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TECHNICAL RESPONSES

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Response to Comments on "Recent global decline of CO_2 fertilization effects on vegetation photosynthesis"

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Our study suggests that the global CO_2 fertilization effect (CFE) on vegetation photosynthesis has declined during the past four decades. The Comments suggest that the temporal inconsistency in AVHRR data and the attribution method undermine the results' robustness. Here, we provide additional evidence that these arguments did not affect our finding and that the global decline in CFE is robust.

On the basis of long-term satellite datasets and statistical methods, we argued that the global CO_2 fertilization effect (CFE, β factor) on vegetation photosynthesis had declined during the past four decades (*1*). Three Comments have been received, which supported and disputed our results (*2*–*4*). Their claims include the following four main points: (i) Inconsistencies in the time series of AVHRR data affect the magnitude of β declining trends, (ii) NIRv and solar-induced chlorophyll fluorescence (SIF) should perhaps not be used as the perfect proxy of gross primary production (GPP), (iii) there is inconsistency of the β results between the factorial simulation–based method and the regression-based method, and (iv) the fusion of the AVHRR and MODIS data may lead to some biases.

Frankenberg *et al.* (*2*) support the first point by correcting the interannual biases in AVHRR reflectance according to multiple-site observations or using a statistical method. They conclude that "systematic biases in [AVHRR] data affect their analysis to the degree that the key finding is not robust" (*2*). As reported, the LTDR and GIMMS products used in this analysis have extensively included the post-launch sensor calibration, bias corrections for systematic orbital shifts, cloud screening, sensor degradations, and atmospheric corrections (*5*, *6*). After applying a simple empirical correction to account for orbital drift, Frankenberg *et al.* show that the global declining trends of CFE are smaller but still significant (their figure 2, −0.21 to −0.44% 100 ppm^{-1} year^{-1}), which substantially confirms our main finding of a global declining trend of CFE (*1*) and contradicts their own conclusion. On the other

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hand, we acknowledge that the orbital shifts would induce changes of the solar zenith angle (SZA) and could affect the interannual variations of AVHRR reflectance. We claim that this problem does not greatly affect the declining trend of β. In fact, after including or omitting the SZA as predictor in the regression for the estimation of β, the global declining trend remains almost the same (Fig. 1A), for both the 15- and 12-year moving-window analyses. The resulting declining trend of β from satellite data is also notably higher than those from terrestrial ecosystem models.

Frankenberg *et al.* also question NIRv by stating that "any relative error in NIR reflectance propagates directly into NIRv" and highlight the reliability of NDVI: "some calibration errors of the red and NIR reflectance partially cancel out if errors covary" (*2*). We agree with this comment, although NDVI would saturate at high GPP and is therefore a less appropriate proxy for GPP than NIRv (*7*). A recent study proposed a new formulation of NDVI (kNDVI) (*8*), which could fit this analysis because it is a better linear proxy for GPP than NDVI and NIRv. In addition, kNDVI, being a differential index, mitigates the sensitivity to orbital drifts of indices based on absolute reflectance (such as NIRv), as stated by Frankenberg *et al.* We therefore conducted an analysis based on both GIMMS NDVI and kNDVI, and also found a significant declining trend of global β (Fig. 1, B and C). The declining trend using kNDVI (−0.81% 100 ppm^{-1} year^{-1}) is similar to that using NIRv; more important, both are notably higher than those from terrestrial ecosystem models. Frankenberg *et al.* also point out the use of CO_2 data and argue that using GPP and CO_2 for the same year would ignore the effect of GPP increases on CO_2 growth. We addressed this issue by reanalyzing the global trend of β using 1-year lagged CO_2 data [following a previous study (*9*)] and again found a similar global declining β trend at −1.01% 100 ppm^{-1} year^{-1} (Fig. 1D). We therefore stress that using the original measured CO_2 data instead of the statistically fitted CO_2 data in Frankenberg *et al.* is more appropriate for this analysis, because the fitted values may incorrectly dampen the subtle signals of interannual variations.

