Review of bg-2017-64
Global high-resolution monthly pCO_2 climatology for the coastal ocean derived from neural network interpolation by Laruelle et al.
Reviewer: Rik Wanninkhof, NOAA/AOML
This is largely a descriptive paper of procedures to create monthly estimates of coastal pCO_2 levels. As mentioned in the abstract, Laruelle et al. use a modified version of a two-step artificial neural network method (SOM-FFN) to interpolate the pCO_2 data along the continental margins with a spatial resolution of 0.25 degrees and with monthly resolution from 1998 until 2014.
The effort is clearly an impressive one and an important contribution to coastal ocean science. However there are some shortcomings. Many readers will not fully understand the approach and assumptions in SOM-FNN. and this needs more discussion. The manuscript lacks in context and interpretation. Some of the procedural shortcomings that were in the initial global open ocean effort as described in Landschützer et al., (2013; 2015) prevail.

We are grateful for the reviewer's evaluation and his constructive suggestions. Please find bellow a detailed answer to each comment. All our answers are written in.
On behalf of all co-authors,

Goulven Laruelle

We have introduced a new section to the manuscript, which critically discusses the strength and weaknesses of the approach and its changes since the first open ocean version from Landschützer et al. (2013). This new section permits to better appraise the improvements achieved by tailoring the oceanic set-up for the coastal region and identify the remaining knowledge gaps.
We further understand that one of the main reviewer's concerns relates to the choice of validating the results using a database that largely overlaps with the one used to calibrate the model. Following his recommendation, we modified our approach and, using the latest versions of both SOCAT (i.e. version 4) and LDEO (i.e. v2015), we have now created two entirely independent datasets: one for the calibration (named SOCAT*) and one for validation (LDEO*). These two datasets were generated by randomly assigning each measurement common to both original databases to either SOCAT* or LDEO* (see comment 3 below for further details on the new approach). Another important suggestion was to further elaborate on the comparison between the simulated pCO_2 field and the validation dataset. We thus created new maps displaying the mean residuals errors between the pCO_2 values generated by the SOM_FFN, on the one hand, and those extracted from LDEO* and SOCAT*, on the other hand. This representation allows for a more detailed analysis of the performance of the model. As suggested by the reviewer, histograms of residual errors were also computed for each biogeochemical province and will be discussed in the updated manuscript. In addition, we have also introduced a new predictor (wind speed), which helped improve the performances of the SOM_FFN compared to those presented in the previous version of the manuscript.

While there are comparisons and validations of the SOM-FNN approach it mostly in terms of a RMSE. It is unclear what impact the RMSE would have on the phenomena investigated. Other means of comparison of how well the approach works should be performed. Rödenbeck et al (2015) present some nice diagnostics that could be applied.

At very least examples of the distribution of errors in pCO_2 should be shown in histograms.

[1] We agree with the reviewer that the assessment of the performance of the model only relied on averaged biases and RMSE calculated for each biogeochemical province. In the updated manuscript, we propose to include maps presenting the average residual errors between the pCO_2 field generated by the model and pCO_2 data extracted from the calibration (SOCAT*) and validation (LDEO*) datasets. They are obtained by subtracting the observed values from model output in each grid cell for every month where observations are available. This representation not only allows to assess which regions provide the best match with the observations but also to identify where the simulated pCO_2 overestimates (positive values, in red on the figure below) or underestimates (negative values, in blue on the figure below) the field data. Moreover, as suggested by the reviewer, we introduce a new figure, presenting the distribution of the residual errors between the results of the SOM_FFN and LDEO* for each biogeochemical province. This figure reveals nearly Gaussian distributions of the residuals for every biogeochemical province with the exception of province P8, for which the spread is not only the highest (indicating the largest discrepancy between model and observations), but also slightly skewed toward high values, thus revealing a tendency to overestimate the observed pCO_2.

