A CAUTIONARY NOTE FOR THE USE OF AVHRR DATA IN CO_2 FERTILIZATION TREND DETECTION

TECHNICAL COMMENT SUBMITTED TO SCIENCE

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Comment on "Recent global decline of CO_2 fertilization effects on vegetation photosynthesis"

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Abstract

Wang et al. (Science 370, 1295–1300, 2020) report a significant decline in CO_2 fertilization effects using photosynthesis proxies from long-term satellite records. We find that small systematic biases in AVHRR data impact their analysis to the degree that the key finding is not robust.

To predict the future of the land carbon sink, knowledge of current trends in carbon uptake and their underlying mechanisms is crucial (1,2). Wang et al. (W2020 hereafter) estimate that the global CO_2 fertilization effect (CFE) has declined across most vegetated areas from 1982 to 2015, with a trend about 5-10 times larger than that of terrestrial carbon cycle models. This finding would have significant implications for the fate of the carbon sink, as it implies a weakening negative carbon-climate feedback of the terrestrial biosphere. We argue that problems in the data selection, orbital changes and issues with the analysis undermine the main conclusion in their report.

To quantify CFE, W2020 compute the derivative dGPP/dCO_2 (so called β factor) as dNIRv/dCO_2.Temporal changes in β retrieved through remote sensing are subtle signals, hence potential calibration errors need to be properly evaluated (5,6). A major challenge in constructing a long-term NIRv record (defined as the product of NDVI with NIR reflectance) (3) is that it requires consistent reflectance products. Any relative error in NIR reflectance propagates directly into NIRv. In contrast, the beauty of the NDVI vegetation index is that some calibration errors can partially cancel out if the errors in red and NIR reflectance co-vary, as it is defined as the ratio between reflectances.

W2020 claim that they obtain changes in β with three remote sensing products. However, the satellite datasets used in W2020 are not independent: the pre-2000 periods are all based on NIRv from the Advanced Very High Resolution Radiometer (AVHRR). This is an issue as the AVHRR reflectance record comes from a series of different satellites, each of them with their own orbital changes (Fig. 1). Constructing consistent long-term records requires carefully harmonizing data collected from the AVHRR instruments on different satellites (7). Even within a single satellite period, there is a drift in the equator crossing time (Fig. 1a), as the early NOAA satellites carrying AVHRR did not include a propulsion system to maintain orbit. Consequently, the solar zenith angles at acquisition strongly varied in time (Fig. 1b), which impacts measured reflectances (Fig. 1c, (10)), the computation of NIRv, and the duration of valid measurements, especially at higher latitudes. After 2000, AVHRR orbits and records were more stable (Fig. 1c) and inter-calibration with MODIS became feasible, rendering the pre-2000 time period critical for this analysis.

First, we identified considerable interannual variations in the normalized AVHRR NIR reflectance that were consistent over multiple Pseudo-Invariant Calibration Sites (PICS, 21 sites following (6)), especially in the critical 1994-1999 time-period. Fig.1c shows that the detrended NIRv global mean used in W2020 has similar temporal variations as the NIR of the vegetation-free PICS (r=0.62 for the full 34-yr records, r>0.8 for the pre-2000 period). In particular,

