 4 hidden layers in the areas between 50-60°S based on changes in RMSE with the number of hidden layers. The loss function also suggested the best performance when using 4 hidden layers. Here is the loss function plot of the BEL FFNNs when using one hidden layer, 4 hidden layers, and 10 hidden layers. The FFNNs with one hidden layer are slightly underfitting, while the FFNNs with 10 hidden layers are overfitting, and both of them have a higher mean squared error and RMSE. In other regions, we also compared the RMSE when using different numbers of hidden layers to determine the structure. Since the loss functions are not used to validate the FFNNs performance in our work, the figure of loss functions is not put in the main text or supplemental materials.



The loss function of the BEL FFNNs in region 50-60°S when using one hidden layer, 4 hidden layers, and 10 hidden layers

3) The paper is missing a comparison with a classic regression approach which would highlight why choosing the feedforward neural network can be a good choice. I highly recommend adding it.

Response: The *p*CO_2 predicting error from two classic approaches has been added for comparison, including a multiple linear regression (MLR) and a multiple non-linear regression (MNLR). The classic approaches suggested a higher RMSE and a more severe underestimation of Southern Ocean pCO_2 than the FFNN methods (Table 2). The newly added contents are as follows:

In addition, we also test the pCO_2 RMSE and bias of traditional regression methods for comparison, including a multiple linear regression (MLR) and a multiple non-linear regression (MNLR). As expected, the traditional regression methods are more susceptible to seasonal uneven measurements, showing higher RMSE and more severe underestimation of Southern Ocean pCO_2. In particular, the MLR using measurements from all months resulted in a winter RMSE of 34.02 μatm in the region south of 60°S, and output pCO_2 values lower than the real measurements by an average of 17.29 μatm. This result is barely acceptable, and it also explains why traditional regression methods in previous research were generally limited to specific seasons. Although the MNLR performs better than the MLR, its RMSE was still much higher than that of the FFNN methods, and the MNLR output pCO_2 during winter was also significantly lower than measurements in regions south of 50°S. Similar to the treatment of the training period of the two FFNN methods, a lesser underestimation of Southern Ocean pCO_2 in winter was found when using only partial winter measurements for regression. In the 35-50°S region, the RMSE of traditional regression methods was still higher than the two FFNN methods, and the influence of seasonal uneven measurements was not significant.

Table 2. Comparison of pCO_2 predicting error in the Southern Ocean during May-September among different methods and regression periods

Regression Method	Regression Period	35-50° S		50-60° S		S of 60° S	
		RMSE (μatm)	bias (μatm)	RMSE (μatm)	bias (μatm)	RMSE (μatm)	bias (μatm)
BEL	May-Sep	12.01	+0.61	11.97	+0.22	14.76	+0.33
FFNNs	Apr-Sep	10.70	+0.38	11.88	-0.36	14.87	-0.90
	May-Oct	11.39	-0.36	12.07	-0.66	14.50	-0.07
	Apr-Oct	11.10	-0.68	12.09	-1.16	14.20	-1.38
	Mar-Nov	11.32	-1.26	12.51	-2.13	15.50	-4.47
	All Months	**9.86**	**-0.39**	13.27	-3.13	16.09	-5.77
BEL	May-Sep	12.24	+0.74	11.93	+0.17	14.44	+1.17
FFNNs	Apr-Sep	10.76	+0.30	11.26	+0.09	13.49	-0.06
with	May-Oct	12.81	-0.28	11.44	+0.04	14.27	-0.20
corrected	Apr-Oct	11.83	-0.79	**10.93**	**-0.25**	**13.29**	**-0.74**

predictors	Mar-Nov	11.69	-1.49	13.07	-0.46	14.07	+0.02
	All Months	9.88	-0.29	11.49	-1.08	14.61	-0.90
Individual FFNN	May-Sep	12.05	+0.50	11.99	+0.07	15.15	0.36
	Apr-Sep	10.58	+0.30	12.02	-0.52	15.04	-1.14
	May-Oct	11.43	-0.59	12.21	-0.75	14.92	-0.32
	Apr-Oct	11.19	-0.83	12.29	-1.49	14.86	-1.47
	Mar-Nov	11.64	-1.43	12.82	-2.56	15.76	-3.95
	All Months	9.95	-0.34	13.31	-3.33	17.14	-5.38
Individual FFNN with corrected predictors	May-Sep	12.57	+0.50	12.30	+0.37	14.54	+0.83
	Apr-Sep	10.72	+0.27	11.45	+0.14	13.79	-0.27
	May-Oct	13.09	-0.45	11.52	-0.07	14.46	-0.23
	Apr-Oct	11.35	-0.92	11.06	-0.09	13.63	-0.27
	Mar-Nov	12.02	-1.55	11.55	-0.09	17.86	+0.50
	All Months	9.95	-0.28	12.06	-1.04	15.85	-0.05
MLR with corrected predictors	May-Sep	16.34	-2.33	13.67	-1.71	21.12	+1.09
	Apr-Sep	15.48	-0.67	14.51	-2.29	22.21	-3.00
	May-Oct	16.98	-4.55	16.29	-4.83	23.46	-0.89
	Apr-Oct	15.87	-2.93	16.39	-5.56	24.79	-6.69
	Mar-Nov	16.09	-2.53	16.75	-6.22	29.21	-13.40
	All Months	17.70	-2.30	19.01	-6.11	34.02	-17.29
MNLR with corrected predictors	May-Sep	14.37	-0.83	12.17	-0.62	17.04	+2.41
	Apr-Sep	13.51	+0.67	11.20	-0.95	17.70	-2.86
	May-Oct	14.55	-4.06	13.18	-3.47	17.70	+2.41
	Apr-Oct	14.35	-3.45	13.53	-3.76	20.21	-6.64
	Mar-Nov	14.21	-1.72	12.72	-4.70	18.81	-8.01
	All Months	15.02	+0.90	13.92	-5.35	25.68	-13.41

(BEL FFNNs: boosting ensemble learning based on three FFNNs constructed in this work; Individual FFNN: one FFNN with the same structure used in the BEL; MLR: multiple linear regression; MNLR: multiple non-linear regression, see Supplementary Note 2; Regression period: a period of SOCAT samples used for training neural networks or performing classic regression to predict pCO_2 during May-September; RMSE and bias: calculated from the difference between predicted pCO_2 and SOCAT measurements during May-September based on the K-fold cross validation method. Corrected predictors: pCO_2 predictors selected by a stepwise BEL FFNNs algorithm based on increasing weightings of winter measurements, see Table 1. Bold numbers:

the regression period with the lowest RMSE adopted in the final pCO_2 product construction.)

4) In line 99 the author has used the SOCAT pCO_2 measurements, the authors should talk more about the dataset including the time range of it.

Response: Thanks for the suggestion. We have added a description of the SOCAT dataset in the method section as follows:

The SOCAT dataset includes quality controlled global observations of in-situ surface ocean fugacity of carbon dioxide (fCO_2), sea surface temperature, and salinity on ships, moorings, autonomous and drifting surface platforms for the global oceans and coastal seas from 1957 to 2023. This dataset is provided as a synthesis version and a gridded version, with an estimated fCO_2 accuracy of better than 5 μatm. The gridded fCO_2 was converted to pCO_2 using in-situ sea surface temperature and atmospheric pressure (Landschützer et al., 2013), and then the converted pCO_2 was used in training neural networks:

$$pCO_2 = fCO_2 \cdot \exp(P_{atm}^{surf} \frac{B+2\cdot\delta}{R\cdot T})^{-1} \tag{1}$$

where P_{atm}^{surf} is the atmospheric pressure using ERA5 sea level pressure product (Hersbach et al., 2020), B and δ are viral coefficients calculated from temperature (Weiss, 1974), R is the gas constant and T is the absolute temperature.

5) In line 104 the author mentioned K-fold cross validation with a number of folds equal 4. Is the number 4 arbitrary?

Response: Setting K equal to 4 is not arbitrary but reasonable to be consistent with previous research. We set the K value to 4 in order to retain 25% measurements as an independent validation set during the validation process. In previous research, it has been common practice to set aside 20-25% of the measurements for independent validation to assess the accuracy of the neural network outputs. The K-fold cross-validation method used in this work is repeating this usual validation process for K times, to eliminate the influence of validation set selection.

6) In line 188 the authors train a neural network with SOCAT measurements only from April to October. The resulting RMSE is lower in this case. The author should emphasize more why it should be the case. This section 188-200 needs further confirmation.

Response: Thanks for the suggestion. This is mainly because of the effect of imbalanced data with data-rich summer and data-sparse winter. When training with imbalanced data, the neural network tends to perform better in data-rich seasons and significantly worse in data-sparse seasons. Recent studies suggested the effect of imbalanced data can be mitigated through data distribution re-balancing, control of loss function, and using transfer-learning based methods (Kang et al., 2020). Training a neural network with measurements only from April to October is a data distribution re-balancing method, which can effectively mitigate the influence of imbalanced data. The description of why RMSE is lower in the case using sectional winter measurements has been added in section 188-200 as follows:

This is because the quantity of pCO_2 measurements is significantly imbalanced among different seasons, with data in winter much less than in summer. T When training with such seasonal imbalanced data, the neural network tends to perform better in data-rich summer, while the performance is significantly worse in data-sparse winter. This effect of imbalanced data can be mitigated through re-balancing data distribution and using re-balancing design in the loss function or learning algorithm of neural networks (Kang et al., 2020). Training the neural networks with partial winter measurements is a data distribution re-balancing method, as the number of measurements is less unbalanced after the data-rich summer was removed from the training set. As a result, in the areas south of 50°S, the BEL FFNNs and the individual FFNN trained with sectional winter measurements suggested a significantly lower RMSE during winter than those trained with all-month measurements.