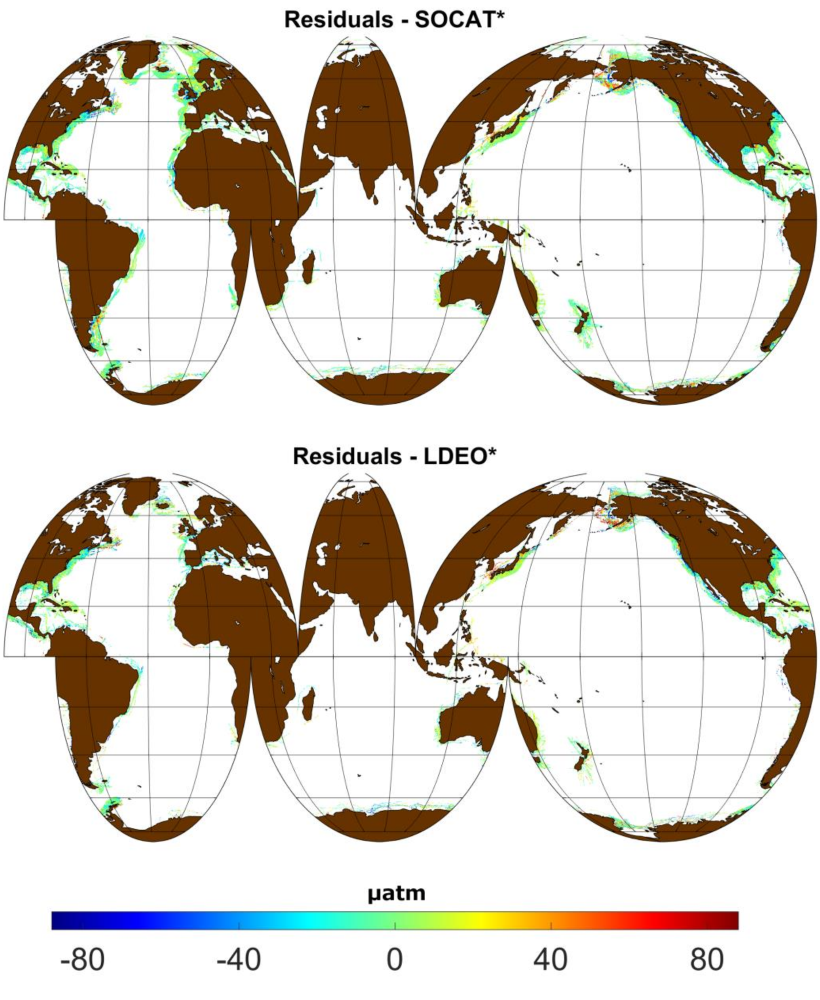

Figure 1: Mean residuals calculated as the difference between the SOM_FFM pCO_2 outputs and pCO_2 observations from SOCAT* (top) and LDEO* (bottom).

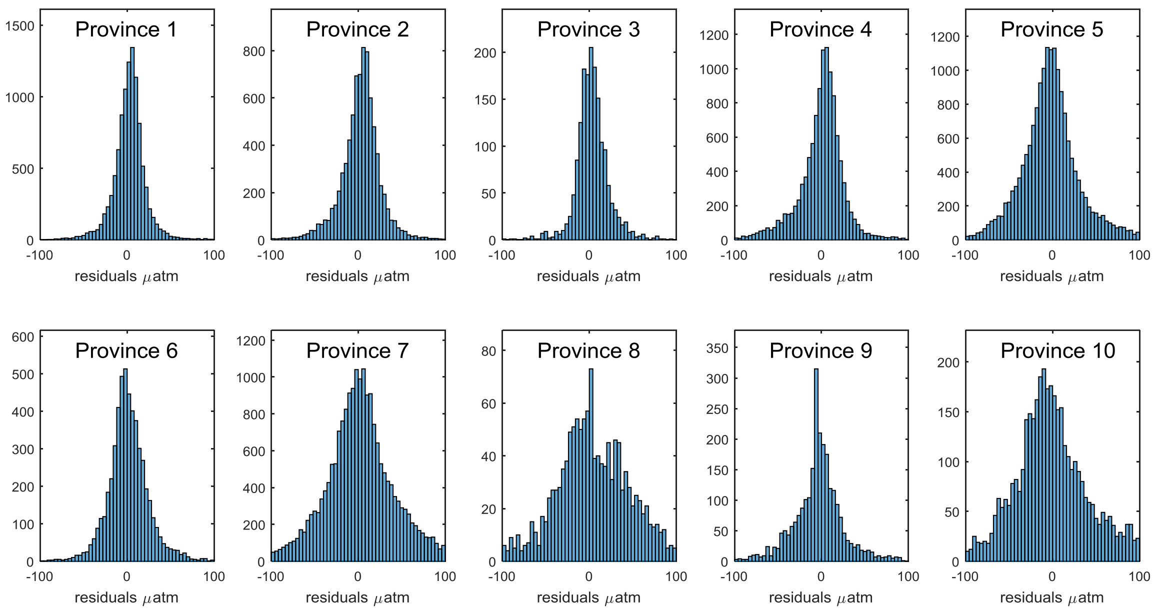

Figure: Histograms reporting the distribution of residuals between observed (LDEO*) and computed (SOM_FFN) pCO_2 in each biogeochemical province.