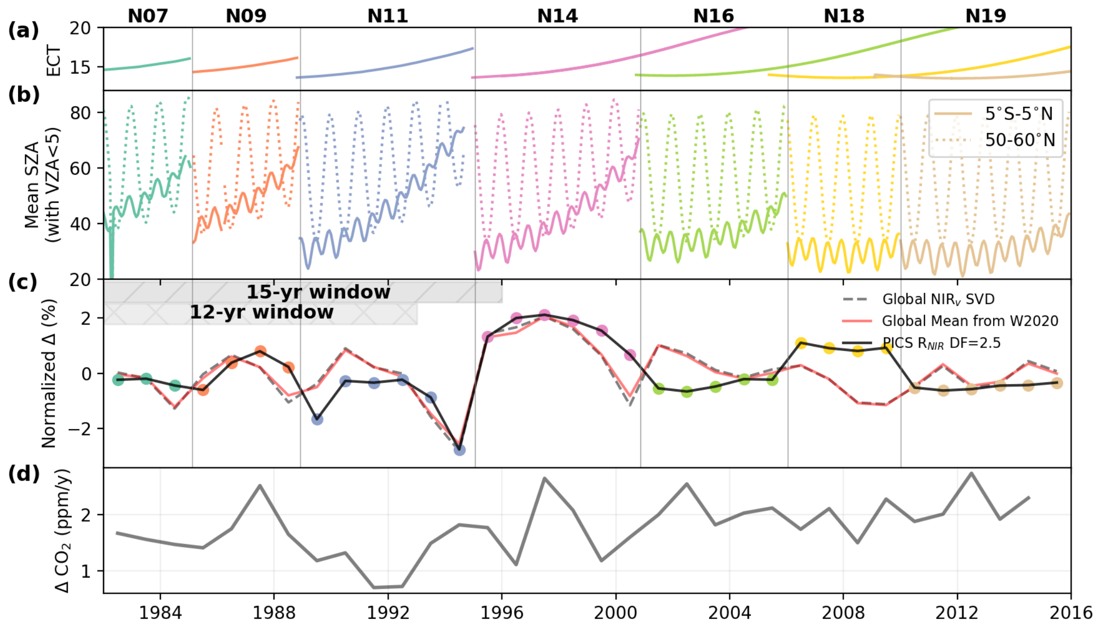

Figure 1: (a) Changes in local Equator Crossing Times (ECT) of all NOAA satellites (color-coded and labeled on top) which constitute the long-term AVHRR dataset; (b) Corresponding changes in solar zenith angles (SZA) at the sub-satellite point during overpass near the equator (solid) and at 50-60°N (dashed); (c) Normalized and linearly detrended anomaly time-series of the globally averaged AVHRR NIRv dataset as used in W2020, the first temporal eigenvector of an SVD analysis, and the median of the annual mean NIR reflectance acquired over 21 Pseudo Invariant calibration sites (PICS, amplitude dampened by a factor 2.5); colored dots indicate the NOAA satellite which contributed most to the annual mean; (d) Annual atmospheric CO_2 growth rate as used in W2020. Our linear CO_2 assumption forces a constant mean growth rate but largely maintains the overall CO_2 growth in time

variations in detrended NIRv over the 1994-2000 closely track PICS. In W2020, is fitted using a 15-year moving window, hence their results of the first window (1982-1996) are already impacted by these biases. Shortening the window to 12 years, where the first (1982-1993) and last (2004-2015) windows are not impacted by the most severe AVHRR biases, the fitted slopes of $d\beta/dt$ change from -1.07 to -0.8 (Fig. 2a). Looking at the spatial variations following W2020, the differences in median β between the first and last window change from 10.2 to 2.4 (equivalent to a $d\beta/dt$ of -0.53 and -0.11 %/100ppm, respectively (Fig. 2b), clearly demonstrating the sensitivity of the inferred dβ/dt to small NIRv biases.

We further test the impact of correcting those key biases in AVHRR using two simple methods: 1) correcting annual mean NIRv with NIR reflectance anomalies observed at PICS, 2) performing a Singular Value Decomposition (SVD) on the annual W2020 NIRv data and reconstructing the record by removing the interannual variations in the first temporal eigenvector. The first eigenvector represents a globally uniform scaling of NIRv, hence it captures the overall change in all vegetated areas but not interannual variations as the latter tend to be spatially heterogeneous. The SVD first temporal component is almost identical with global annual means, suggesting similar year-to-year NIRv variations across all biomes (Fig 1c). For the PICS correction, we apply various damping factors (DF) to their amplitude, as it appears higher than in the global mean NIRv. The fitted slopes reduce to -0.21 to -0.44 %/100ppm, depending on the choice of correction (Fig. 2c). An uncertainty analysis using bootstrapping shows that these slopes are not systematically different from TRENDY model estimates (-0.12 %/100ppm as per W2020.), but significantly different from the W2020 trend. Thus their claim that trends are more than 5 times higher than in biosphere models is invalid.