Kang, B., Xie, S., Rohrbach, M., Yan, Z., Gordo, A., Feng, J., & Kalantidis, Y. (2020). Decoupling representation and classifier for long-tailed recognition. In *8th International Conference on Learning Representations, ICLR 2020*.

7) The predictors used for the neural network have been put in supplemental materials. I would encourage to talk more in the text about these predictors and why they are important.

Response: Thanks for the suggestion. We have added a new section in the method part to interpret the importance of pCO_2 predictors and how they are selected. The predictors reflect the drivers that affect pCO_2 and its variability, and directly influence the pCO_2 predicting error of neural network methods. However, the factors driving pCO_2 and its variability differ significantly among different regions. Therefore, it is important to select a combination of $p\mathrm{CO_2}$ predictors that are most relevant to the $p\mathrm{CO_2}$ drivers in different regions for improving neural network performance. We have moved the context in supplemental materials to the main text, and added a section describing the data source of used data products for $p\mathrm{CO_2}$ predictors in supplemental materials. The newly added section is as follows:

2.2 Selection and correction of $p\mathrm{CO_2}$ predictors

The $p\mathrm{CO_2}$ predictors input into the FFNN reflect the drivers of surface ocean $p\mathrm{CO_2}$ and its variability. When changing the input $p\mathrm{CO_2}$ predictors, both the FFNN predicted $p\mathrm{CO_2}$ value and the predicting error significantly change, and these changes can be even greater than those caused by altering the FFNN structure. However, the environmental factors driving $p\mathrm{CO_2}$ and its variability differ significantly among different regions. The surface ocean $p\mathrm{CO_2}$ is largely affected by the upwelling and biological drawdown in the Antarctic region, and is affected by meridional overturning circulation in the subantarctic region (DeVries et al., 2017; Gruber et al., 2019). This means that using different predictors in different latitude regions can better reflect the regional influencing factors of $p\mathrm{CO_2}$ and its variability. To find the best combination of $p\mathrm{CO_2}$ predictors in different regions, we have proposed a Stepwise FFNN algorithm in previous work, where the changes in predicting error are fed back to the selection of input $p\mathrm{CO_2}$ predictors (Zhong et al., 2022). This algorithm allows for the objective selection of $p\mathrm{CO_2}$ predictors in different regions that result in the lowest $p\mathrm{CO_2}$ predicting error. The procedure of the Stepwise FFNN algorithm is determining $p\mathrm{CO_2}$ predictors one by one until no further reduction in predicting error is achieved by either adding or removing any predictors. Specifically, the first $p\mathrm{CO_2}$ predictor is selected by comparing predicting errors when individually using each collected environmental variable (listed in Table S1) as input of the FFNN. The variable with the lowest error is determined as the first $p\mathrm{CO_2}$ predictor, which is also the predictor that has the greatest impact on the distribution or variability of regional surface ocean $p\mathrm{CO_2}$. Subsequently, leaving the first predictor unchanged, the predicting errors are compared when using each environmental variable as the second input of the FFNN. The environmental variable with the lowest error is determined as the second $p\mathrm{CO_2}$ predictor. In the same way, new predictors are continuously determined one after another, until the predicting error no longer continues to decrease regardless of which one variable is added as a $p\mathrm{CO_2}$ predictor. Meanwhile, whenever a new predictor is determined, the algorithm also tests if the predicting error will decrease when sequentially removing each determined predictor, in order to eliminate co-correlation and prevent overfitting. For example, when the fourth predictor is determined, the model tests the change in predicting error by individually removing each one from the previously determined three predictors. If the error decreases after removing a previously determined predictor, this predictor is highly correlated with other determined predictors. By adding and removing variables in the input of the FFNN one by one in this way, the algorithm ultimately identifies a set of $p\mathrm{CO_2}$ predictors that minimize the $p\mathrm{CO_2}$ predicting error. In this work, the single FFNN structure used in the previous Stepwise FFNN algorithm has been replaced with a structure of ensemble learning FFNNs with stronger fitting capabilities (see Figure 1), referred to as the Stepwise BEL algorithm.

However, the Stepwise BEL algorithm relies on predicting errors for determination of $p\mathrm{CO_2}$ predictors, and the number of SOCAT $p\mathrm{CO_2}$ measurements in the Southern Ocean during the winter season is much lower than in the summer, leading to a lower weighting on winter predicting errors compared to summer in the determination. As a result, the selected predictors are more reflective of factors influencing $p\mathrm{CO_2}$ distribution in the summer (such as biological drawdown) while neglecting those in the winter (such as enhanced vertical mixing). Therefore, we increased the weighting of winter data to be nearly equal to that of summer, to carry out a winter correction of $p\mathrm{CO_2}$ predictors in the Southern Ocean:

$$RMSE = \sqrt{\frac{3*\sum(\Delta p\mathrm{CO_2}_{\,\mathrm{May-Sep}})^2+\sum(\Delta p\mathrm{CO_2}_{\,\mathrm{Oct-Apr}})^2}{3*N_{\mathrm{May-Sep}}+N_{\mathrm{Oct-Apr}}}} \tag{2}$$

where the $\Delta p\mathrm{CO_2}$ was the difference between predicted $p\mathrm{CO_2}$ and SOCAT $p\mathrm{CO_2}$ measurements, and N was the number of monthly SOCAT measurements ($3*N_{\mathrm{May\text{-}Sep}} \approx N_{\mathrm{Oct\text{-}Apr}}$). Based on a self-organization map method, the Southern Ocean was divided into different regions according to the similarity of $p\mathrm{CO_2}$ drivers, including two belt regions and three sectors connecting to major basins (Zhong et al., 2022). Therefore, the selection of $p\mathrm{CO_2}$ predictors and reconstruction of $p\mathrm{CO_2}$ in this work was based on three latitude areas: 35-50°S, 50-60°S, and south of 60°S (Table 1). Since there were no observed effects of uneven seasonal distribution on the neural network training in the 35-50°S region connecting the major basins, the correction of $p\mathrm{CO_2}$ predictors is only conducted in the area south of 50°S.

Table 1 Winter correction of $p\mathrm{CO_2}$ predictors.

Area		**$p\mathrm{CO_2}$ predictors**
35-50°S	Pacific sector	SST, sin(Longitude), $\mathrm{xCO_2}$, Latitude, SSS, Photosynthetically Available Radiation, Chlorophyll, Mixed layer depth, cos(Longitude), Mixed layer depth $_{\mathrm{anom}}$, Remote sensing reflectance at 531nm and 555nm

Indian sector	SST, Total absorption at 645nm, Number of months since January 1992, Mixed layer depth, SSS, W velocity of ocean currents at 105m, Surface pressure, Total absorption at 678nm, W velocity of ocean currents at 195m, Total backscattering at 667nm, Nitrate, Total absorption at 555nm, Mixed layer depth $_{anom}$, Particulate organic carbon, DIC, W velocity of ocean currents at 65m, Remote sensing reflectance at 488nm, Total backscattering at 443nm
Atlantic sector	Latitude, SSS, Dry air mixing ratio of atmospheric CO_2, Particulate organic carbon, Total backscattering at 488nm, Mixed layer depth, Diffuse attenuation coefficient, Total backscattering at 412nm, Sea surface height, cos(Longitude), SST, Remote sensing reflectance at 460nm, Total backscattering at 547nm, Bathymetry, Total absorption at 678nm, Total backscattering at 469nm, Remote sensing reflectance at 678nm
50-60°S uncorrected	SSS_{anom}, SST, Mixed layer depth, Dry air mixing ratio of atmospheric $CO_{2\ anom}$, Bathymetry, Sea surface height $_{anom}$, W velocity of ocean currents at 105m, DIC, Dissolved oxygen, Nitrate
50-60°S corrected	Dry air mixing ratio of atmospheric CO_2, Mixed layer depth, SST, DIC, month, SSS, Bathymetry, Latitude, W velocity of ocean currents at 105m, Dissolved oxygen, W velocity of ocean currents at 5m, Dry air mixing ratio of atmospheric $CO_{2\ anom}$, Mixed layer depth $_{anom}$
S of 60°S uncorrected	DIC, Bathymetry, SSS, Alkalinity, cos(Longitude), SST, Sea surface height $_{anom}$, W velocity of ocean currents at 195m, 5m, and 65m, SSS_{anom}
S of 60°S corrected	Bathymetry, SSS, Alkalinity, SST, month, W velocity of ocean currents at 65m, 105m, and 195m, Dissolved oxygen, cos(Longitude), Sea surface height, Latitude, SSS_{anom}

(Uncorrected predictors were selected by a Stepwise BEL algorithm updated from Zhong et al., 2022, corrected predictors were selected using the same algorithm but increasing the weighting of winter SOCAT measurements; The sort order of $p$$CO_2$ predictors indicated a relative contribution on decreasing predicting errors. The predictors denoted by subscript "anom" represent the monthly anomaly obtained by subtracting the monthly climatology. Data sources of used products are listed in Supplementary Table 1.)

