RENEWABLE FUELS ASSOCIATION

April 9, 2014

Katrina Sideco
Air Resources Engineer, Fuels Section
California Air Resources Board
1001 "I" Street
Sacramento, CA 95812

Dear Ms. Sideco,

The Renewable Fuels Association (RFA) appreciates the opportunity to provide comment on the California Air Resources Board's (CARB) draft indirect land use change (ILUC) analysis, which was the subject of a stakeholder workshop held March 11, 2014.

We are encouraged by the fact that CARB staff is finally revising its ILUC analysis, as directed by a November 2010 Board resolution.[1] However, we are greatly concerned by many aspects of the draft analysis and we believe it needs significant revision before it can be presented to the Board for approval. While the attached report includes detailed comments on specific technical aspects of CARB's draft analysis, we also wanted to voice several general concerns with the draft ILUC analysis.

Most importantly, the results of CARB's draft analysis are in conflict with the results of recent independent ILUC studies. As described in a recent letter to CARB Chair Mary Nichols from 14 scientists and researchers (including CARB-appointed Expert Work Group members), the corn ethanol ILUC results from CARB's draft analysis are significantly higher than estimates from recent peer-reviewed scientific analyses (see Appendix A to the attached analysis). We believe CARB should explain and justify the divergence of its draft results with estimates from other recent studies.

In addition, during the March 11 workshop, a stakeholder asked why the reduction in CARB's corn ILUC estimate was of a far lesser magnitude than the reductions in sugarcane and soy ILUC values. Indeed, CARB's draft ILUC value for soy biodiesel is 59% lower than the current value, while the draft value for sugarcane ethanol was similarly lowered by 47%. Meanwhile, the new draft value for corn ethanol is only 20% lower than the current value. At a fundamental level, one would expect the magnitude of the reductions resulting from GTAP improvements to be to relatively consistent across all crops and biofuels. Unfortunately, CARB staff did not adequately answer the stakeholder's question during the workshop. We believe CARB should explain the large difference in the magnitude of reductions for corn ethanol ILUC compared to soy biodiesel and sugarcane ethanol.

Notably, several of the assumptions and methodological approaches chosen for CARB's draft analysis run counter to the recommendations of the Expert Work Group (EWG). In particular, the values selected

[1] California Air Resources Board Resolution 10-49. November 2010.

by CARB for key GTAP elasticities are in conflict with values recommended by EWG and well-known agricultural economists. More generally, CARB's draft analysis lacks sufficient justification for certain judgment calls made by staff with regard to important model parameters. We believe CARB should clearly explain and justify its decision to disregard certain EWG recommendations.

Finally, while we appreciate that CARB extended the deadline for submittal of comments in response to the March 11 workshop, stakeholders have not been given a sufficient opportunity to review and validate the models and data used for CARB's draft analysis. For example, the version of GTAP used by CARB was finally made publically available late on April 1 and some related files were posted on April 8 (three days before the comment deadline). Given the complex nature of the GTAP model and the time involved in performing model runs, it was simply not possible to replicate and evaluate CARB's 1,440 model runs in the time allotted.

We appreciate CARB's consideration of these general concerns and the attached technical comments. We welcome further dialog on this subject and look forward to responses to any of the comments offered in the attached document. We will continue to analyze the version of GTAP used for the draft analysis, review the information provided by CARB, and respond with additional comments as appropriate.

Sincerely,

Geoff Cooper
Senior Vice President

cc:
Richard Correy
Mike Waugh
John Courtis
Anil Prabhu
Jim Duffy

EVALUATION OF
CALIFORNIA AIR RESOURCES BOARD (CARB)
INDIRECT LAND USE CHANGE (ILUC) DRAFT ANALYSIS

The California Air Resources Board (CARB) staff held a stakeholder workshop March 11, 2014, to discuss the draft results of new analysis on indirect land use change (ILUC). It is expected that the staff analysis will inform potential amendments to the carbon intensity values used for the LCFS program.