On the second point, Frankenberg *et al.* and Sang *et al.* question whether NIRv and SIF are not the perfect proxies of GPP (*2*, *3*). Their concern is that using NIRv and SIF to derive β may ignore the CO_2 effects on light use efficiency (LUE) and RuBisCO. We agree that measuring photosynthesis beyond the leaf scale has been challenging for decades and that no perfect proxy of GPP from spaceborne measurements yet exists. Since the breakthrough of satellite SIF retrieval from the core authors of Frankenberg *et al.* (*10*), many recent studies have demonstrated satellite SIF data to be a good proxy of GPP (*11*, *12*) and have described large-scale spatiotemporal patterns of GPP as acknowledged in (*2*). Using satellite data, Badgley *et al.* also suggested that "NIRv has a robust physical interpretation, as it relates directly to the number of NIR photons reflected by plants [...] should scale with the capacity to fix CO_2, providing a strong basis for new, satellite-derived estimates of GPP" (*13*). A number of recent studies based on ground measurements have shown that NIRv and NIRv radiance are highly correlated with GPP at multiple temporal scales (*7*, *14*, *15*). More important, a previous study based on ground measurements, involving many of the core authors of Frankenberg *et al.*, suggested that SIF contains information on vegetation canopy LUE, and therefore that using SIF to infer CFE would include the CO_2 effect on LUE (*16*).

Nonetheless, we acknowledge that CFE is a complex signal derived from a combination of direct and indirect effects [e.g., greening, change in canopy structure, improvement of water use efficiency (WUE), direct effect on RuBisCO, interactions with changing water and nutrient availability, etc.] (*17*). Although individual components of CFE "in the model world" can be isolated to some extent by running factorial experiments with process-based models, the separation of CFE from Earth observations is difficult because all factors are in play at once. For this reason, proxies of vegetation productivity, such as NIRv and SIF, have to be used to assess the integrated actions of most of the direct and indirect processes behind CFE dynamics. On the other hand, although Earth observations might have biases and cannot measure GPP directly, it has the advantage of representing "reality" with a high degree of confidence, whereas vegetation models offer a simplified representation of reality, poorly describing key constraints of GPP (e.g., water limitations), providing uncertain parameterization of physiological processes, and missing key drivers for CFE (e.g., phosphorus and potassium limitation) (*18*). The overall validity of our approach is implicitly confirmed by Sang *et al.* (*3*), who state that "The CO_2 fertilization effect (CFE) is a major driver of vegetation greening and the terrestrial carbon sink," confirming that greening depends largely on CFE and can therefore be used to infer its trends. We therefore argue that products closely associated with greening and productivity, such as NDVI, kNDVI, NIRv, and SIF, do actually capture a large fraction of the indirect CFE [e.g., the amplification effects mediated by the dynamics of leaf area index (LAI) and by the increase in WUE]. Even if the direct effect of CO_2 on RuBisCO is not captured at foliar and short-term scales, it should be translated into an increase in GPP at ecosystem level over longer-term scales, and therefore should have an impact on productivity and greening, which are well captured by satellite NIRv and SIF.

Our original findings are further strengthened by an

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additional analysis that used two completely independent data streams [Ku-band vegetation optical depth (VOD) (*19*) and carbonyl sulfide (COS) amplitude]. VOD and COS are effective indicators of vegetation productivity (*20*). COS measurements directly relate to the CO_2 uptake of terrestrial photosynthesis. COS observations from different sites (Fig. 3, E and F) were consistent with the spatial distribution of the CFE trends from satellite data—that is, a much higher reduction of β in northern high latitudes than in the northern subtropics. VOD most directly tracks changes in the water content of aboveground vegetation, but it can also be applied to infer changes in aboveground biomass, or at least foliage upper canopy biomass (*21*). The important point is that VOD is a long record completely independent from AVHRR data, because it is based on a different technology and platforms. We found a similar declining trend of CFE based on both VOD and COS data (Fig. 3, D and E), which provides additional independent evidence in support of our findings. Our original proxies (NDVI, kNDVI, NIRv, and SIF) better track changes in the total light absorbed for photosynthesis, whereas VOD and COS better track canopy biomass and leaf CO_2 uptake, respectively. Thus, together these proxies can track changes in canopy biomass per unit light absorbed (i.e., a proxy for LUE) (*22*). A main strength of integrating these independent records is that each offers unique global-scale insight into CFE, mediated by multiple interacting biophysical and biogeochemical factors.