Section added in the supplement:

Note 1 Products of pCO_2 predictors

We have collected gridded products of different environmental variables as potential pCO_2 predictors (Table S1), and the selection of these products was based on two reasons. The first reason was their potential association with physical, chemical, and biological ocean processes which may affect the surface ocean pCO_2. Another reason was the sufficient availability in time and spatial coverage and their potential association with the unavailable interannual variability of some climatological products used.

Most predictor products were obtained with a monthly and 1°×1° resolution, which can be directly used without any treatments. Differently, products with higher resolutions were integrated into the same monthly and 1°×1° resolution by averaging, before they can be used in the relationship fitting. For instance, the mixed layer depth product, originally obtained with a resolution of 0.25°×0.25°, was converted to a 1°×1° resolution by averaging 16 0.25° grids into one 1° grid. Similarly, predictor products obtained with daily or weekly resolutions were converted to the monthly resolution by directly averaging all values within the same month, such as the ocean currents product.

Supplementary Table 1. Data products used as pCO_2 predictors.

Predictor	Data product	Reference	Resolution
Sine of latitude		-	-
Sine of longitude		-	-
Cosine of longitude		-	-
Number of months since January 1992		-	-
Year		-	-
Month		-	-
SST and monthly anomaly	ECCO2 cube92	Menemenlis et al., 2008	0.25°, 1992-2022
SSS and monthly anomaly	ECCO2 cube92	Menemenlis et al., 2008	0.25°, 1992-2022
Climatological total alkalinity	AT_NNGv2_climatology	Broullón et al., 2019	1°
Climatological	TCO2_NNGv2LD	Broullón et al.,	1°

dissolved inorganic carbon	EO_climatology	2020	
Climatological dissolved oxygen	WOA18	Garcia et al., 2019a	1°
Climatological nitrate	WOA18	Garcia et al., 2019b	1°
Climatological phosphate	WOA18		
Climatological silicate	WOA18		
Mixed layer depth and monthly anomaly	ECCO2 cube92	Menemenlis et al., 2008	0.25°, 1992-2022
Sea surface height and monthly anomaly	ECCO2 cube92		
W velocity of ocean currents at 5 m, 65m, 105m, 195m, and in-situ depth	ECCO2 cube92		
Sea level pressure	ERA5	Hersbach et al., 2020	1°, 1979-2022
Surface pressure	ERA5		
dry air mixing ratio of atmospheric CO_2 and monthly anomaly	NOAA Greenhouse Gas Marine Boundary Layer Reference	Lan et al., 2023	0.25°, 1979-2022
Oceanic Nino Index	bi-monthly Multivariate El Niño/Southern Oscillation index	Wolter et al., 2011	1979-2023
Arctic Oscillation index	Climate Prediction Center Daily Arctic Oscillation Index	CPC, 2002	1950-2023
Southern Oscillation Index	Climate Prediction Center Southern Oscillation Index	CPC, 2005	1951-2023
Bathymetry	GEBCO_2022 Grid	GEBCO, 2022	15 arc-second
10 m Wind speed and monthly anomaly	ERA5	Hersbach et al., 2020	1°, 1979-2022

Climatology of Surface Ocean pCO_2	MPI-ULB-SOM_FFN_clim	Landschützer et al., 2020	0.25°
Chlorophyll concentration and monthly anomaly*	MODIS-Aqua Chlorophyll Data	NASA, 2022	9km, 2002-2023
Surface particulate organic carbon concentration	MODIS-Aqua Particulate Organic Carbon Data		
Photosynthetically Available Radiation	MODIS-Aqua Photosynthetically Available Radiation Data		
Diffuse attenuation coefficient at 490 nm	MODIS-Aqua Downwelling Diffuse Attenuation Coefficient Data		
Remote sensing reflectance at 412-678 nm	MODIS-Aqua Remote-Sensing Reflectance Data		
Total absorption at 412-678 nm	MODIS-Aqua Inherent Optical Properties Data		
Total backscattering at 412-678 nm	MODIS-Aqua Inherent Optical Properties Data		

(*: products from Chlorophyll concentration to Total backscattering are satellite remote sensing products; Remote sensing reflectance, total absorption, and total backscattering both include 10 wavelengths: 412nm, 443nm, 469nm, 488nm, 531nm, 547nm, 555nm, 645nm, 667nm, and 678nm, with each wavelength regarded as one individual predictor.)

8) In the conclusion part the authors should emphasize more about the broader impacts of their findings and how these methods can be beneficial to the scientific community.

Response: Thanks for the suggestion. We have modified the conclusion part as follows:

Our method provides a feasible solution for handling the impact of uneven measurements on the performance of neural networks. It also helps to improve the high uncertainty in pCO_2-based carbon sink estimates for special regions with limited and unevenly distributed data, such as polar regions. Furthermore, although the pCO_2 difference after correction was more notable in the Southern Ocean south of 60°S, the extensive sea ice coverage almost eliminates the CO_2 flux and mitigates the underestimation of winter surface ocean pCO_2. Therefore, the difference in carbon sink intensity before and after correction in the Southern Ocean was mainly observed in the 50-60°S region. If sea ice melts and exposes all currently covered surface Southern Oceans, the high pCO_2 seawater will release an additional 0.28 PgC yr^{-1} of CO_2 to the atmosphere in winter of each year, leading to an average reduction of 0.14 PgC yr^{-1} in the overall annual Southern Ocean carbon sink. This means that in the future, as global warming causes the melting of sea ice in the Southern Ocean, a portion of CO_2 trapped under the sea ice may be released into the atmosphere. Additionally, as the seawater warms, it can lead to an increase in surface ocean pCO_2 levels. The combined effects of global warming would limit the ocean's capacity to absorb atmospheric CO_2, which in turn could exacerbate global warming, potentially accelerating the pace of global climate change.

Given the interested topic covered by the article I would recommend major revision to the editor in order to address the changes written above.

Reviewer #2:

The manuscript describes an approach to reduce the uncertainty/discrepancy in data products and model outputs for surface ocean pCO_2 in the Southern Ocean.

The authors state that this is mainly due to the lack of in situ observations during winter (compared to summer).

They have applied the boosting ensemble learning feed forward neural networks (BEL FFNNs) method using a gridded version of SOCAT data, and data from the Southern Ocean flux station (SOFS, 142.0°E, 46.8°S), south of Tasmania (Australia) for validation.

Question:

1) Aren't there any other pCO_2 observing time series in other sector of the S. Ocean? Or only for summer periods?

Response: There are a few other pCO_2 observing time series stations in the Southern Ocean, such as the Drake time series across the Drake Passage and the KERFIX time series in the Indian sector. The Drake time series station consists primarily of 15 stations across the Drake Passage in the Southern Ocean from 2002 to 2018. However, the mooring measurements are ship-based and moving across the Drake Passage between 55-70°W and 55-65°S, and the winter period was less sampled. It is difficult to validate the winter pCO_2 from our method using these data, so the Drake time series was not used. In addition, there is a KERFIX station located in the Indian sector of the Southern Ocean (50.6°S, 68.4°E), but it is only from 1990 to 1995. The measurements of DIC and Alkalinity are only available from 1992 to 1993, and the calculated winter pCO_2 in the KERFIX station was only available in 1993, with calculated values lower than all existing machine learning pCO_2 products. In addition, there are a few other time series stations, but both of them lack winter measurements or lack pCO_2 measurements. Therefore, we only used the SOFS time series station, as this station has many winter measurements with good continuity.

2) My main question for the methods section concerns the following (l. 76-78): "The surface ocean pCO_2 converted from the Surface Ocean CO_2 Atlas version 2023 (SOCAT v2023) dataset was used for pCO_2 mapping by fitting the non-linear relationship between pCO_2 and environmental variables"

To which environmental variables?

Response: The conversion was carried out using in-situ sea surface temperature and atmospheric pressure. The description of conversion between pCO_2 and fCO_2 has been added in the method section as follows:

The gridded fCO$_2$ was converted to pCO$_2$ using in-situ sea surface temperature and atmospheric pressure (Landschützer et al., 2013), and then the converted pCO$_2$ was used in training neural networks:

$$pCO_2 = fCO_2 \cdot \exp(P_{atm}^{surf} \frac{B+2\cdot\delta}{R\cdot T})^{-1} \tag{1}$$

where P_{atm}^{surf} is the atmospheric pressure using ERA5 sea level pressure product (Hersbach et al., 2020), B and δ are viral coefficients calculated from sea surface temperature (Weiss, 1974), R is the gas constant and T is the absolute temperature.

3) Additionally, the list of predictors appears in the supplementary material only, and it is hard for the reader to understand why the winter predictors were chosen for each latitude area.