This report critically evaluates the information presented by CARB staff during the workshop, as well as material released subsequently. We also offer recommendations for improvement of CARB's draft analysis. This report is organized in the following manner:

- Discussion and recommendations on yield-price elasticity
- Discussion and recommendations on elasticity of yield with respect to area expansion
- Initial evaluation of emissions factors (AEZ-EF model)
- Recommendation regarding purported "food consumption" effects

The report contains the following Appendices:

- **Appendix A**: Letter from scientists and researchers to CARB Chair Mary Nichols regarding advancements in ILUC analysis
- **Appendix B**: Note from Taheripour & Tyner to CARB staff following March 11 workshop
- **Appendix C**: Comparison of YDEL values used by CARB to long-run yield-price elasticities from the literature
- **Appendix D**: Comparison of ETA values used by CARB to values from Tyner et al. (2010)
- **Appendix E**: L. Guanter et al. 2014. "Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence." PNAS 2014, published ahead of print March 25, 2014.

1. **CARB should adopt a range of 0.14-0.53 for the yield-price elasticity based on the most recent studies of <u>long-run</u> yield responses. At a minimum, CARB's range for this elasticity should reflect the Expert Work Group's recommendation to use a central value of 0.25.**

The yield-price elasticity (represented by the code "YDEL" in the GTAP model) is an important parameter that significantly influences the final results of CARB's ILUC analysis. In essence, the parameter simulates the responsiveness of crop yields to changes in the net crop returns. It is a basic concept that rational economic actors will endeavor to maximize returns by increasing productivity in response to higher prices. In the case of crop production, the most economical and efficient method of increasing productivity to capture higher market prices is to invest in technologies that increase crop yields on existing cropland.

CARB utilized a range of 0.05-0.30 for the YDEL parameter in its draft analysis (implying a central value of 0.175). The range used in CARB's draft analysis disregards the recommendations of the CARB Expert Work Group (EWG), is inconsistent with recently estimated long-run elasticity values from the literature, confuses short-term versus long-term responses, and ignores the effect of double-cropping. Additionally, CARB appears to misrepresent the results from some price-yield elasticity studies.

As described in more detail below, a range of 0.14-0.53 is scientifically justified, properly recognizes that the price-yield effect occurs primarily over the medium or long term, and appropriately incorporates the effect of double-cropping.

a. ***Values at the low end of the range used in CARB's draft analysis represent <u>short-run</u> yield responses to price changes. Values representing a short-run response are inappropriate for use in medium or long-term modeling scenarios and should therefore be removed from CARB's analysis.***

The literature review presented by CARB showed price-yield elasticity estimates ranging from 0.00 to 0.76 (average value of 0.29).[1] However, the older studies (which generally show higher elasticity values) were excluded by CARB when deriving the YDEL range used in the draft analysis. CARB staff stated that "<u>recent</u> estimates…vary from zero to 0.30," but noted that 0.05 was selected as the lower bound because using a value of 0.00 in GTAP results in error generation. Importantly, in deriving the range used in the draft analysis, CARB made no distinction between elasticity estimates that represent short-run yield responses (e.g., intra-seasonal or one-year) and estimates that represent medium- or long-run yield responses.

During the March 11 workshop, Purdue University Prof. Wally Tyner explained why it is inappropriate to include short-run estimates in the range used for CARB's analysis, stating:

> The yield-price elasticity is a *medium-term elasticity*…and we normally think of that as about 8 years. I personally

[1] CARB Presentation, Slide 27. March 11, 2014. Available at: http://www.arb.ca.gov/fuels/lcfs/lcfs_meetings/iluc_presentation_031014.pdf

> think, and our group thinks, that any of those papers in the literature that represent one year are totally irrelevant to this. They may be fine for a one-year estimate, but a one-year estimate is totally irrelevant. Most of the short-term estimates are very low and most of the medium-term [estimates] were much higher—in the range of the 0.25 that we currently use.[2]

Prof. Tyner underscored this point again in a note to CARB (Appendix B) following the March 11 workshop: "The yield to price elasticity does not measure changes over one crop year. In fact, any estimate done over one year would be totally inappropriate for GTAP and should be excluded from consideration in determining appropriate values for the parameter."