As the authors indicate, their definition of the coastal realm (200 nm or 1000 m depth) covers a much greater region than commonly viewed as coastal. The outer edge of the domain for much of the ocean can be considered "blue water". Therefor it is surprising that the differences between the coastal SOM-FFNN and open ocean SOM-FNN in Landschützer et al. are large. A more comprehensive diagnostic comparison should be made as it could suggest some fundamental issues with the approach.

[2] Although both the coastal SOM_FFN presented in this study and the oceanic SOM_FFN published in Landschützer et al. have a significant overlapping domains, they were not trained with the same datasets. For the most part, the coastal data from SOCAT used here to calibrate our model were not included in the data pool used for the open ocean simulations. In addition, the characteristic ranges of values within which both models are trained are also different for some of the environmental parameters. In particular, the average bathymetry and sea surface salinities are often significantly lower for data used. It is thus not surprising to observe significant differences between the results produced by both models, yet we agree with the reviewer that the magnitude of difference is somewhat interesting and highlights current knowledge gaps regarding the coastal ocean to open ocean transition zone. This certainly deserves some further investigation; however, we do believe that this is beyond the scope of this study. Nevertheless, in the updated manuscript, we will further discuss the differences between coastal and open SOM-FFN in the transition zone.

The validation approach is weak. There is significant (complete?) overlap between the data in SOCAT and that of Takahashi. The biases in datasets are likely due to different data reduction approaches. More comparisons should be made with actual data not used in the training, and more data should be excluded from the training for validation purposes.

[3] As mentioned by the reviewer, the SOCAT and LDEO databases have a large overlap, and the two datasets cannot be considered independent. In order to provide robust calibration and validation we now created two fully independent datasets based on SOCAT and LDEO, which do not contain any common measurement. We used the latest releases of both databases (i.e. SOCATv4 and LDEOv2015) and filtered out all non-coastal data points, as was already done in the previous version of the manuscript. Under our definition of the coastal zone, SOCATv4 contains ~8 10^6 data points and LDEO ~5.6 10^6, over 70% of which are also part of SOCATv4. We then randomly assigned each of those common data point to either database to insure that each data only belongs to one dataset. In the updated manuscript, the new datasets are renamed SOCAT* which is used to train the SOM_FFN, and LDEO* which is only used for validation purposes. In the new manuscript, the procedure used to create SOCAT* and LDEO* will be detailed in section 2.2 (Data Sources and processing).

The use of a more robust validation did not alter significantly the performances of the SOM_FFN and, combined with the inclusion of wind speed as a new predictor, the biases and RMSE generated by the model when compared with LDEO* are actually slightly lower than those presented in the original simulations (see table below). Also, note that the use of SOCATv4 and LDEOv2015 provides a significant number of data for the year 2015, which motivated us to expend our simulation period from 17 to 18 years.

