

Biogeosciences Discuss., referee comment RC2  
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## Comment on bg-2021-344

Anonymous Referee #2

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Referee comment on "The sensitivity of  $p\text{CO}_2$  reconstructions in the Southern Ocean to sampling scales: a semi-idealized model sampling and reconstruction approach" by Laique Merlin Djeutchouang et al., Biogeosciences Discuss.,  
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### Summary and overall impression

The paper addresses an important question for the global carbon cycle community: how to reduce the uncertainties and biases of machine-learning based mapping approaches in the Southern Ocean, a data-sparse but globally important region. The authors create synthetic data by subsampling a high-resolution model in a subregion of the Southern Ocean over 1 year. The synthetic data resembles different observational platforms in terms of the typical temporal resolution of the different platforms. These platforms include ship, float, Windglider, and Saildrone data. They then run two different machine learning mapping approaches with these synthetic observations and compare the mapped reconstruction of the seasonal cycle to the actual model field to estimate the biases and uncertainties. They run the method multiple times with different subsets of synthetic data to highlight how sampling in different seasons, as well as with different types of observational platforms affect the uncertainty and bias. They find that the addition of wintertime ship data would greatly reduce the errors in the reconstructions. They also find that Saildrones are an optimal platform to address both the large-scale spatial and high-resolution temporal sampling and have the most effective impact on reducing the uncertainties and biases of the seasonal and annual mean reconstructions of air-sea  $\text{CO}_2$  fluxes in the Southern Ocean.

This paper addresses a crucial gap in our current knowledge and provides suggestions on how the carbon cycle community can improve current estimates of the Southern Ocean carbon fluxes, through an improved sampling strategy. I very much support the method of using synthetic data to create a sampling strategy, the paper is well-written and has clear figures that support the findings. However, I have some major comments, which I believe should be addressed before publication. In my review, I mostly focus on the Methods section, as requested by the editor.

## General comments

- My main concern is that the machine-learning approach used to reconstruct the model fields is very different to the common methods (e.g., by Landschuetzer, and Gregor...) and thus, I am not convinced that the lessons learned from the authors' approach can be directly translated to these methods. Specifically, the established mapping methods use training data from quite large regions (from a clustering step), which are a lot bigger than the region of this study. Thus, more data flows in, and they might be more robust to be able to reconstruct the seasonal cycle despite the sparsity in winter data. In addition, there are zonal differences and hot spots of in the Southern Ocean, and the subregion might not be representative for the Southern Ocean as a whole. I do think we can still learn from this current study, but this issue should be discussed thoroughly. A follow-up study could later focus on the Southern Ocean as a whole (or even globally within e.g., the clusters by Landschuetzer or Gregor et al.).
- I think it's great that the authors use an ensemble of two ML-based approaches. However, I would appreciate a short analysis of how the two estimates differ, to understand how robust the findings are.
- The authors say that there is very limited data to allow for both training and testing/validation data. But how do the authors then know that the outcome is not overfitted? As the data is synthetic, could one not add more synthetic data that would then allow for both training and testing data?

## Specific and minor comments to the text:

### Introduction:

I found the introduction a bit misleading. After reading the introduction, I expected that the paper would include the interannual to decadal variability, but it "only" focuses on the seasonal cycle based on data from one year. Consider rephrasing this to not disappoint the reader.

Similarly, the introduction should mention clearly that this study "only" focuses on a subregion within the Southern Ocean.

Gloege et al. 2021 did an in-depth analysis of the uncertainty of ML-based mapping

approaches, using synthetic data at a global scale. I think the introduction should mention that study and be explicit about how this current approach differs and what's new about this study in comparison.

L.114: It's mentioned later that how well the model matches the observations does not really matter in this context. However, please consider mentioning here already why using that model works (considering e.g., the Mongwe et al. 2018 study that showed how the CMIP models completely disagree on the phase and magnitude of the seasonal cycle).

L.196: Is this really the case? I would assume that any differences between the model and the observations could matter. I.e., the model might be generally a lot smoother than reality and thus the sampling strategy might be less sensitive in the model than in the real world. I would appreciate a short discussion on that.

L.335: I think the explanation of error and uncertainty is the wrong way round.