The third claim mainly concerns the effectiveness of the regression method in factoring out the CO_2 effect from covarying factors. To demonstrate that our regression method is not appropriate for estimating CFE, both Zhu *et al.* and Sang *et al.* apply the same methods to derive CFE from TRENDY simulations performed with dynamic global vegetation models (DGVMs) under varying CO_2 and climate (S2) and compare it to CFE estimated under constant "pre-industrial" climatic conditions with rising CO_2 only (S1 – S0) (*3*, *4*) or from MsTMIP simulations forced with varying climate and land use and varying (SG3) or constant (SG2) CO_2. We argue that this approach has several limitations due to the simplistic model representation of the relationships between climate drivers and GPP (which may translate into artificially high correlations between GPP and climate predictors in our regression-based method) and to the lack of land-climate feedbacks in the DGVM schemes. The impact of changing climate (e.g., water availability and associated impacts on stomatal conductance and CO_2 concentration in the mesophyll) on the dynamics of CFE was notably well stressed in our paper (*1*) as a possible reason for the observed declining trend. Unfortunately, the key role of the changing climate in CFE trends is not properly accounted for in the experiment based on TRENDY simulations, as Sang *et al.* also recognize (*3*). In fact, CFE derived under the dynamic climate of the past three decades (1982–2015) from simulation S2 is expected to deviate from the steady-state CFE derived from S1 – S0 under fixed pre-industrial climate. CFE values estimated from these two methods therefore have different meanings and should not match. In addition, CFE is affected by the feedbacks between vegetation and climate. For instance, under increasing CO_2 concentration, water use efficiency will change with potential impacts on transpiration, cloud cover, and precipitation. In the real world, and therefore in Earth observations, these changes in atmospheric conditions have feedbacks on GPP, and also affects CFE. On the contrary, in DGVMs simulations forced with prescribed climates, such as TRENDY and MsTMIP, these land-atmosphere feedbacks are not accounted for in the estimation of CFE. For these reasons, the CFE estimated from DGVMs is not directly comparable to that derived from Earth observations. In addition, Sang *et al.* base their conclusion about the robustness of our method only on the pixel-level spatial correlation between the two approaches for the derivation of CFE. On the contrary, their model experiment did not investigate the crucial aspect of our analysis, namely the temporal trends of CFE at global scale. We acknowledge that our methodology may lead to pixel-level uncertainty driven by the potential impact of local effects (e.g., land use change in MsTMIP) or simply by the uncertainty of regression coefficients at pixel level. However, this uncertainty mostly affects the high-resolution spatial pattern and not the global temporal patterns, which are the key subject of our analysis. For these reasons it cannot be concluded that the results reported from these model experiments refute our methodology for the specific scope of detecting temporal variation in CFE across large spatial scales.

Sang *et al.* also suggest that "this regionally large β decline does not result from low β during 2001–2015, but from extremely high β during 1982–1996." However, the extremely high β (>50% 100 ppm^{-1}) during 1982–1996 only accounts for ~7% of all pixels, mostly located in croplands such as the heavily managed crop areas in India, and is likely due to management intensification (e.g., increased use of chemical fertilizer and irrigation). When excluding these pixels with extremely high β, the global median β still shows a large decline from 20.7% to 12.1% 100 ppm^{-1} (Fig. 2A), therefore confirming the robustness of our conclusions. To assess the dynamic of CFE in the absence of land management, we further isolated the trend for intact forests, areas characterized by the absence of remotely detected signs of human activities (*23*). The declining trend of CFE observed in these pristine ecosystems clearly shows that our results are not driven by human management and