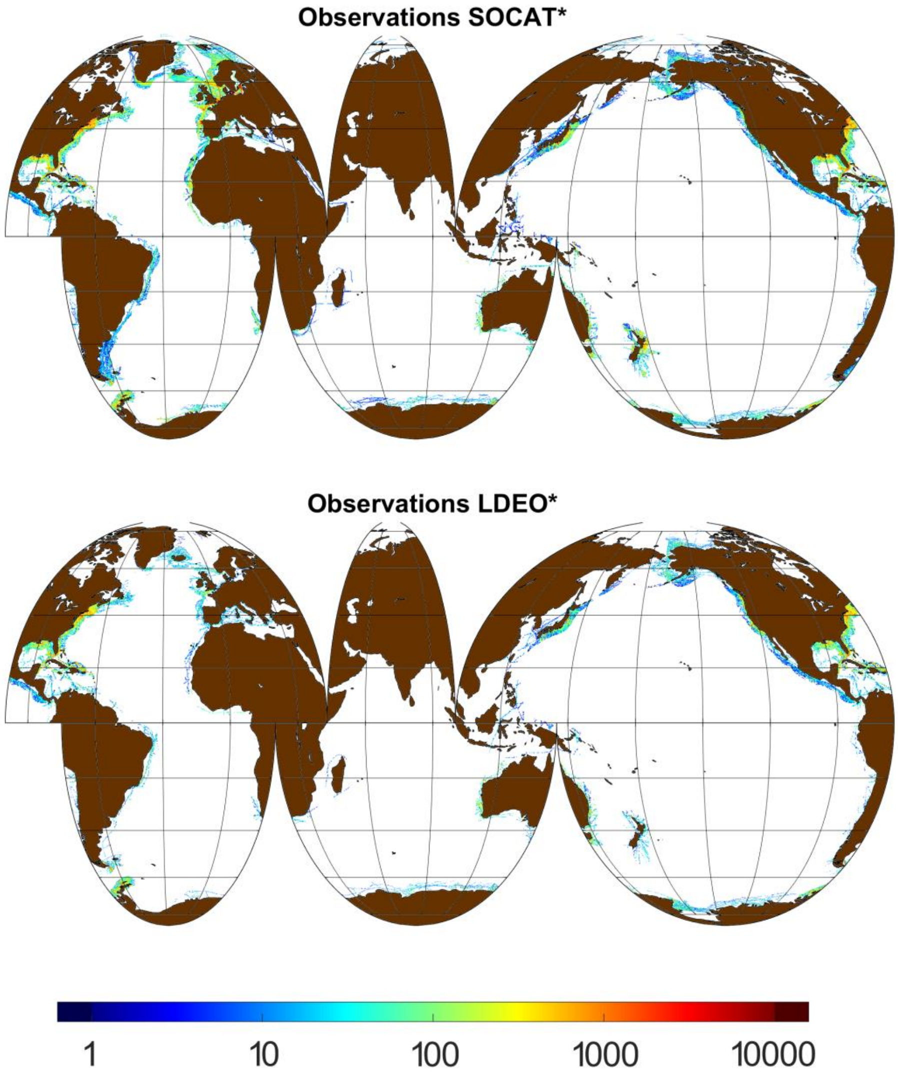

Figure: Number of observations contained in each 0.25° grid cell of the SOCAT* (top) and LDEO* (bottom) databases.

Table: Root mean squared error between observed and calculated pCO_2 in the different biogeochemical provinces. The SOM-FFN results are compared to data extracted from the SOCAT* and the LDEO* databases.

	SOCAT*		LDEO*	
Province	**Bias (µatm)**	**RMSE (µatm)**	**Bias (µatm)**	**RMSE (µatm)**
P1	0.0	19.1	2.0	20.5
P2	0.2	24.7	1.3	27.2
P3	-0.3	16.1	2.3	22.7
P4	-0.2	31.2	-1.6	33.0
P5	0.0	34.2	-1.4	38.0
P6	0.0	24.3	1.3	27.9
P7	0.1	37.2	-0.2	52.5
P8	0.2	46.8	3.9	51.4
P9	-0.1	23.0	-2.5	33.4
P10	0.0	35.7	1.6	53.1
Global	0.0	32.9	0.0	39.2

It is unclear how the change in surface water over time is dealt with. Are the pCO_2 data normalized like in the Takahashi monthly climatology? SST and SSS from the WOA are used but are these monthly climatologies that do not reflect change over time. This exercise provides monthly maps from 1998-2014 and it is clear how this is done. Also, the product is referred to as a climatology but it sounds like it is a monthly time series. That is, climatology mostly refers to a (multi) decadal average.

[4] During the training of the SOM_FFN, all pCO_2 data from SOCAT* are associated to a set of environmental conditions corresponding to the location and moment in time when the pCO_2 was measured. The relationships linking pCO_2 to environmental conditions as established by the FFN are then applied in each cell of the simulation domain for each of the 216 month of the simulation period. The inputs used for these calculations are 3 dimensional fields (latitude, longitude and time) containing values for each grid cell at every monthly time step. We will make sure to clarify this procedure in the updated manuscript. All the data used as inputs for both SOM and FFN are thus monthly times series and no normalization was applied to the data as was performed in Takahashi et al. (2009).
We realize that our frequent use of the word climatology may be misleading as to what our product really is. In the updated manuscript and the abstract, we will state more clearly that our calculations are performed for every month of the simulation period and thus produce monthly maps for each of the years simulated. Only then, a monthly climatology is derived from those results.
Also note that, in the new simulations, SST and SSS data are not taken from the World Ocean Atlas anymore but from the Met Office's EN4: quality controlled subsurface ocean temperature and salinity profiles and objective analyses (Good et al., 2009). This change was implemented following a comment from reviewer #2 regarding mismatches in spatial resolution of some datasets (the new SST/SSS datasets are at the spatial resolution of 0.25 degree as opposed to WOA which only provides values at 1 degree).