Response: Thanks for the suggestion. A new section about the use of predictors has been added in the method section, and the context in supplementary material has been also moved to this new section. The predictors were chosen for each latitude area because of the latitude differences in pCO$_2$ drivers. The surface ocean pCO$_2$ is largely affected by the upwelling and biological drawdown in the high latitude Antarctic region, and is affected by meridional overturning circulation in the subantarctic region. While in the 35-50°S region, the variability of surface ocean pCO$_2$ was mainly driven by the notable seasonal change in SST. The dividing of biogeochemical provinces using a self-organizing map method based on the similarity of environmental variables also presents a belt province south of 60°S and a belt province covering nearly 50-60°S in our previous work. Therefore, we chose pCO$_2$ predictors for different latitude areas. The new section was as follows:

2.2 Selection and correction of pCO$_2$ predictors

The pCO$_2$ predictors input into the FFNN reflect the drivers of surface ocean pCO$_2$ and its variability. When changing the input pCO$_2$ predictors, both the FFNN predicted pCO$_2$ value and the predicting error significantly change, and these changes can be even greater than those caused by altering the FFNN structure. However, the environmental factors driving pCO$_2$ and its variability differ significantly among different regions. The surface ocean pCO$_2$ is largely affected by the upwelling and biological drawdown in the Antarctic region, and is affected by meridional overturning circulation in the subantarctic region (DeVries et al., 2017; Gruber et al., 2019). This means that using different predictors in different latitude regions can better reflect the regional influencing factors of pCO$_2$ and its variability. To find the best combination of pCO$_2$ predictors in different regions, we have proposed a Stepwise FFNN algorithm in previous work, where the changes in predicting error are fed back to the selection of input pCO_2 predictors (Zhong et al., 2022). This algorithm allows for the objective selection of pCO_2 predictors in different regions that result in the lowest pCO_2 predicting error. The procedure of the Stepwise FFNN algorithm is determining pCO_2 predictors one by one until no further reduction in predicting error is achieved by either adding or removing any predictors. Specifically, the first pCO_2 predictor is selected by comparing predicting errors when individually using each collected environmental variable (listed in Table S1) as input of the FFNN. The variable with the lowest error is determined as the first pCO_2 predictor, which is also the predictor that has the greatest impact on the distribution or variability of regional surface ocean pCO_2. Subsequently, leaving the first predictor unchanged, the predicting errors are compared when using each environmental variable as the second input of the FFNN. The environmental variable with the lowest error is determined as the second pCO_2 predictor. In the same way, new predictors are continuously determined one after another, until the predicting error no longer continues to decrease regardless of which one variable is added as a pCO_2 predictor. Meanwhile, whenever a new predictor is determined, the algorithm also tests if the predicting error will decrease when sequentially removing each determined predictor, in order to eliminate co-correlation and prevent overfitting. For example, when the fourth predictor is determined, the model tests the change in predicting error by individually removing each one from the previously determined three predictors. If the error decreases after removing a previously determined predictor, this predictor is highly correlated with other determined predictors. By adding and removing variables in the input of the FFNN one by one in this way, the algorithm ultimately identifies a set of pCO_2 predictors that minimize the pCO_2 predicting error. In this work, the single FFNN structure used in the previous Stepwise FFNN algorithm has been replaced with a structure of ensemble learning FFNNs with stronger fitting capabilities (see Figure 1), referred to as the Stepwise BEL algorithm.

However, the Stepwise BEL algorithm relies on predicting errors for determination of pCO_2 predictors, and the number of SOCAT pCO_2 measurements in the Southern Ocean during the winter season is much lower than in the summer, leading to a lower weighting on winter predicting errors compared to summer in the determination. As a result, the selected predictors are more reflective of factors influencing pCO_2 distribution in the summer (such as biological drawdown) while neglecting those in the winter (such as enhanced vertical mixing). Therefore, we increased the weighting of winter data to be nearly equal to that of summer, to carry out a winter correction of

pCO$_2$ predictors in the Southern Ocean:

$$RMSE = \sqrt{\frac{3*\sum(\Delta pCO_{2\ \mathrm{May-S}}\ \ )^2+\sum(\Delta pCO_{2\ \mathrm{Oct-Apr}})^2}{3*N_{\mathrm{May-S}}\ \ +N_{\mathrm{Oct-Apr}}}} \tag{2}$$

where the ΔpCO$_2$ was the difference between predicted pCO$_2$ and SOCAT pCO$_2$ measurements, and N was the number of monthly SOCAT measurements ($3*N_{\mathrm{May\text{-}Sep}} \approx N_{\mathrm{Oct\text{-}Apr}}$). Based on a self-organization map method, the Southern Ocean was divided into different regions according to the similarity of pCO$_2$ drivers, including two belt regions and three sectors connecting to major basins (Zhong et al., 2022). Therefore, the selection of pCO$_2$ predictors and reconstruction of pCO$_2$ in this work was based on three latitude areas: 35-50°S, 50-60°S, and South of 60°S (Table 1). Since there were no observed effects of uneven seasonal distribution on the neural network training in the 35-50°S region connecting the major basins, the correction of pCO$_2$ predictors is only conducted in the area south of 50°S.

Table 1 Winter correction of *p*CO₂ predictors.

Area		***p*CO$_2$ predictors**
35-50°S	Pacific sector	SST, sin(Longitude), xCO$_2$, Latitude, SSS, Photosynthetically Available Radiation, Chlorophyll, Mixed layer depth, cos(Longitude), Mixed layer depth $_{\mathrm{anom}}$, Remote sensing reflectance at 531nm and 555nm
	Indian sector	SST, Total absorption at 645nm, Number of months since January 1992, Mixed layer depth, SSS, W velocity of ocean currents at 105m, Surface pressure, Total absorption at 678nm, W velocity of ocean currents at 195m, Total backscattering at 667nm, Nitrate, Total absorption at 555nm, Mixed layer depth $_{\mathrm{anom}}$, Particulate organic carbon, DIC, W velocity of ocean currents at 65m, Remote sensing reflectance at 488nm, Total backscattering at 443nm
	Atlantic sector	Latitude, SSS, Dry air mixing ratio of atmospheric CO$_2$, Particulate organic carbon, Total backscattering at 488nm, Mixed layer depth, Diffuse attenuation coefficient, Total backscattering at 412nm, Sea surface height, cos(Longitude), SST, Remote sensing reflectance at 460nm, Total backscattering at 547nm, Bathymetry, Total absorption at 678nm, Total backscattering at 469nm, Remote sensing reflectance at 678nm
50-60°S	uncorrected	SSS$_{\mathrm{anom}}$, SST, Mixed layer depth, Dry air mixing ratio of atmospheric

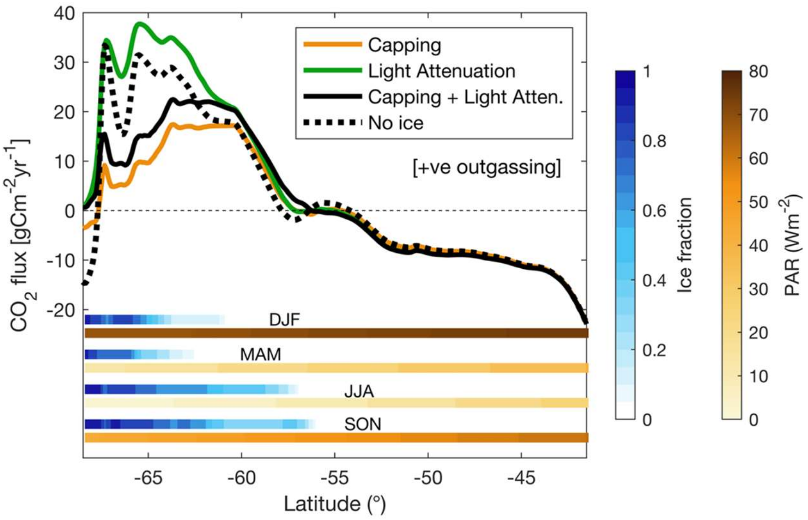
	$CO_{2\ anom}$, Bathymetry, Sea surface height $_{anom}$, W velocity of ocean currents at 105m, DIC, Dissolved oxygen, Nitrate
50-60°S corrected	Dry air mixing ratio of atmospheric CO_2, Mixed layer depth, SST, DIC, month, SSS, Bathymetry, Latitude, W velocity of ocean currents at 105m, Dissolved oxygen, W velocity of ocean currents at 5m, Dry air mixing ratio of atmospheric $CO_{2\ anom}$, Mixed layer depth $_{anom}$
S of 60°S uncorrected	DIC, Bathymetry, SSS, Alkalinity, cos(Longitude), SST, Sea surface height $_{anom}$, W velocity of ocean currents at 195m, 5m, and 65m, SSS_{anom}
S of 60°S corrected	Bathymetry, SSS, Alkalinity, SST, month, W velocity of ocean currents at 65m, 105m, and 195m, Dissolved oxygen, cos(Longitude), Sea surface height, Latitude, SSS_{anom}

(Uncorrected predictors were selected by a Stepwise BEL algorithm updated from Zhong et al., 2022, corrected predictors were selected using the same algorithm but increasing the weighting of winter SOCAT measurements; The sort order of pCO_2 predictors indicated a relative contribution on decreasing predicting errors. The predictors denoted by subscript "anom" represent the monthly anomaly obtained by subtracting the monthly climatology. Data sources of used products are listed in Supplementary Table 1.)

4) In the conclusion section, my concern is about the statement on lines 502-506: Is there an estimate for this in the future? In figure 9 we see the decrease in the S. Ocean carbon sink in the scenarios where 50% or 100% of the sea ice melts - but within the period ~1992-2022 considered in this study. What are the modelled predictions (please cite the models, like in figure 7, for instance), despite the discrepancy in the ocean carbon sink?

Response: We did not estimate the specific carbon sink intensity in the future. Predicting the future variability is not what machine learning pCO_2 mapping is skilled in. But based on current estimate that the atmospheric pCO_2 increases at an average rate of 1.90 μatm yr^{-1} in the Southern Ocean areas with sea ice, compared to the 1.53 μatm yr^{-1} of surface ocean pCO_2, we can suppose that the high latitude Antarctic seawaters would be still a carbon source but inhibited by sea ice in the future.

