

In this study, the authors aimed to create a method for fixing gaps in satellite carbon dioxide data. Although this is valuable, I believe it falls short of article publication. They filled in missing CO2 data using extra satellite info and simulations. Here are the main problems:

1. The study treats satellite CO2 as observations. While satellite data can replace actual observations in some cases, it must fully match observations. Past studies found significant differences between oco-2 measurements and ground observations.
2. Before building the model, CT assimilation system simulations closely matched observations. The model's high accuracy is because CT's CO2 simulation was precise. So, developing a machine-learning model just to reduce a not-so-significant error rate doesn't make sense.
3. To show the model's quality, the authors used ground-based data. CAMS and CT assimilation systems use ground data to improve predictions. CT simulations matching observations well is likely because these systems previously used ground-based data to correct simulations.
4. Similarly, satellite CO2 is used in assimilation systems for correction. The CT and CAMS simulations used as inputs depend on the machine learning model's output (satellite CO2). This dependency raises questions about the model's reliability.
5. Creating a machine learning model for satellite data using dynamic model simulations contradicts the main advantage of statistical models—low computational cost. In reality, implementing this model means getting outputs from both CT and CAMS, undermining its intended efficiency.

While there are additional aspects to consider, fundamental issues in developing the model for this study hinder further exploration. Regrettably, given these challenges, I anticipate difficulties in publishing this article in a reputable journal such as ESSD.