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further support our conclusions (Fig. 2B). Sang *et al.* state that "the large β decline reported by [Wang *et al.*] was largely a result of Northern Hemisphere high latitudes [...] suggest that Wang *et al.* misinterpreted the impacts of non-CO_2 factors, such as climate warming in cold regions." We argue that the accelerated warming and drying at northern latitudes may lead to a decline in water availability during the growing season (*24*, *25*) and to a lockup of nutrients in the accumulating organic matter (progressive nutrient limitation) (*26*). Because of the high pace of warming/drying and the increase in CO_2 concentrations relative to the time needed for ecosystems to adapt to new conditions, it is likely that ecosystems are affected by declining nutrient and water availability. The decreased availability of nitrogen and therefore the enzyme RuBisCO, together with the decline of water availability, may have ultimately amplified the declining trend of CFE at northern high latitudes. Meanwhile, the emerging arctic phenological onset stalling in response to warming may have implied a loss of an early-season CFE at northern high latitudes (*27*). Also, because our regression is based on a 15-year moving window (15 data points on a single pixel) and the degrees of freedom of the equation are limited, the calculated β values at several areas based on 1° resolution are not statistically significant. This low significance is largely an artifact of the spatial averaging of the satellite data to the 1° grid cells performed for the analysis in (*1*). When the regression is computed on the original high-resolution data at 0.25° over a 1° cell, and therefore is based on 15 × 16 data points, we again find the large declines in global CFE, and ~90% of the pixels are significant (Fig. 2, C andD).

On the fourth point, Zhu *et al.* argue that the fusion between AVHRR and MODIS data may lead to some biases. However, on the basis of the cumulative distribution frequency (CDF) matching approach, the interannual trend of matched MODIS NIRv is almost similar to that of the original MODIS NIRv, as shown in Fig. 3A. The global median β during 2001–2015 calculated from the original MODIS NIRv [MCD43A4 data used in (*1*) but not the MCD43C4 data used in (*4*)] is about 14.3% 100 ppm^{-1} (Fig. 3B), which is slightly larger than that from the matched MODIS NIRv (13.3% 100 ppm^{-1}) but also significantly lower than that from AVHRR NIRv during 1982–1996 (22.5% 100 ppm^{-1}). Zhu *et al.* also argue that "rather than adjusting the less accurate and unreliable AVHRR data according to the more accurate and reliable MODIS data, they corrected the MODIS data to match the AVHRR data." To address this criticism, we tested the opposite process (correcting AVHRR data to match MODIS data) and again found a significant declining trend of global β, which indicates that the global decline of CFE is not dependent on the harmonization of AVHRR and MODIS time series (Fig. 3C).

In summary, our findings in (*1*), further corroborated by the results reported here, suggest that the global declines in CFE are robust despite the issues of data and method raised by the Comments. We agree that the orbital drift of AVHRR may introduce some variations into the long-term satellite observations, which need a physically based correction. We stress that AVHRR is a unique long suite of sensors to investigate greening trends and patterns since the 1980s, and that there is no parallel measurement available to check the sensors' cross-consistency, as has become possible in the modern satellite era. Our analysis here, moreover, indicates that the SZA variations in the satellite records did not affect the declining trend of global β. We also agree that statistical attribution may not fully separate the CO_2 effects from confounding factors, also due to the complex interplay and numerous feedbacks between climate drivers and CFE. We acknowledge that comparing Earth observation products with modeled GPP is quite challenging, given their different nature and associated uncertainties. Our results, however, call for the development of better Earth observation products (e.g., long-term SIF products) and improved process-based models. Altogether these issues do not affect our conclusions on the global CFE trend, they highlight the need for even more detailed analysis using advanced methods and approaches to improve estimation of global CFE dynamics. The lively discussion about our findings proves that the paper has raised an important issue, and more studies on this difficult but crucial problem are called for.