The modeled predictions similarly suggested a winter CO_2 release inhibited by sea ice in the Southern Ocean. The recent research based on a 2-D channel model and an analytical model indicated that sea ice coverage affects the air-sea CO_2 flux by physical barrier and limiting biological photosynthesis, and CO_2 emissions to the atmosphere will increase significantly in the area around 65°S if the sea ice completely melts (Gupta et al., 2020). Also, research based on mooring observations in the West Antarctic Peninsula continental shelf suggested that a reduction in sea ice may be expected to weaken the Southern Ocean oceanic CO_2 sink, by allowing additional outgassing in autumn and winter (Shadwick et al., 2021).



The figure cited from Gupta et al., 2020. They compared CO_2 flux that the seasonal ice cover affects physical CO_2 exchange only (Capping in orange), biological photosynthesis only (light attenuation in green), both together (solid black), and no ice cover (dotted black). If there is no ice cover, the no-ice carbon source (dotted black) around 65°S would be stronger than the result with the current ice cover fraction (solid black), which is consistent with our results.

Gupta, M., Follows, M. J., & Lauderdale, J. M. (2020). The effect of Antarctic sea ice on Southern Ocean carbon outgassing: Capping versus light attenuation. *Global Biogeochemical Cycles*, *34*(8), e2019GB006489.

Shadwick, E. H., De Meo, O. A., Schroeter, S., Arroyo, M. C., Martinson, D. G., & Ducklow, H. (2021). Sea ice suppression of CO_2 outgassing in the West Antarctic Peninsula: Implications for the evolving Southern Ocean carbon sink. *Geophysical Research Letters*, *48*, e2020GL091835.

5) How does the calculated uncertainty in sea-air CO2 fluxes (section "uncertainty") affect the estimates of the decreasing C sink from this manuscript?

Response: The uncertainty did not affect the result that the seawater under sea ice coverage acts as a carbon source and the additional CO_2 release caused by sea ice melting will decrease the Southern Ocean carbon sink intensity. The uncertainty represents the potential difference between estimated carbon sinks and the true values caused by the bias in $p$$CO_2$ mapping and gas transfer velocity. This difference only affects the intensity of carbon sources covered by sea ice and is not big enough to turn carbon sources into carbon sinks. Therefore, the uncertainty may make the estimated additional CO_2 release (or decrease in the total Southern Ocean carbon sink) caused by sea ice melting differ from the real situation to some extent.

Annotation:

1) Line 45: gas transfer?

Response: The word has been corrected into "gas transfer velocity".

2) Line 56: Is this relative to the last 3 decades, as in the paragraph above?

Response: The 40% was estimated for the historical period since the Industrial Revolution. Specifically, the contribution of the Southern Ocean on global ocean anthropogenic CO_2 uptakes was estimated to be 43% from 1870 to 1995 by Frölicher et al., 2015. The original text has been modified as:

The Southern Ocean south of 35°S was a strong carbon sink and has contributed to about 40% of global ocean anthropogenic CO_2 uptakes from 1870 to 1995 (Sabine et al., 2004; Fletcher, S. E. M. et al., 2006; Frölicher et al., 2015; Landschützer et al., 2015).

3) Line 70: overestimation in comparison to the in situ observations? Or to model outputs?

Response: The overestimation refers to the stronger carbon sink of machine learning methods compared to the in-situ observations. The original text has been modified as:

The strongly seasonally uneven surface ocean $p\mathrm{CO_2}$ measurements with missing winter observations may result in an overestimation of the Southern Ocean carbon sink from $p\mathrm{CO_2}$ products compared to the in-situ observations (Bushinsky et al., 2019; Hauck et al., 2020; Gloege et al., 2021; Friedlingstein et al., 2022). Besides supplying more measurements from sailboats or floats (Landschützer et al., 2023), whether the overestimation in $p\mathrm{CO_2}$-based machine learning methods compared to the in-situ observations can be solved by improving algorithms is worth investigating.

4) Line 78: which ones?

Response: A new section about the selection of $p\mathrm{CO_2}$ predictors has been added in the method section, and the used $p\mathrm{CO_2}$ predictors are listed in Table 1 now.

5) Line 90: which drivers were more relevant in winter and summer?

Response: In the areas between 50-60°S, the $p\mathrm{CO_2}$ distribution was more relevant to the enhanced vertical mixing in summer and to the biological drawdown in winter. The original text has been modified as follows:

However, the Stepwise BEL algorithm relies on predicting errors for determination of pCO_2 predictors, and the number of SOCAT pCO_2 measurements in the Southern Ocean during the winter season is much lower than in the summer, leading to a lower weighting on winter predicting errors compared to summer in the determination. As a result, the selected predictors are more reflective of factors influencing pCO_2 distribution in the summer (such as biological drawdown) while neglecting those in the winter (such as enhanced vertical mixing).

6) Line 129: please check the format o "k" along the text - you stated using it in italic font

Response: Thanks for the suggestion. The velocity *k* has been all corrected to the italic font.

7) Line 154: how this affects the numbers for the correction of the size of the Southern Ocean carbon sink at section 3 in this manuscript?

Response: The uncertainty did not affect the difference between uncorrected and corrected carbon sinks. As it was calculated from the pCO_2 RMSE of corrected neural networks, the uncertainty only affects the size of the corrected Southern Ocean carbon sink. The numbers for the correction of the size of the Southern Ocean carbon sink were mainly related to the decrease in mean pCO_2 bias from -3.13~-5.77 μatm to -0.25~-0.74 μatm after the winter correction. The RMSE decrease after correction also makes the carbon sink uncertainty smaller than the uncorrected result, but the corrected uncertainty and the correction size of carbon sinks are not directly related.

8) Strikeout in Line 166

Response: The sentence has been modified as follows:

Original: The SOCAT measurements in the Southern Ocean are concentrated in summer with low surface ocean pCO_2 (Figure 2a). While in winter, the number of measurements with high surface ocean pCO_2 was only about one-fifth of that in summer.

Modified: The SOCAT measurements in the Southern Ocean are concentrated in summer with low surface ocean pCO_2 (Figure 2a), with the number of high-pCO_2 winter measurements only about one-fifth of that in summer.

9) Strikeout in Line 166

Response: The unnecessary title "the" has been removed.

10) Table 1: what is the meaning of the bold numbers?

Response: The bold numbers are the lowest RMSE, which is also the adopted training period in the final pCO_2 product construction. The description has been added in the table annotation.

11) Line 221: add "between"

Response: the sentence has been modified as follows:

In contrast, there is no significant underestimation of winter surface ocean pCO_2 in the Southern Ocean between 35-50°S.

12) Line 240: would be good to have a list of the predictors, in a table or in the main text, not only in the supplementary file. In the discussion, you should also name the predictors.

Response: A new section about predictors has been added in the method section, and the predictor list has been moved to Table 1 of this section now. The predictors have been listed in the full name, and the data source of used products has been listed in the supplementary Table S1.

13) Line 267: Where is the SOFS station located (latitude area - between 35-50S, or between 50-60S, or further south of 60S?) I have found it, but the reader may not be familiar to it.

Response: The location of the SOFS station (142.0°E, 46.8°S) has been added in the method section where the SOFS station is first referred.

14) Line 376: driven?

Response: The text has been corrected as follows:

Research based on an idealized upper ocean box model also suggested that the slowed growth rate of atmospheric pCO_2 and the global sea surface temperature response to the 1991 eruption of Mt Pinatubo volcanic were two external forces to explain the global-scale reduction in the ocean carbon sink, and the reinvigoration of carbon sink was driven by the acceleration of atmospheric pCO_2 growth after 2001 (McKinley et al., 2020).

15) Line 398: how many models? where is the data available? directly from

Friedlingstein et al. 2022?

Response: The GOBMs are an average of 10 global ocean biogeochemical models. The data is available at https://doi.org/10.18160/GCP-2022, this link can be found in Friedlingstein et al. 2022. The description in Figure 7 annotation has been modified as follows:

Figure 7. Global ocean carbon sink over the past three decades after the Southern Ocean correction. GOBMs: average results of 10 global ocean biogeochemical models (https://doi.org/10.18160/GCP-2022, Friedlingstein et al., 2022);

16) Line 442: One should avoid writing that "figure X shows" - it is better if you describe and discuss your result, then direct the reader to the figure.

Response: Thanks for the suggestion. The sentence has been modified as follows:

If sea ice melted completely, the changes in simulated carbon sink intensity without considering indirect factors based on the recent sea-air pCO_2 difference were different between summer and winter periods in the Southern Ocean (Figure 9).

17) Line 503: Is there an estimate for this in the future? In figure 9 we see the derease in the sink in the scenarios where 50% or 100% of the sea ice melts - but within the period ~1992-2022.

Response: We did not perform a quantitative future estimate, but only speculated the theoretical future change based on current data. Predicting future changes is not what the used machine learning is good at. In addition, the released CO_2 from areas with melting sea ice may further affect the sea ice melting speed, and predicting the sea ice melting speed is not in our expertise area. The quantitative prediction may be carried out in future works through model simulations.