The grouping of provinces such that a coastal region can include an inshore and open ocean province is odd. Perhaps limit the coastal area to just one province

[5] The biogeochemical provinces generated by the Self Organizing Maps regroup ensembles of cells together because of similarities in their environmental characteristics. Within each biogeochemical province, however, some variability can be found and, while bathymetry may significantly contribute to the grouping of cells within a given province, so do the other environmental parameters (i.e. SSS, SST, wind speed and sea ice). As a consequence, some provinces have an extension that includes nearshore and more open waters but for which the range of temperature for example might be limited (see figure below displaying the spatial extent of the updated biogeochemical provinces). The choice to use the SOM and divide the coastal ocean into several provinces as was done for the open ocean in Landschützer et al. (2013) was motivated by the large variety of environmental settings that can be found in the coastal ocean. The current number of 10 provinces was selected as the optimal number during the calibration phase. When developing the model, several simulations were performed with the SOM using increasing numbers of biogeochemical provinces (from 6 to 20) and 10 was the number of biogeochemical provinces yielding the best results in terms of RMSE when compared with both SOCAT and LDEO databases. This number of biogeochemical provinces also guarantees that sufficient data will be located in each biogeochemical province, thus insuring both a proper training of the algorithm and the possibility of a validation against a significant number of observations. For instance, the spatio-temporal distribution of the biogeochemical provinces used in our last simulation allows for at least 1000 different grid cells to be used for validation against LDEO*.

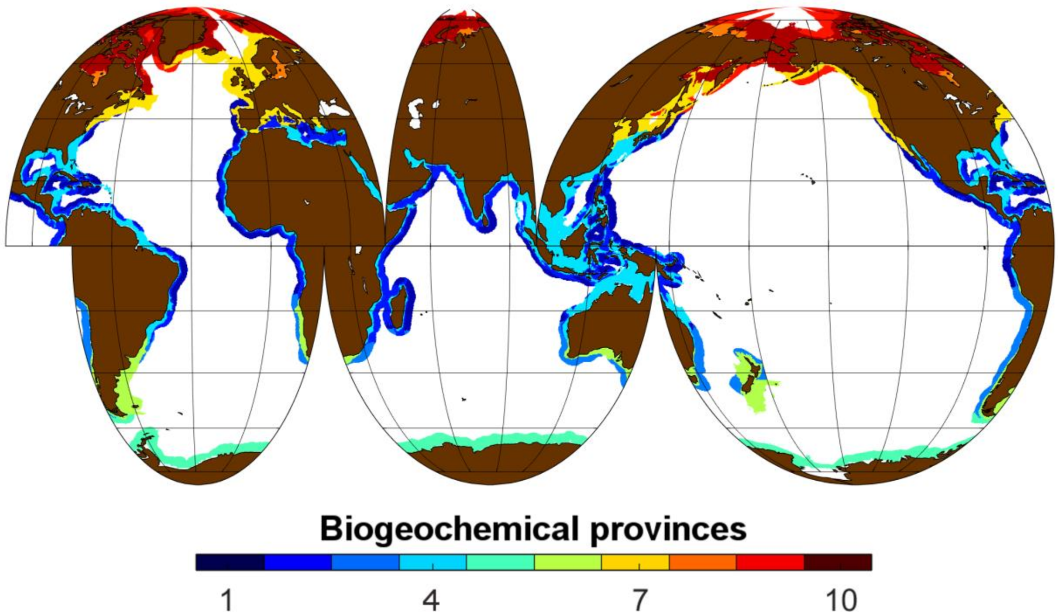

Figure 1: Map of the 10 different biogeochemical provinces generated by the SOM.

It is difficult to assess the data density for the different provinces using as validation or training.

[6] We understand the reviewer's concern and agree that, in the original version of the manuscript, limited information was provided regarding the spatial distribution of the

pCO_2 data used for calibration or validation. In the updated manuscript, a new figure (see comment [3]) now shows the data density of the SOCAT* and LDEO* databases for each grid cell of the simulation domain, thus providing a clear view of the amount and spatial distribution of data used both for calibration and validation..

Specific comments often relating to the general observations are below. The referenced text is in italics:
Line 125:" *motivated a number of modifications of the global ocean SOM-FFN method, including a 16 fold increase in spatial resolution from 1 degree to 0.25 degree, the introduction of a second neuron layer in the FFN calculations, the addition of new environmental variables as biogeochemical predictors, and a shortening of the simulation period to the period 1998 through 2014, rate of sea ice SST, SSS, bathymetry, sea-ice concentration and chlorophyll a second artificial neuron layer*". Some more detail on how these modification impact the results would be worthwhile .

[7] As mentioned by both reviewers, the different modifications introduced compared to the original set-up of the global ocean SOM_FFN are only mentioned in our method section but not discussed in details in our results. In the updated manuscript, we discuss the impact of those modifications (i.e. resolution and new predictors such as sea ice and wind speed). For instance, the added value of performing our simulations at the spatial resolution of 0.25° is discussed using examples such as the ability of our model to capture the plumes of larges rivers such as the Amazon, which produces an area located North of its river mouth characterized by pCO_2 values significantly lower than those of the surrounding waters (Cooley et al., 2007; Ibanez et al., 2015). The new discussion will also involve the addition of results from simulations performed only using SST, SSS, bathymetry and chlorophyll as predictors (as suggested by reviewer #2). The results of those simulations are presented in the table below and allow quantifying how the addition of new predictors affects the performance of the model. For instance, it can be noticed that, overall, the global RMSE increase significantly (from 39.2 to 48 µatm in the comparison with LDEO* when chlorophyll, sea ice and wind speed are not taken into account and from 39.2 to 45 µatm when only sea ice and wind speed are not taken into account). This deterioration of the performance of the model, however, is not evenly affecting all provinces and it can be observed in particular that provinces located at high latitudes (i.e. P8, P9 and P10) perform significantly worse without the inclusion of wind speed and sea ice.

