The manuscript effectively quantifies the contributions of various factors to land surface greening and LAI changes. The aim of the manuscript is clearly articulated, and the background for the problem in the study area is well presented. However, I have some concerns regarding the methods and results that need clarification for further consideration. Below are my major and minor comments:

1. About the LUCC detection methods

The main conclusion of the manuscript is that cropland expansion acts as the primary factor offsetting the greening trend resulting from climate change and CO_2 elevation. While this finding is good, I have big concerns regarding the robustness of the input data used in this manuscript. The authors take the percentiles of crop expansion in 500m grid cells equal to the available 0.25-degree cells introduced many uncertainties. Representing higher resolution grid cells with coarser ones is unconventional. In this way, it is not able to identify differences among individual 500m pixels, further complicating the analysis.

A common technique for addressing such challenges in remote sensing is data fusion, although it requires many additional efforts. One potential solution to enhance the robustness of the manuscript's findings could involve conducting analyses using a matched resolution of 0.25 degrees rather than 500m. This adjustment would mitigate uncertainties associated with the coarse-to-fine representation of data.

Moreover, the methodology described in section 2.3 is long with text. it would be beneficial to include a conceptual figure illustrating a comparison of pixels. This would improve the clarity of the methodology section.

Additionally, when upscaling global forest change maps from 30m to 500m resolution, the issue of non-integer pixel numbers within a 500m grid cell arises. How did you treat the boundary cells? Clarification and a clear explanation are needed regarding how the methodology addresses boundary cells for the analysis.

2. About the Machining learning Approaches

Machine learning methodologies, however, have often remained as "black boxes" to ecologists due to their intricate algorithmic nature and limited interpretability regarding their predictive power (Simon, Glaum and Valdovinos 2023). In the manuscript, the authors establish five scenarios for predicting Leaf Area Index (LAI) by maintaining certain variables unchanged. However, it remains unclear how the machine learning method treats the unchanged variables within each scenario. Furthermore, the manuscript lacks description on the disparities in predicted LAI across scenarios, particularly concerning the inclusion of varying changed variables. It is important for the authors to select specific pixels to show the gradual changes in prediction results and accuracy, from the first, second, and to the last scenario.

In Figure 3, the specific scenario being shown here is not mentioned. Clarification regarding which scenario is represented in the figure is necessary. Additionally, inclusion of a time-series curve, focusing on a specific pixel, would provide valuable insight into the predictions generated by the machine learning algorithms.

Moreover, the manuscript fails to show details about splitting the data into training and testing sets, and how different splitting ratios may impact the conclusions drawn. A comprehensive explanation of the data splitting process and its potential implications on the study's findings is essential.

3. About the LAI change trend

I have concerns regarding the GLOBMAP LAI dataset, which is also the only LAI product used in the manuscript. There is substantial variability among global LAI products. However, it is notable that even most LAI datasets depict an increasing trend in LAI changes, the GLOBMAP dataset stands out as an exception, which characterized by notably lower values (Jiang, Ryu et al. 2017), see the figure below.

The slight change trend observed in the LAI within the study area could potentially be attributed to the specific LAI products utilized by the authors. To enhance the confidence in the conclusions, the inclusion of additional LAI products is essential to provide a more comprehensive assessment of vegetation dynamics.

4. About the assessing trend contribution from variables

In section 3.3, the authors outlined their approach to calculating the contributions of various variables to LAI trends. However, there appears to be confusion regarding the methodology's assessment. As stated, did the authors evaluate the contribution of elevated CO2 to greening by comparing the LAI trend from Scenario 1 to that from Observation? If so, authors should present scatterplots and regression lines for each scenario, and their statistical significance to allowing readers to know the differences among them.

In addition, it seems the authors calculated the average value of the trend for all the pixels as the final conclusions. How did you examine the significant of the machine learning results for each pixel before calculating the mean value? Furthermore, considering pixels with no significance, how might this bias the conclusion? It's crucial for the authors to address these concerns to ensure the reliability of their findings.

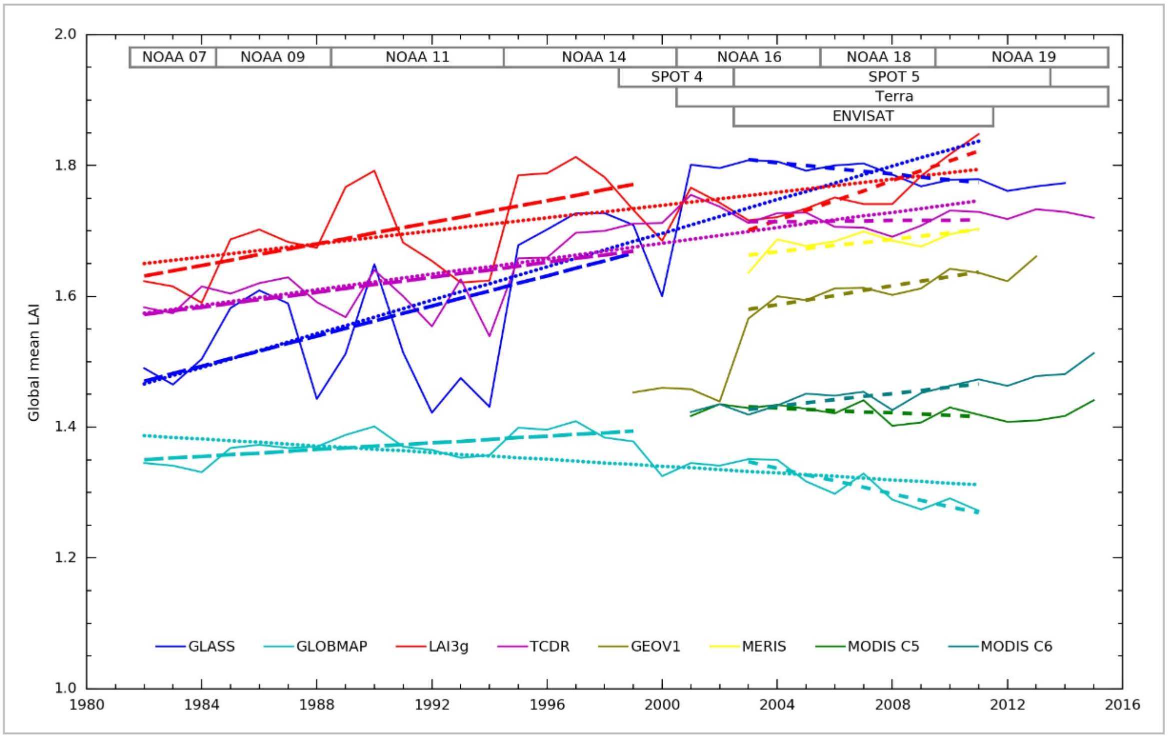

Figure 1

Open in figure viewer | PowerPoint

Global mean LAI (solid curves) and linear trends during 1982–2011 (dotted lines), 1982–1999 (long dashed lines), and 2003–2011 (short dashed lines) for different LAI products. Trend values are listed in Table 2. Lifespans of different satellite platforms are also illustrated

Jiang, C., et al. (2017). "Inconsistencies of interannual variability and trends in long-term satellite leaf area index products." Global Change Biology **23**(10): 4133-4146.

Simon, S. M., et al. (2023). "Interpreting random forest analysis of ecological models to move from prediction to explanation." Scientific Reports **13**(1): 3881.