Decision letter and referee reports: second round

15th May 24
Dear Professor Li,

Your manuscript titled "Melting sea ice will weaken carbon sinks in the Southern Ocean" has now been seen by 2 reviewers, and we include their comments at the end of this message. They find your work of interest, but some important points are still raised. We are interested in the possibility of publishing your study in Communications Earth & Environment, but would like to consider your responses to these concerns and assess a revised manuscript before we make a final decision on publication.

We therefore invite you to revise and resubmit your manuscript, addressing the remaining concerns of both reviewers, along with a point-by-point response that takes into account the points raised. Please highlight all changes in the manuscript text file.

We are committed to providing a fair and constructive peer-review process. Please don't hesitate to contact us if you wish to discuss the revision in more detail.

Please use the following link to submit your revised manuscript, point-by-point response to the referees' comments (which should be in a separate document to any cover letter), a tracked-changes version of the manuscript (as a PDF file) and the completed checklist:
[redacted]
** This url links to your confidential home page and associated information about manuscripts you may have submitted or be reviewing for us. If you wish to forward this email to co-authors, please delete the link to your homepage first **

We hope to receive your revised paper within six weeks; please let us know if you aren't able to submit it within this time so that we can discuss how best to proceed. If we don't hear from you, and the revision process takes significantly longer, we may close your file. In this event, we will still be happy to reconsider your paper at a later date, as long as nothing similar has been accepted for publication at Communications Earth & Environment or published elsewhere in the meantime.

Please do not hesitate to contact us if you have any questions or would like to discuss these revisions further. We look forward to seeing the revised manuscript and thank you for the opportunity to review your work.

Best regards,

Jose Luis Iriarte Machuca, PhD
Editorial Board Member
Communications Earth & Environment

Alireza Bahadori, PhD
Associate Editor
Communications Earth & Environment

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Please refer to our data policies at http://www.nature.com/authors/policies/availability.html.

REVIEWER COMMENTS:

Reviewer #3 (Remarks to the Author):

Dear Drs. Li and Song,

Thank you for addressing the comments in your comprehensive rebuttal letter, to both reviewers. The revised manuscript is much clearer now, especially now listing the chosen pCO2 predictors.

The abstract could be a little clearer, as the following:

"This overestimation can be mitigated by a winter correction in
algorithms, with the average Southern Ocean carbon sink during 1992-2021 corrected to -0.87 PgC yr-1 from the original -1.01 PgC yr-1. Furthermore, the most notable underestimation of surface ocean pCO2 mainly occurred in regions south of 60°S and
was hiding under ice cover. If sea ice melts completely, there could be a further reduction of about 0.14 PgC yr-1 in the Southern Ocean carbon sink due to exposure of high pCO2 seawater to the atmosphere in winter."

I understand that the authors have improved/corrected the prediction of the S. Ocean C sink for 1992-2021 to -0.87 PgC/yr but the assumption of total melting of sea ice isn't something of a future scenario? Maybe you should add a sentence from the text (page 20) in the abstract (suggestion):

"This overestimation can be mitigated by a winter correction in
algorithms, with the average Southern Ocean carbon sink during 1992-2021 corrected to -0.87 PgC yr-1 from the original -1.01 PgC yr-1. Furthermore, the most notable underestimation of surface ocean pCO2 mainly occurred in regions south of 60°S and
was hiding under ice cover. As the surface ocean pCO2 under sea ice coverage in the winter is much higher than the atmosphere, if sea ice melts completely, there could be a further reduction of about 0.14 PgC yr-1 in the Southern Ocean carbon sink."

In page 21 there is still a sentence beginning with "Figure 9 shows the simulated carbon sink intensity in the Southern Ocean under different sea ice coverage without considering indirect factors based on the recent sea-air pCO2 difference..." - I suggest rewriting and starting with the main information first and then cite the figure (fig. 9).

I have noticed that there were a change in the authors' list, is there a reason why Dr. Fan Wang no longer is a co-author?

Reviewer #4 (Remarks to the Author):

Thanks for your answer, the article has shown good improvements.
This article offers a promising approach for dealing with PCO2 bias measurements, it is definitely worth publishing. However, I notice some issues that needs to be resolved:
-The label format is not consistent across the article (fig. 9 as label in bold format while fig.8 has not for example). I would recommend the authors put a title to all figures (one for each subfigure) and use the same format for all of them.
-Fig.5 has a) and b) label figure in bold and c) and d) labels not in bold. Be consistent.
-The references need to be in a different color compared to the rest of the text.
-Also to make the result more robust I would encourage to try the same methodology with another data set so to compare with SOCCAT results. The authors can add this second dataset results in supplemental material.

Ones this is done I will endorse the publication of it.

Author responses: second round

Reviewer #3:

Thank you for addressing the comments in your comprehensive rebuttal letter, to both reviewers. The revised manuscript is much clearer now, especially now listing the chosen pCO_2 predictors.

1) The abstract could be a little clearer, as the following:

"This overestimation can be mitigated by a winter correction in algorithms, with the average Southern Ocean carbon sink during 1992-2021 corrected to -0.87 PgC yr^{-1} from the original -1.01 PgC yr^{-1}. Furthermore, the most notable underestimation of surface ocean pCO_2 mainly occurred in regions south of 60°S and was hiding under ice cover. If sea ice melts completely, there could be a further reduction of about 0.14 PgC yr^{-1} in the Southern Ocean carbon sink due to exposure of high pCO_2 seawater to the atmosphere in winter."

I understand that the authors have improved/corrected the prediction of the S. Ocean C sink for 1992-2021 to -0.87 PgC/yr but the assumption of total melting of sea ice isn't something of a future scenario? Maybe you should add a sentence from the text (page 20) in the abstract (suggestion):

"This overestimation can be mitigated by a winter correction in algorithms, with the average Southern Ocean carbon sink during 1992-2021 corrected to -0.87 PgC yr^{-1} from the original -1.01 PgC yr^{-1}. Furthermore, the most notable underestimation of surface ocean pCO_2 mainly occurred in regions south of 60°S and was hiding under ice cover. As the surface ocean pCO_2 under sea ice coverage in the winter is much higher than the atmosphere, if sea ice melts completely, there could be a further reduction of about 0.14 PgC yr^{-1} in the Southern Ocean carbon sink."

Response: Thanks for the suggestion. The abstract has been modified as the suggestion.

2) In page 21 there is still a sentence beginning with "Figure 9 shows the simulated carbon sink intensity in the Southern Ocean under different sea ice coverage without considering indirect factors based on the recent sea-air pCO_2 difference..." - I suggest rewriting and starting with the main information first and then cite the figure (fig. 9).

Response: Thanks for the suggestion. The beginning of the paragraph has been modified as the following:

"Assuming complete sea ice melt and neglecting indirect factors based on the recent sea-air pCO_2 difference, the changes in simulated carbon sink intensity vary between summer and winter periods in the Southern Ocean (Figure 9)."

3) I have noticed that there were a change in the authors' list, is there a reason why Dr. Fan Wang no longer is a co-author?

Response: Thanks for the notification. Wang Fan made an important contribution to this article, but we mistakenly deleted in the re-submission when we wanted to put Wang Fan in a more forward position. The mistake has been corrected and the co-author Fan Wang has been put in fourth place now.

Reviewer #4:

Thanks for your answer, the article has shown good improvements.

This article offers a promising approach for dealing with PCO_2 bias measurements, it is definitely worth publishing. However, I notice some issues that needs to be resolved:

1) The label format is not consistent across the article (fig. 9 as label in bold format while fig.8 has not for example). I would recommend the authors put a title to all figures (one for each subfigure) and use the same format for all of them.

Response: Thanks for the suggestion. We have corrected all labels to in bold format as the following:

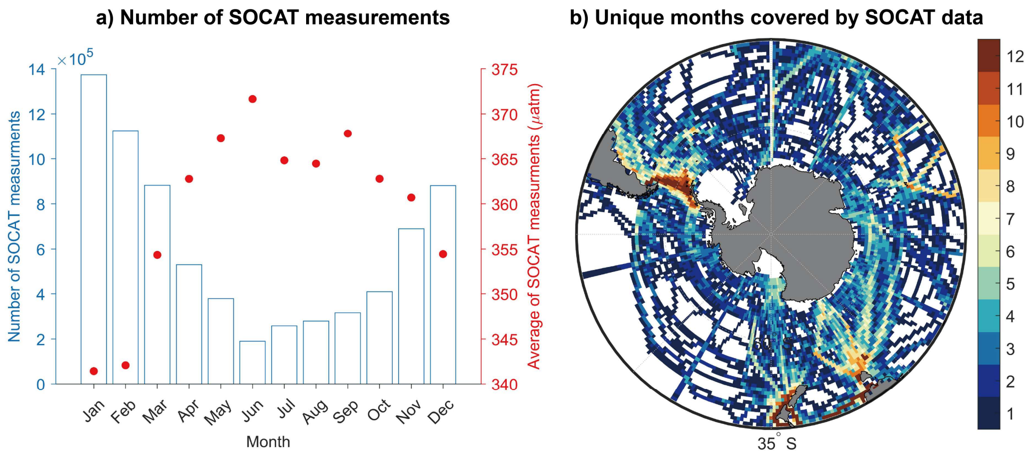

Figure 2. The number of a) SOCAT fCO_2 measurements in each month and b) unique months covered by SOCAT measurements in the Southern Ocean south of 35°S from 1992 to 2021.