Second, W2020 aims to analyze the sensitivity of GPP to CO_2, however, GPP modulates the CO_2 growth rate in return (11,12), potentially reversing cause and effect at shorter time-scales. An increase in GPP could lead to a decrease in CO_2 growth, resulting in an overestimate of dGPP/dCO_2 when such feedback is ignored. To test this impact on $d\beta/dt$, we replaced the observed CO_2 concentration with a linear and quadratic fit, both of which caused only small residuals

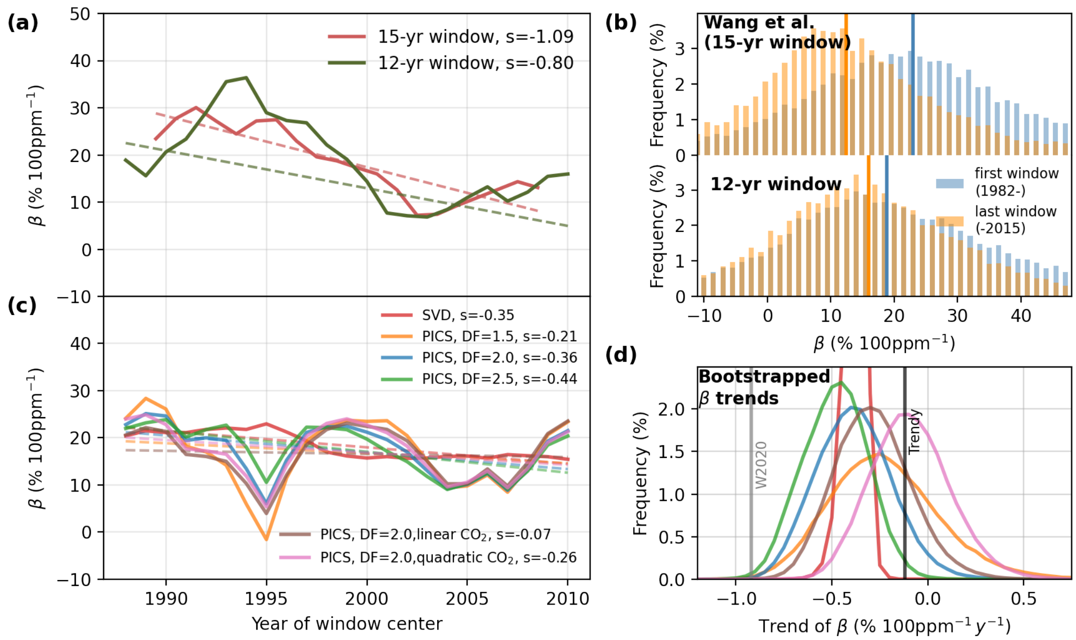

Figure 2: (a) β (solid) and linear regressions (dashed) with a 15- and 12- year moving window, respectively, using the original NIRv and climate data as provided by the authors. (b) Histograms of β for the start and end periods using different window lengths. Results using the 15-yr window are shown in Fig. 1a and b of W2020. The differences in β between the start and end period are reduced to about 1/3 when using a 12-year window. (c) Trend of β (solid lines) computed using a 12-year moving windows with different corrections applied to the AVHRR NIRv data and assumptions made on CO_2. DF refers to the damping factor for PICS calibration site correction curves. Dashed lines show linear regressions for β estimates (d) Histograms of the trends in β using bootstrapping (sampling a subset of 15 random windows for the linear fit with 100,000 repeats). Bootstrapping provides more realistic uncertainty estimates, especially as the moving window analysis in W2020 causes individual windows to not be statistically independent. Results obtained in W2020 are outside our rather large uncertainty range.

within 3ppm over the entire time-period. When we eliminate high frequency variations in CO_2 through a quadratic fit, $d\beta/dt$ decreases by another 0.1 %/100ppm (to -0.26, Fig. 1c), and a linear fit (which makes dNIRv/dCO_2 directly proportional to dNIRv/dt) reduces it to -0.07%/100ppm. This shows how trends in dNIRv/dCO_2 as analyzed in W2020 are clearly affected by subtle changes in both NIRv and CO_2. Systematic errors of only 1-3% can cause biases that are on the order of derived trends found in W2020. Our analysis shows that the key conclusion in W2020 is thus not robust.

In addition, we have concerns about the assumption that NIRv and SIF are perfect proxies for gross primary production (GPP) to derive such subtle signals, even though this may hold true to describe large-scale spatiotemporal patterns. To first order, NIRv captures effects of light interception and mostly canopy structure, which results in a reasonable correlation with GPP, especially on interannual time scales. Second order effects, such as CO_2 fertilization trends, change the overall efficiency of the dark reactions in photosynthesis and are thus neither captured by NIRv nor by solar induced chlorophyll fluorescence (SIF). As the effects investigated in W2020 are subtle and unobservable with neither NIRv nor SIF, these crucial assumptions are incorrect (8,9), yet are the foundation of W2020, thus invalidating the results.

Last, we commend the authors to publicly provide code and data. This is exemplary and helps the community make robust progress.

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