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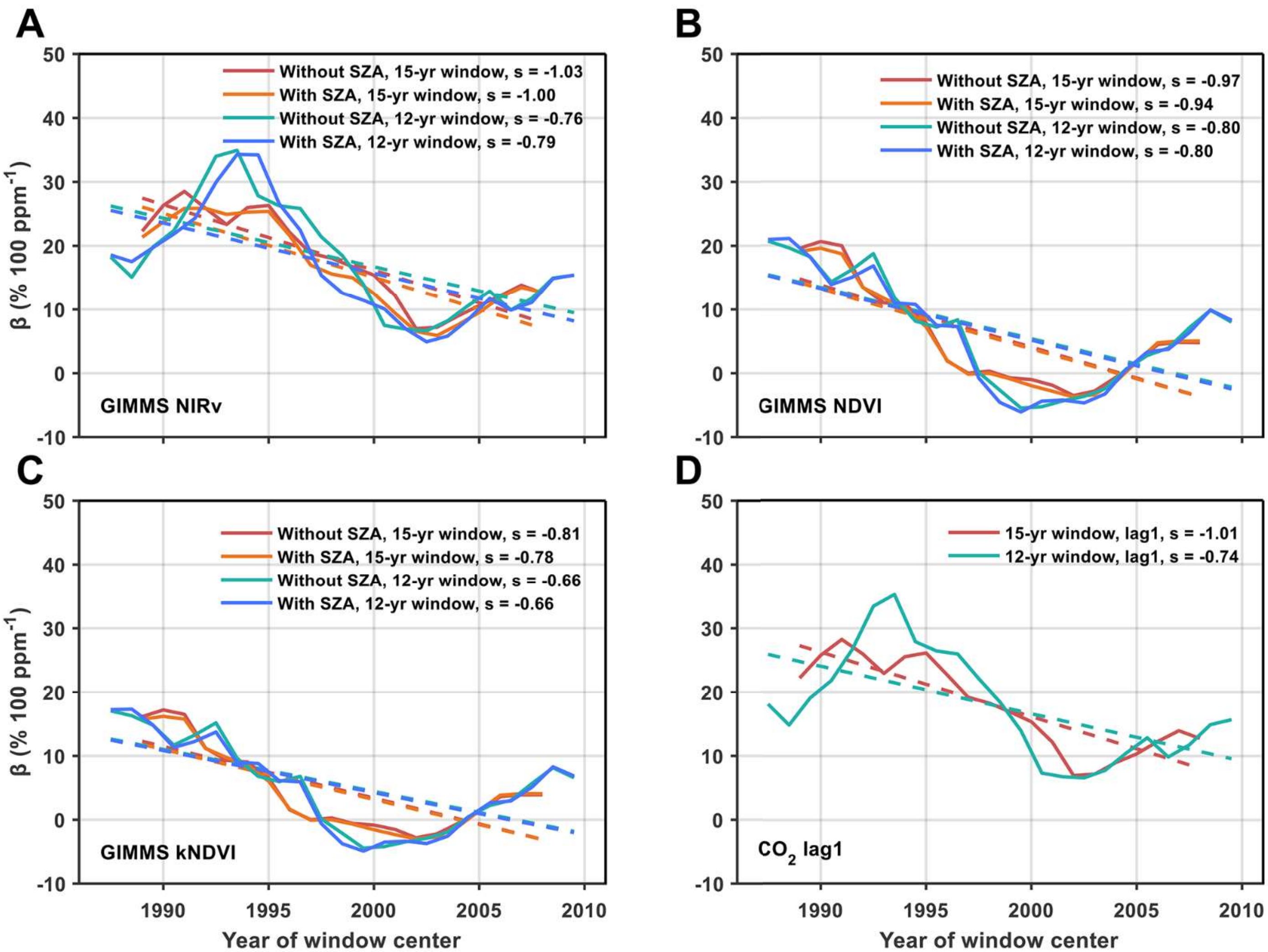

Fig. 1. Declining trend of global β. (**A**) Temporal dynamics of β derived from GIMMS NIRv with or without accounting for SZA changes in AVHRR retrievals with 15- or 12-year moving windows (*s* refers to the linear trend). (**B** and **C**) Similar to (A), but based on GIMMS NDVI and GIMMS kNDVI. (**D**) Temporal dynamics of β using 1-year lagged CO_2 data and GIMMS NIRv.