Table: Biases and root mean squared error (RMSE) between observed and calculated pCO_2 using only SST, SSS and bathymetry (STB) or SST, SSS, bathymetry and chlorophyll (STBC) as predictors.

	SOCAT*				**LDEO***			
Province	**Bias (µatm)**		**RMSE (µatm)**		**Bias (µatm)**		**RMSE (µatm)**	
	STB	STBC	STB	STBC	STB	STBC	STB	STBC
P1	0.0	-0.2	20.8	21.0	2.4	2.0	21.7	21.5
P2	-0.1	0.1	26.9	27.8	0.5	0.8	29.0	29.6
P3	0.0	-0.5	22.7	21.3	3.0	2.3	27.1	26.8
P4	0.0	-0.2	33.0	33.0	-1.7	-2.3	33.8	33.8
P5	0.2	0.1	52.7	42.2	-1.7	-0.9	56.9	44.5
P6	0.0	0.1	26.8	26.5	-0.5	0.6	28.9	28.0
P7	0.4	0.3	44.3	44.1	1.2	0.3	59.3	58.8

P8	0.1	0.4	82.6	80.0	9.1	9.0	56.3	58.5
P9	0.1	0.9	34.7	36.5	-2.6	-2.8	39.8	41.8
P10	-0.3	0.7	49.8	49.5	-3.9	-3.0	76.5	75.4
Global	0.1	0.2	43.9	42.4	0.0	0.0	48.0	45.0

Line 175: "*SOM-FFN from generating negative values*." This suggests that there are issues with the original setup. Adding a second neuron layer to prevent negative values certainly is unorthodox.

[8] The SOM-FFN method is some form of a non-linear regression model, which in cases of bad conditioning also produces out of range values. We point here that the negative values do not suggest issues with the model as a whole, but rather issues with the setup of the model. While we did not face the problem of negative values using a standard hidden layer in the open ocean, the added complexity combined with little data in certain province can cause this behaviour in coastal seas. For instance, there exist very few measurements for shallows waters with very low salinity and high sea ice coverage. Faced with conditions for which it was not trained, the SOM_FFN does not perform ideally and may generate unrealistic values. In our original manuscript we solved this by introducing a second hidden layer of neurons, however, we found a more stable solution in terms of negative values, i.e we replaced the second neuron layer with the use of a sigmoid activation function bounded between 0 and 1 (normalized pCO_2 units) in the hidden layer. This means that per definition our results are bound to stay above 0. The implementation of this solution did not deteriorate the overall results but prevented the SOM_FFN from generating negative pCO_2 values. The new simulations for the revised manuscript were thus carried out with this new setting, which now only uses a single neuron layer.

Line 193: "*All the datasets used in our calculations were converted from their original spatial resolutions to a regular 0.25 degree resolution grid*." Specify what the original resolution was for each dataset.

[9] A more thorough description of the datasets used in the study will be included into section 2.2 (Data Sources and processing). This description explicitly states the original temporal and spatial resolution of each dataset used. This information will be compiled in the new table reported below. In addition, for the sake of reproducibility, a link toward all datasets used will be provided in the 'Data Availability' section at the end of the manuscript. Note that, as already reported in comment 4, all our products have now an original resolution of 0.25° or finer.

Table: Datasets used to create the environmental forcing files. The original spatial and temporal resolution and the main manipulations applied for their use in the SOM_FFN are also reported.

Predictor	dataset	resolution	reference	Manipulation
SST	EN4	0.25°, daily	Good et al., 2013	Monthly average
SSS	EN4	0.25°, daily	Good et al., 2013	Monthly average
Bathymetry	ETOPO2	2 minutes	US Department of Commerce,	Aggregation to 0.25°

			2006	
Sea ice	NSIDC	0.25°, monthly	Cavalieri et al., 1996	Monthly rate of change in sea ice coverage
Chlorophyll a	SeaWifs, MODIS	9km, monthly	NASA, 2016	Aggregation to 0.25°
Wind speed	ERA	0.25°, 6hours	Dee et al., 2011	Monthly average

Line 196: "*SST and SSS maps were taken from the World Ocean Atlas (Antonov et al., 2010 for SST and Locarnini et al., 2010 for SSS)*." Are these monthly climatologies or monthly time series? If the former it is unclear how the time element from 1998-2014 is incorporated.