Iowa State University Prof. Bruce Babcock and other members of the Expert Work Group's Elasticity Subgroup agreed that the use of a short-run elasticity is inappropriate for the purposes of CARB's GTAP scenario runs:

> …to the extent that existing studies provide reliable one-year estimates, they underestimate the long-run response of yields to price. There are sound theoretical reasons for believing that there are lags in the response to higher crop prices. Farmers have an incentive to adopt higher-yielding seed technologies and other management techniques with higher prices. Switching from one seed variety or technology such as seed-planting populations, may require more than a single season to accomplish. And there are likely five to 15 year lags involved in developing new seed varieties and new management techniques that may be only profitable under high prices.[3]

The Berry & Schlenker paper that serves as the basis for the lower end of CARB's price-yield elasticity range is based on the *short-run* response of yield to price changes. Moreover, the Berry & Schlenker paper draws heavily from work by Roberts & Schlenker, which was critiqued by the EWG's Elasticities Subgroup. The subgroup raised several concerns with the Roberts & Schlenker work, none of which (to our knowledge) have been adequately addressed by CARB staff. In short, the Elasticities Subgroup found that, "[t]he Roberts and Schlenker (2010) results provide *no evidence* that there is not a price-yield relationship, they just find evidence that any short-run price yield relationship is overwhelmed by variations in yields caused by weather."[4]

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[2] Audio of Prof. Tyner comments are available at: http://domesticfuel.com/2014/03/12/carb-stresses-iluc-update-is-preliminary/. (emphasis added)
[3] ARB Expert Work Group. 2011. "Final Recommendations from the Elasticity Values Subgroup." Available at: http://www.arb.ca.gov/fuels/lcfs/workgroups/ewg/010511-final-rpt-elasticity.pdf
[4] *Id.* (emphasis added)

It is also important to point out that the Berry & Schlenker paper cited by CARB overtly admits that "…we don't have an estimate for a price-yield elasticity…"[5] Indeed, rather than using a method that directly estimates the price-yield elasticity, Berry & Schlenker "…*back out* an *implied* yield-price elasticity for non-marginal land…" using an opaque and convoluted methodology that involves estimating the productivity of marginal lands relative to non-marginal lands relative to changes in price.[6] Importantly, Berry & Schlenker say the short-run price-yield elasticity is "…no higher than roughly 0.1." While 0.1 is a low estimate compared to others in the literature, it is *not zero*, as characterized by CARB. In the end, however, whether the Berry & Schlenker estimate was 0.0 or 0.1 is not relevant because they examined a short-run response.

CARB also referenced work by Smith & Sumner that purportedly shows a *negative* elasticity value. After an exhaustive search of the literature, we were unable to locate any publications by Smith & Sumner that estimated price-yield elasticity. RFA requested that CARB staff make the cited Smith & Sumner paper available for public review. In response, RFA received a 2011 slide presentation by Smith & Sumner that presents some price-yield elasticity values estimated by the authors; the presentation makes clear that the effects modeled are "short-term," and therefore would be inappropriate for use by CARB in a long-term modeling scenario. In any event, it is not clear from the slide presentation how the elasticity values were estimated.

Because CARB's GTAP modeling scenarios are meant to simulate ethanol expansion over an 11-year period, the use of short-term price-yield elasticities is clearly indefensible and inappropriate. CARB should re-run its GTAP analysis using a range of price-yield elasticity values that omits values representing short-term responses (i.e., short-run values from Berry & Schlenker and Smith & Sumner should not be used in the range).

b. CARB appears to have misrepresented the results of some price-yield elasticity studies. In particular, the upper bounds of estimated elasticity values from recent studies were omitted and the results of Kaufmann & Snell were incorrectly reported.

The literature review presented by CARB often included the extreme lower price-yield elasticity estimates from recent studies, but curiously omitted the extreme higher-end estimates. The Goodwin et al. paper cited by CARB found that "[t]he long-run price-yield elasticities range from 0.15 to 0.43 at the state-level."[7] Yet, CARB represented Goodwin et al. as finding a long-run range of 0.19-0.27. Similarly, the Rosas Perez research cited by CARB estimated the long-run price-yield elasticity at 0.14-0.53.[8] However, CARB's literature review presented only the median value (0.29) from this work. CARB's reasoning for excluding the upper bounds from these studies in its

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[5] S. Berry & W. Schlenker. 2011. "Technical Report for the ICCT: Empirical Evidence on Crop Yield Elasticities." Prepared for ICCT.
[6] *Id.*
[7] B.K. Goodwin, M. Marra, N. Piggott & S. Mueller. 2012. "Is Yield Endogenous to Price? An Empirical Evaluation of Inter- and Intra-Seasonal Corn Yield Response." Available at: http://ageconsearch.umn.edu/bitstream/124884/2/Goodwin_Marra_Piggott_Mueller.pdf
[8] Rosas Perez, J.F. 2012. "Essays on the environmental effects of agricultural production." Ph.D. Dissertation, Iowa State University, 186 pages; Pub. No. 3539418.

literature review is unclear, particularly when extreme lower bounds were included for several studies.