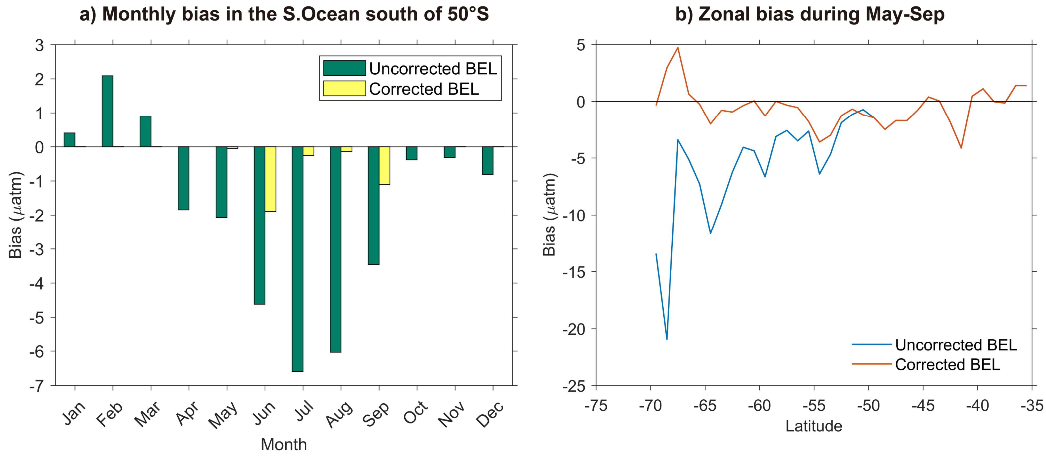

Figure 3. Distribution of bias between predicted pCO_2 and SOCAT measurements in the Southern Ocean south of 35°S.

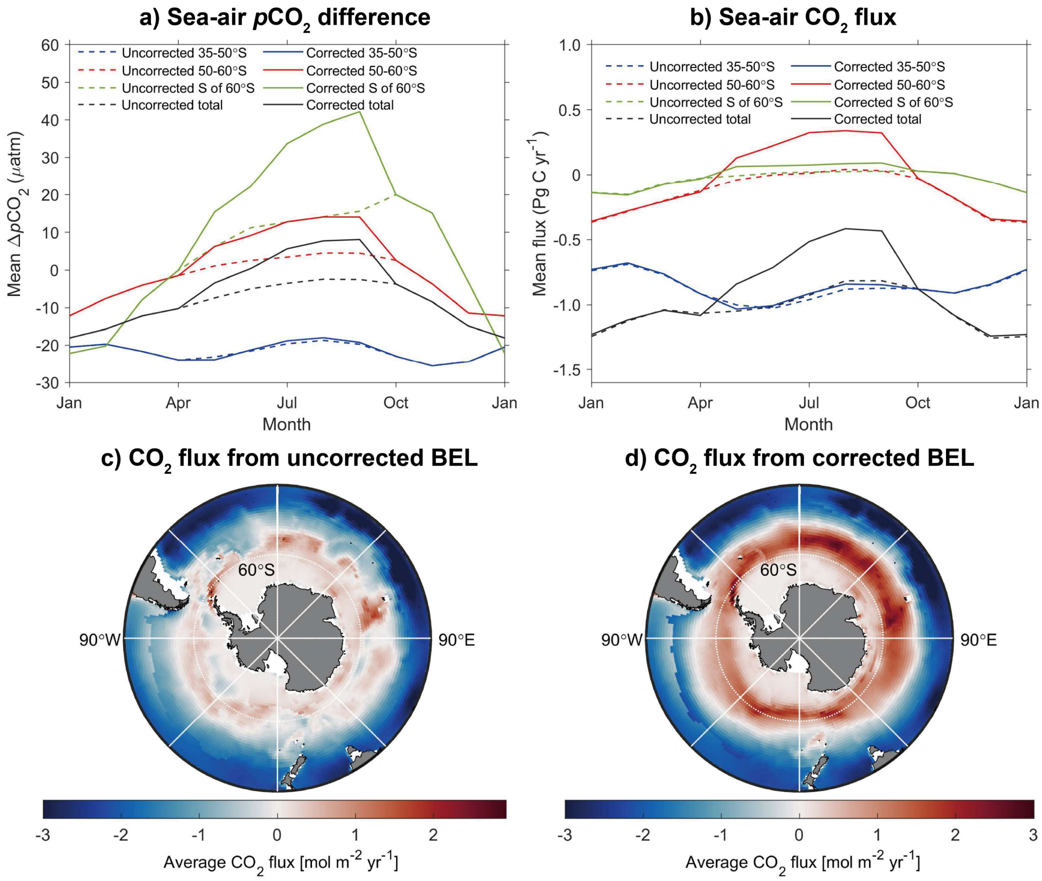

Figure 5. Distribution of average sea-air pCO_2 difference and CO_2 flux from May to September during 1992-2021.

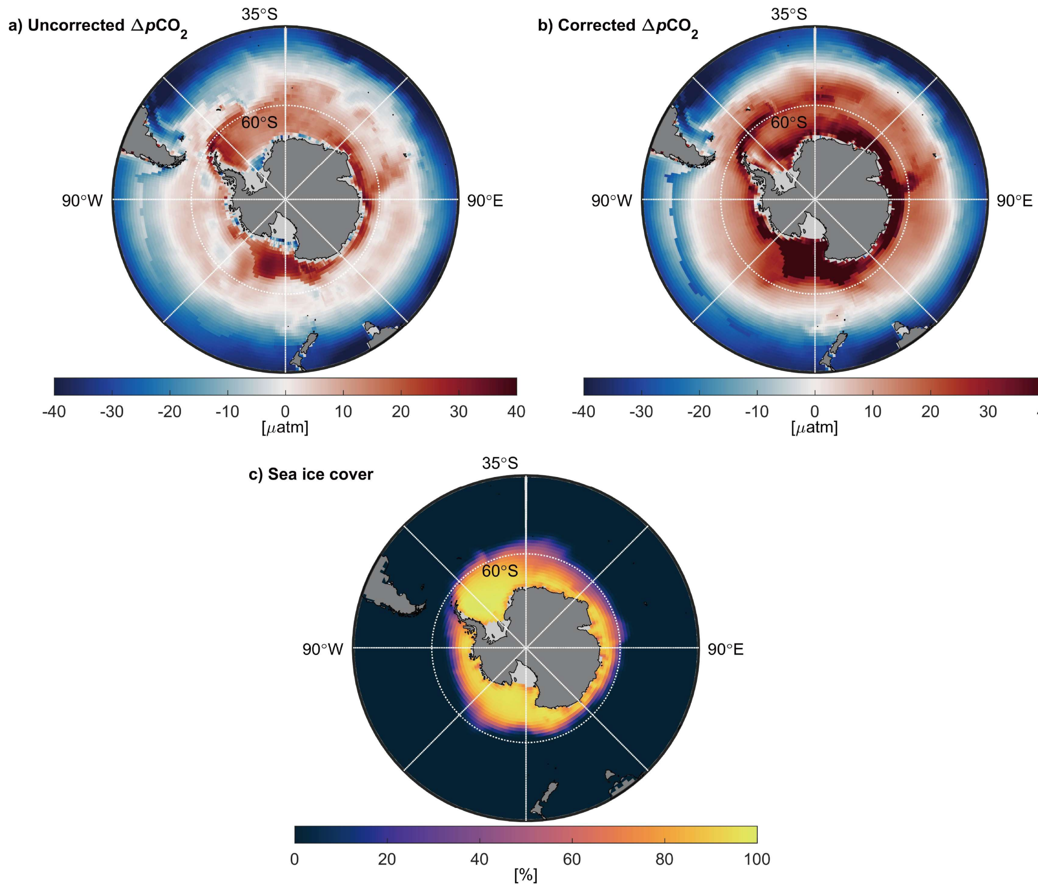

Figure 8. Distribution of average sea-air ΔpCO_2 and sea ice coverage during May-Sep in the Southern Ocean.

2) Fig.5 has a) and b) label figure in bold and c) and d) labels not in bold. Be consistent.

Response: The label of Figure 5 has been corrected in bold.