[10] The new simulations do not use SST and SSS from the World Ocean Atlas anymore but from the Met Office's EN4: quality controlled subsurface ocean temperature and salinity profiles and objective analyses (Good et al., 2009). Those data are time series and contain individual values in each grid cell of the simulation domain for each of the 216 month of the simulation period. Additional information regarding the incorporation of the time element in our calculation is included in answer [4] and the updated manuscript will be more explicit with respect to the way our calculations are performed.

Line 203 and beyond: " *validation are extracted from the LDEOv2014 database The coastal SOM-FFN results are validated through a comparison with the LDEOv2014 data (Takahashi et al., 2016)*." This is not independent data and not a proper validation in statistical sense.

[11] As discussed in the answer to reviewer's comment [3], we fully agree that the original validation was significantly weakened by the large overlap between SOCAT and LDEO. Now that we created two entirely independent datasets to train the model (SOCAT*) and evaluate its performances (LDEO*), we believe that the term "validation" is now appropriate for the updated manuscript.

Line 280: "*Considering these complexities, the achieved RMSE is quite good*." Two issues here. How are the complexities determined? That is, we know the coastal region is complex but it is unclear if the complexity is incorporated into the analysis using T, S, chl-a and sea ice. And, based on what criteria is the RMSE quite good.

[12] It is true that the coastal region is known to be a complex environment and that was the main message of this sentence. Whether our analysis capture the intricate complexity of the coastal zone has to be indeed better discussed in the revised manuscript. We will thus further develop the section dedicated to the discussion and quantification of the effects induced by modifications in SOM_FFN configuration on its performance (see answer to comment [7]). With respect to the RMSE, our criteria to consider the performance of our model 'quite good' is the comparison with the RMSE reported in regional studies . This is further discussed in the answer [13] below.

Line 306:" *which compares with the most robust pCO2 regional coastal estimates from the literature (Chen et al., 2016*)". Chen et al. 2016 use a crude remote sensing approach. These are by no means "most robust".

[13] The paper by Chen et al. (2016) indeed presents pCO_2 fields for the Western Florida shelf generated using remote sensing. Such methodology certainly is different and arguably less sophisticated that the method described in our study. However, we did not mean to directly compare the performance of our model with those of Chen et al. (2016). Our aim was to find as many recent studies as possible to compare our results and to gain some confidence in our estimates. Their study reports (table 1, page 12) a list of regional coastal models generating pCO_2 fields derived from other environmental factors. Although the methods used in this list varies greatly (including Mutiple Linear Regressions, Mechanistic semi analytical models and Self Organizing Maps), we believe it was relevant to confront the performance of our model applied globally with those of other coastal models, which are only applied at regional scale in well covered areas. What we meant to say is that there exist a body of literature using various methodological approaches to generate pCO_2 fields and the article by Chen was mostly used for his table. Nevertheless, following the reviewer's comment, we will tone down our statement that our results compare with the most robust estimates from the literature. Rather, we'll state that the RMSE calculated in our best constrained biogeochemical provinces (i.e. in the 20-30 μatm range for P1, P2, P3 and P6) can be compared with those obtained by regional models applied in well monitored areas.

Line 349: "*highlight the current knowledge gap regarding the mean state and variability of the transition zone.* " It is unclear if this highlights a knowledge gap or highlights issues wit the SOM_FNN approach. This warrants some discussion

[14] We agree with the reviewer's comment (as well as similar concerns' raised by reviewer 2) and recognise that the original version of the manuscript only briefly compared the results of the updated coastal SOM_FFN with those of the original oceanic model. In the updated manuscript, a more in depth comparison with the results of the open ocean configuration will be provided. This will allow better identifying the added value of the modifications done to the SOM_FFN method in our study and help clearly identify remaining knowledge gaps.

Line 358: "*Our results indicate that the very nearshore processes controlling the CO2 dynamics likely*" Again the SOM-FNN is a mathematical construct. So I guess what the authors are stating is that the SOM-FNN cannot address adequately nearshore dynamics.

[15] The reviewer is correct; this sentence was meant to stress that, in spite of the improvement provided by the new method, some very nearshore processes still cannot be addressed perfectly. As the reviewer pointed out, the problem does not lie with the mathematical approach used by the spatial resolution required to capture very nearshore processes. The sentence was rephrased as follows:
"***Overall, the occurrence of large residuals in the shallowest cells of our calculation domain in*** our results ***(fig. 2) suggest*** that the very nearshore processes controlling the CO_2 dynamics likely are the most difficult to reproduce ***at the global scale.***"

Line 429 "2 ". The "n" generally refers to salinity normalization. Perhaps use pCO2(SSTmean) .