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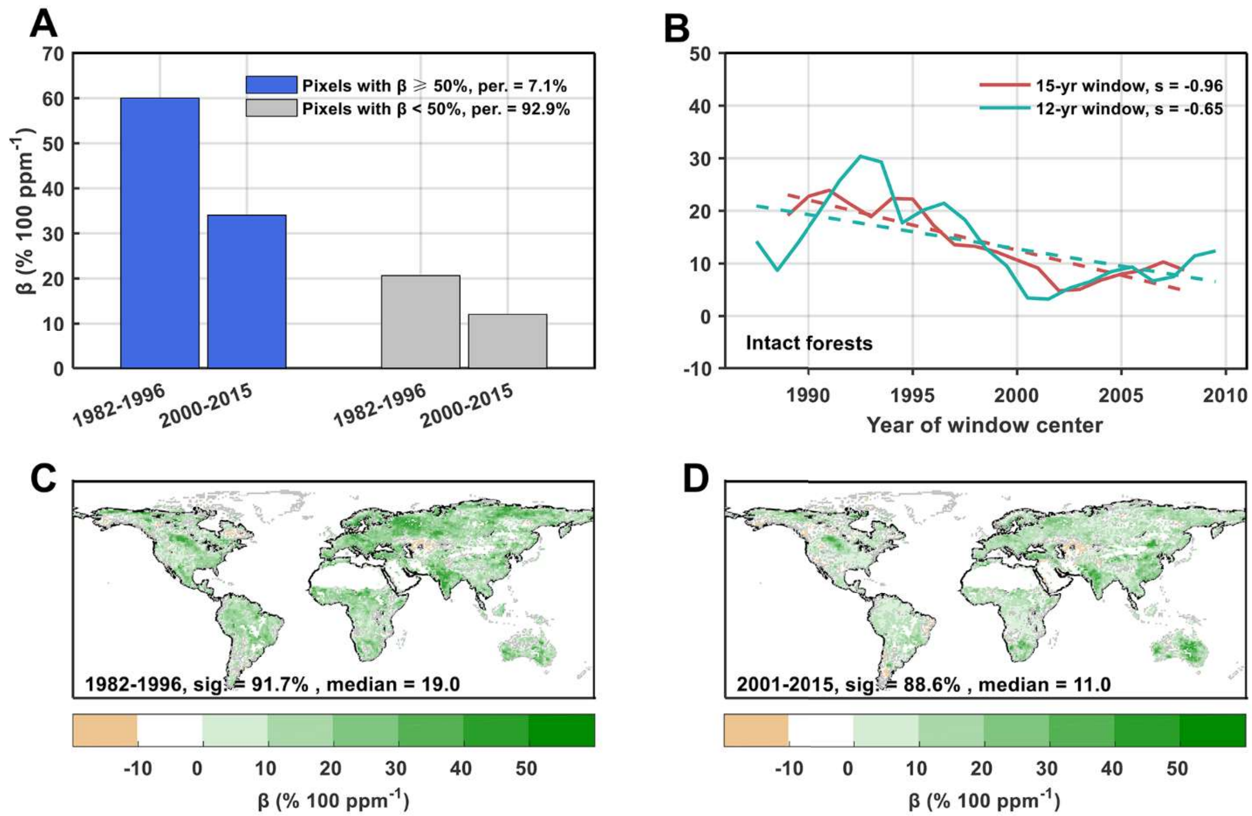

Fig. 2. Robustness of global declining β. (**A**) Median β for the pixels with extremely high β (≥50% during 1982–1996) and other pixels for 1982–1996 and 2001–2015 (per., percentage). (**B**) Temporal dynamics of β for intact forests. (**C** and **D**) Global β results for 1982–1996 (C) and 2001–2015 (D) based on GIMMS NIRv at 0.25° resolution. Gray areas indicate nonsignificant β pixels ($P > 0.05$); sig. denotes the percentage of pixels where β is statistically significant.

