Evaluating pCO₂ interpolation methods using large ensembles preliminary results

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I. Introduction

- •25% of anthropogenic CO₂ is annually taken up by and acidifying the ocean.¹
- •Accurately quantifying ocean uptake is imperative for the global carbon budget¹ and assessing whether the goals of the UNFCC Paris climate agreement are being achieved.
- Surface ocean CO_2 atlas (SOCAT) provides a monthly gridded product of ocean p CO_2 observations.²
- SOCAT observations are sparse with time at any given location (Figure 1). A neural network based approach has been developted to provide monthly maps of global ocean pCO₂ estimates.^{3,4}

Months with measurements







• Here, we present preliminary results from a testbed using large ensembles capable of evaluating the performance of pCO_2 interpolation methods.

II. Methods

The large ensemble testbed

1. Sample 25 members from CESM⁵ and GFDL⁶ large ensemble like SOCAT monthly gridded product²



2. Provide monthly global maps from each member for inputs to the neural network interpolation method



3. Reconstruct pCO_2 using a two-step

neural network^{3,4} driven by global maps

of SST, SSS, MLD, Chl, and xCO₂

4. Statistically compare reconstructed to modeled pCO_2 in each member

2 36 60 84 108 132 Months with measurements 280 320 360 400 440 pCO₂ [μatm]

Figure 1 Left: number of months at each 1x1 grid cell with observations over 47 years. Right: Average pCO₂ at each 1x1 grid cell calculated over 47 year period.





uRMSD







0 2 4 6 8 10 Avg. abs. error [μatm]



uRMSD [µatm]







Linear trend

985 1990 1995 2000 2005 2010 2015

Post-processing each member

- 1. Remove latitudes north of 79°N
- Remove temporal linear trend at each grid cell
 Remove annual cycle with 12-month moving average

Statistical analysis

Each metric is calculated at each grid cell on each member. Displayed in Figure 2 is the average across 25 members from the CESM and GFDL

Average absolute error : measures the size of the discrepency uRMSD : unbiased root mean squared difference (uRMSD) measures the degree to which the reconstruction captures the observed variance^{7,8} Correlation : measures tendency of the reconstruction and model to vary together



Figure 2 Skill metrics are used to compare the neural-network based pCO_2 reconstruction against the simulated pCO_2 in CESM and GFDL ensemble members. Average absolute error, unbiased root-mean-squared-difference (uRMSD), and Pearson correlation coefficient is computed at each grid cell in each member. Displayed is the average across 25 members from the CESM and GFDL large ensembles.

III. Results / Conclusion

Higher correlations in the West Equitorial Pacific and North Atlantic in both the CESM and GFDL
Higher average error and uRMSD appear in regions with lower correlations

• Patterns may be explained by data availability, biological/temperature effects, or ENSO configurations

IV. Next Steps

• Two other interpolation methods^{9,10} will be assessed and compared against the MPI large ensemble¹¹ in addition to the CESM and GFDL

• Inteprolation methods will be evaluated regionally in each large ensemble

• Statistical analysis focusing on the ability of each method to capture patterns and timescales of variability

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