[16] We will follow the reviewer's suggestion in the updated manuscript and use pCO_2(SSTmean) instead of $npCO_2$.

Line 470: "*cells at a 0.25° spatial resolution for each of the 204 month of the simulation period (from January 1998 to December 2014). Climatologically averaged pCO2 maps for each month are*". The use of the term climatology is ambiguous here.

[17] We agree with the reviewer, the term climatology is ambiguous in this sentence and elsewhere. To avoid any confusion, the paragraph was rephrased as follows:

"The data product associated to this manuscript consists of a netcdf file containing the pCO_2 for ice-free cells at a 0.25° spatial resolution for each of the ***216*** month of the simulation period (from January 1998 to December ***2015***). ***12 maps representing mean pCO_2 fields calculated for each month over the simulation period*** are also provided."

Line 471: The province names are peculiar "Deep Polar, Polar Very deep Polar"

[18] Our choice of names for the different biogeochemical provinces was only meant to outline their main geographical distribution. Both reviewers commented on the lack of added value of the distributions of the biogeochemical provinces. In the updated manuscript, the biogeochemical provinces will only be referred to as P1, P2 and so on to avoid confusion. Section 3.1 however, will still discuss the spatial extent of the each biogeochemical province.

Table 1 suggests that Ice is a predictor in the tropics?

[19] We agree that the use of Ice as predictor in the tropics is not relevant, however Ice cover in the tropics in our predictor dataset was 0 at all times, and hence it did not influence the neural network. To avoid confusion, in the updated simulation, Ice is only a predictor in provinces P5 to P10, in which at least partial seasonal ice coverage is reported.

Table 2: List of the biogeochemical provinces, their geographic distribution and the environmental predictors used to calculate surface ocean pCO_2. SSS stands for sea surface salinity, SST for sea surface temperature, Bathy for bathymetry, Ice for sea-ice cover, Chl for chlorophyll concentration ***and Wind for wind speed***.

Province	SSS	SST	Bathy	Ice	Chl	Wind
P1	X	X	X		X	X
P2	X	X	X		X	X
P3	X	X	X		X	X
P4	X	X	X		X	X
P5	X	X	X	X	X	X
P6	X	X	X	X	X	X
P7	X	X	X	X	X	X

P8	**X**	**X**	**X**	**X**	**X**
P9	**X**	**X**	**X**	**X**	**X**
P10	**X**	**X**	**X**	**X**	**X**

Also P3 and P4 appear to have the same "distribution".

[20] In the original simulations, provinces P3 and P4 did not display exactly the same spatio-temporal distribution but were both referred to as "Deep Tropical" which could indeed lead to confusion. Actually, the average water depth of cells included in P4 was deeper than that of those included in P3 and, P4 generally characterized more 'open waters'. As mentioned in answer [5], the updated manuscript will describe and discuss the spatial distributions of the 10 biogeochemical provinces but the restrictive 'distributions' will be removed from table 1.

Figure 1 shows a peculiar extension off of New Zealand. Is this the Chatham Rise and is this considered coastal?

[21] The extension Southward and Eastward of New Zealand are the Campbell Plateau and Chatham Rise, respectively. They are considered coastal following our 'extended' definition of the continental shelf and upper slope because they are characterized by depth shallower than 1000m (our outer limit) and connected to a continental platform.

Figure 2: Perhaps comment on the absence of high pCO_2 in the SOM-FNN for the summer monsoon upwelling region in the Arabian Sea. Data of the Takahashi climatology clearly show this. Figure 2 does not show the high pCO_2 Arabian Sea seasonal (JAS) upwelling off the coast of the Arabian Peninsula.

[22] It is true that high pCO_2 values have been regularly observed along the coast of the Arabian Sea (Sarma et al., 2003) and are considered to be the consequence of monsoon driver upwelling occurring in the region. As noted by the reviewer, the SOM-FFN does not reproduce these oversaturated waters. We now mention and discuss the inability of the SOM_FFN to reproduce this known feature of the Arabian shelf in section 3.3.1, which discusses the general spatial patterns of the pCO_2 fields generated by the model.

Literature cited in the responses:

Cavalieri, D. J., Parkinson, C. L., Gloersen, P., and Zwally, H.: Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data, years 1990–2011, NASA DAAC at the Natl. Snow and Ice Data Cent., Boulder, Colo. (Updated yearly.), 1996.

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