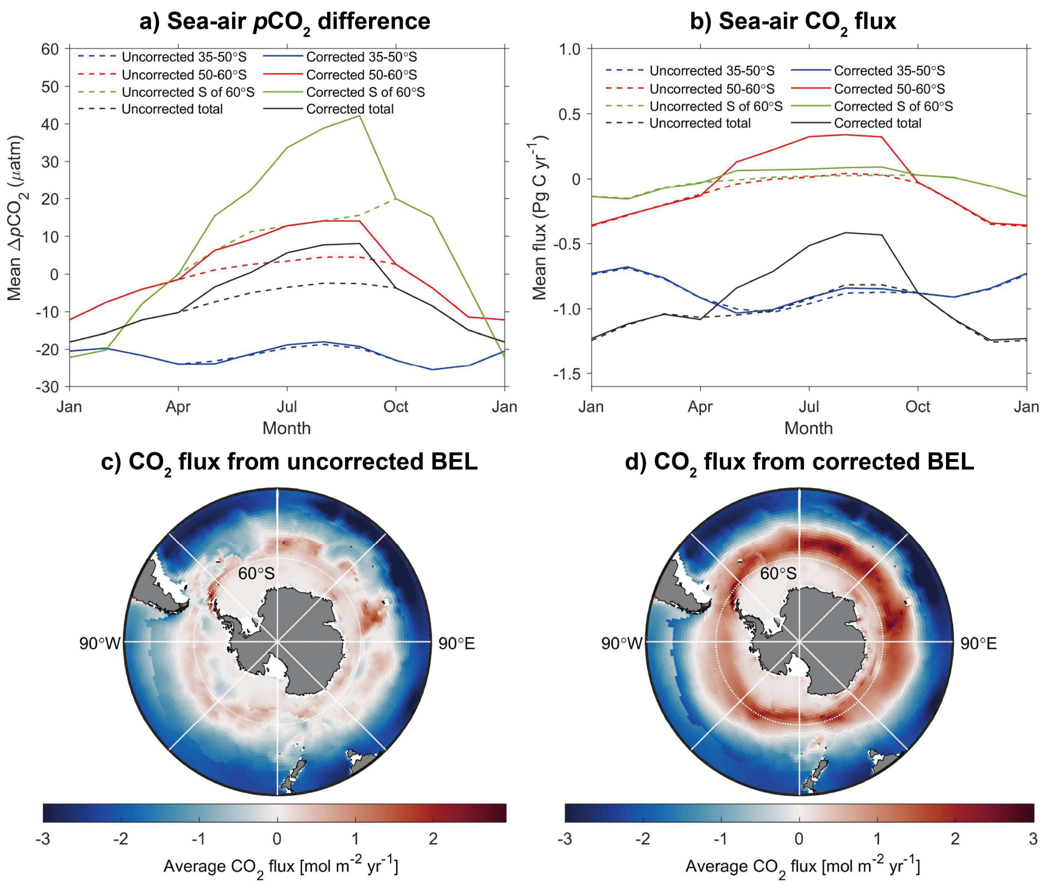

Figure 5. Distribution of average sea-air pCO_2 difference and CO_2 flux from May to September during 1992-2021.

3) The references need to be in a different color compared to the rest of the text.

Response: Thanks for the suggestion. The references have been changed to blue color.

4) Also to make the result more robust I would encourage to try the same methodology with another data set so to compare with SOCAT results. The authors can add this second dataset results in supplemental material.

Response: Thanks for the suggestion. The Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM) float pCO_2 data have been added for further evaluation (Figure S1). The description of the SOCCOM dataset and the results has been placed in supplemental material.

The SOCCOM dataset contains observations from biogeochemical profiling floats, processed with delayed-mode quality control method at the Monterey Bay Aquarium Research Institute (MBARI). The SOCCOM pCO_2 data were derived from estimated total alkalinity and pH sampled every two meters in the upper 1000 meters using LIAR or CANYON algorithms (Johnson et al., 2017).

By averaging the SOCCOM data at depths of 2.77-5.00 m in each month and 1° grid into 230 samples, we estimated the bias between the float pCO_2 data and our BEL FFNNs pCO_2 product during June-September from 2014 to 2019. Although a great discrepancy exists between the BEL FFNNs mapped pCO_2 and SOCCOM float pCO_2, the winter correction in the BEL algorithm still mitigated the underestimation of pCO_2 by FFNNs. The uncorrected BEL FFNNs pCO_2 is about 30 µatm lower than float data along the 60°S areas during the winter period, while the corrected pCO_2 show biases less than -20 µatm in the Indian sector and Pacific sector (Figures S1a and S1b). In the Atlantic sector and the Drake Passage, after the winter correction, the BEL FFNNs pCO_2 underestimated 10-20 µatm compared to float data changed to be less biased. These changes in biases suggested that the regional average pCO_2 of BEL FFNNs product will be closer to the float data. The average bias reduced from -16.8 µatm to -6.5 µatm and was better distributed along the y=x line after the winter correction (Figure S1c). However, a great discrepancy exists between BEL FFNNs pCO_2 and the SOCCOM float data when float pCO_2 is lower than 350 µatm or higher than 450 µatm. Notably, this discrepancy was not a shame in bad machine learning performance, but a difference exists between the SOCAT dataset and the SOCCOM dataset. Previous research also suggested a much weaker Southern Ocean carbon sink derived from the SOCCOM dataset than that from the SOCAT dataset (Bushinsky et al., 2019). Therefore, the evaluation based on SOCCOM float data can also prove the benefits of the winter correction in the estimate of the Southern Ocean carbon sink.

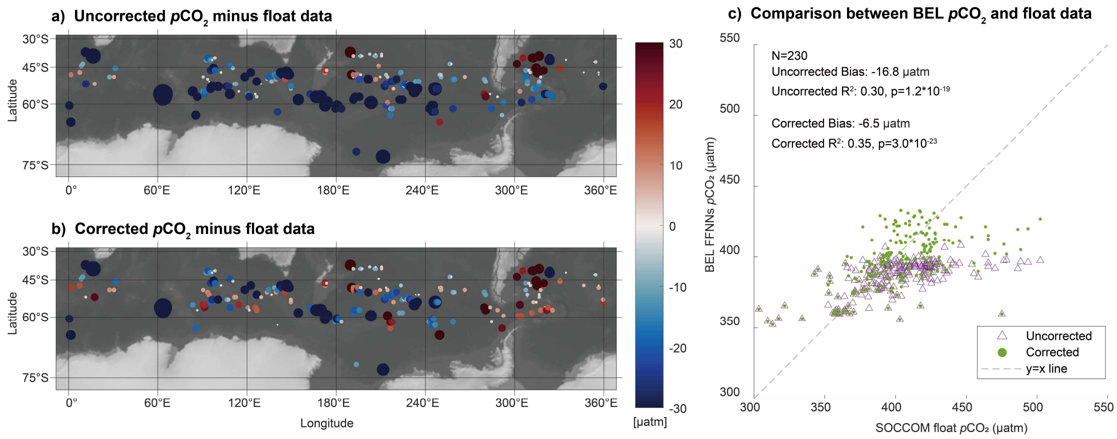

Figure S1. Comparison between BEL FFNNs pCO_2 trained on SOCAT data and the independent SOCCOM float pCO_2 observation during June-September since 2014. a): bias between uncorrected BEL FFNNs pCO_2 and SOCCOM float data; b): bias between corrected BEL FFNNs pCO_2 and SOCCOM float data; larger bubbles represent that the BEL FFNNs pCO_2 is more biased, and blue bubbles represent lower BEL pCO_2 than the float data; c) statical comparison between BEL FFNNs pCO_2 and SOCCOM float *p*CO_2. Uncorrected BEL *p*CO_2: trained on SOCAT dataset using boosting ensemble learning FFNNs; Corrected BEL *p*CO_2: result after applying a winter correction by training BEL FFNNs on only winter SOCAT samples. SOCCOM float *p*CO_2: monthly and 1° averaged results from SOCCOM data at depths of 2.77-5.00 m from 2014 to 2019 (Johnson et al., 2017).

Bushinsky, S. M., Landschützer, P., Rödenbeck, C., Gray, A. R., Baker, D., Mazloff, M. R., ... & Sarmiento, J. L. (2019). Reassessing Southern Ocean air-sea CO_2 flux estimates with the addition of biogeochemical float observations. *Global Biogeochemical Cycles*, *33*(11), 1370-1388.

Johnson, Kenneth S.; Riser, Stephen C.; Boss, Emmanuel S.; Talley, Lynne D.; Sarmiento, Jorge L.; Swift, Dana D.; Plant, Josh N.; Maurer, Tanya L.; Key, Robert M.; Williams, Nancy L.; Wanninkhof, Richard H.; Dickson, Andrew G.; Feely, Richard A.; Russell, Joellen L. (2017). Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM) Float Data Archive. UC San Diego Library Digital Collections. https://doi.org/10.6075/J0TX3C9X.

Decision letter and referee reports: third round

15th May 24
Dear Professor Li,

Your manuscript titled "Melting sea ice will weaken carbon sinks in the Southern Ocean" has now been seen by our reviewers, whose comments appear below. In light of their advice we are delighted to say that we are happy, in principle, to publish a suitably revised version in Communications Earth & Environment under the open access CC BY license (Creative Commons Attribution v4.0 International License).

We therefore invite you to revise your paper one last time to address the remaining concerns of our reviewers. At the same time we ask that you edit your manuscript to comply with our format requirements and to maximise the accessibility and therefore the impact of your work.

EDITORIAL REQUESTS:

Please review our specific editorial comments and requests regarding your manuscript in the attached "Editorial Requests Table".

*****Please take care to match our formatting and policy requirements. We will check revised manuscript and return manuscripts that do not comply. Such requests will lead to delays. *****

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If you have any questions or concerns about any of our requests, please do not hesitate to contact me.

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We hope to hear from you within two weeks; please let us know if you need more time.

Best regards,

Dr Alireza Bahadori
Associate Editor
Communications Earth & Environment

REVIEWERS' COMMENTS:

Reviewer #4 (Remarks to the Author):

Dear Authors,
The revised manuscript looks much better for me, I endorse the publication of it with some additional changes to be added:

-all the equations have to be rewritten using latex form.

-the line number needs to be added in the articles

-Also the references need to be numbered as well.

Author responses: third round

Reviewer #4:

Dear Authors,

The revised manuscript looks much better for me, I endorse the publication of it with some additional changes to be added:

-all the equations have to be rewritten using latex form.

Response: All equations in the manuscript have been rewritten using latex form.

-the line number needs to be added in the articles

Response: Thanks for the suggestion, we have added the line number.

-Also the references need to be numbered as well.

Response: The reference have been numbered in the order of appearance.