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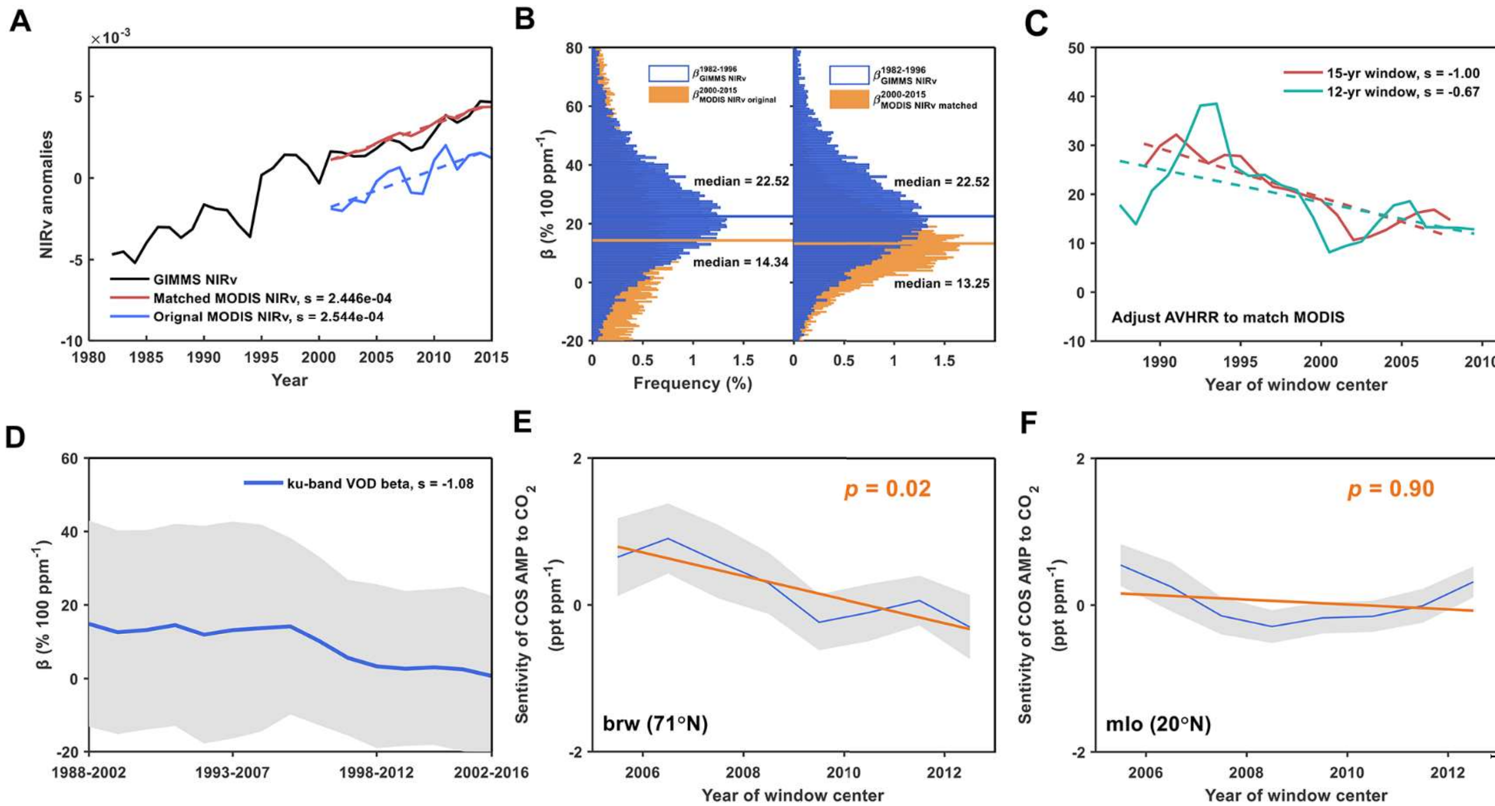

Fig. 3. Robustness of global declining β between the first and last windows, and temporal trend of CFE based on other independent datasets. (**A**) Yearly anomalies of AVHRR NIRv (1982–2015), original MODIS NIRv (MCD43A4, 2001–2015), and matched MODIS NIRv (2001–2015). (**B**) Global β distributions and global median β based on AVHRR NIRv (1982–1996), original MODIS NIRv, and matched MODIS NIRv (2001–2015). (**C**) Temporal dynamics of β based on the newly matched data (i.e., adjusted AVHRR data to match MODIS data). (**D**) Temporal dynamics of β based on Ku-band VOD data. (**E**) Sensitivity of the annual carbonyl sulfide (COS) amplitude (AMP) to atmospheric CO_2 at Barrow Station (brw). (**F**) Sensitivity of the annual COS AMP to atmospheric CO_2 at Mauna Loa Station (mlo).

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