Further, it appears CARB misrepresented the results of the Kaufmann & Snell paper, suggesting that the authors found a price-yield elasticity of "~0." In reality, Kaufmann & Snell estimated the elasticity for corn at 0.0002-0.65, which they wrote is "…similar to the range of 0.24-0.76 calculated by Houck and Gallagher."[9] As stated above, CARB also appears to have misrepresented the short-run estimate from Berry & Schlenker. CARB portrays the estimate as "0", whereas the authors state that the elasticity is "…no higher than roughly 0.1." While not inconsequential to the results of GTAP scenario runs, this distinction is largely irrelevant for the purposes of our comments because we recommend omitting short-run responses when considering the appropriate range for the price-yield elasticity.

c. CARB's Expert Work Group recommended using a central value of 0.25, which is 43% higher than the central value from CARB's draft analysis (0.175).

By using a price-yield elasticity range of 0.05-0.30 (median value of 0.175) for its draft analysis, CARB staff is clearly going against the recommendations of the EWG. In its final report, the Elasticities Subgroup recommended that CARB should "[k]eep the central value of the yield elasticity with respect to price at 0.25 if only one value can be used for all crops and all countries."[10] The subgroup's interim report recommended using a range of 0.1-0.4 for sensitivity analysis around this parameter, while the final report suggested using a central value of 0.25 and an upper bound of 0.35. At the March 11 workshop, CARB staff did not provide any explanation for why it is ignoring the recommendations of the EWG with regard to this elasticity. This is particularly puzzling given that CARB adopted a number of other subgroup recommendations.

It is also worth noting that the EWG recommendations for this elasticity were adopted by the International Food Policy Research Institute (IFPRI) for use in the MIRAGE model, which has been used to inform European Union biofuels policy decision-making.[11]

d. The GTAP model's inability to explicitly consider double-cropping further justifies the use of a higher range of price-yield elasticity values.

As explained by CARB's EWG, "…higher prices give farmers a greater incentive to double crop."[12] Indeed, there is empirical evidence that double-cropping has significantly increased during the recent period of higher commodity prices. For example, Allendale, Inc., a commodity advisory firm, estimates that 10% of soybean acreage was double-cropped in 2013—a record amount and up substantially from just 3% in 2010 (see also Babcock & Carriquiry[13]). Unfortunately, GTAP

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[9] See Keeney, R. and T. W. Hertel. 2008. "Yield Response to Prices: Implications for Policy Modeling." *GTAP Working Paper* 08 - 13.
[10] ARB Expert Work Group. 2011. "Final Recommendations from the Elasticity Values Subgroup." Available at: http://www.arb.ca.gov/fuels/lcfs/workgroups/ewg/010511-final-rpt-elasticity.pdf
[11] Laborde, D. & Valin, H. 2011. "Assessing the EU biofuel land use change effects: estimates with the MIRAGE-BioF model and uncertainty." Paper presented at the 14th GTAP Conference, Venice, June, 16-18, 2011.
[12] *Id.*
[13] Babcock, B. A. and M. Carriquiry, 2010. "An Exploration of Certain Aspects of CARB's

simulations do not explicitly allow increased demand for agricultural commodities to be satisfied through increased double-cropping. Recognizing this shortfall, the Elasticities Subgroup recommended that the price-yield elasticity parameter could be used to partially account for double-cropping responses. In its final report, the subgroup explained that "the reality of double cropping" *by itself* justified the use of a positive (i.e., non-zero) value for the price-yield elasticity.[14] The subgroup recommended that "…for countries that have the opportunity to double crop, such as the U.S., Brazil, Argentina, and some Asian rice producing countries such as Thailand…an additional increment should be given to the price-yield elasticity."[15] To date, CARB staff has failed to account for increased double-cropping in its GTAP modeling scenarios.

e. CARB's derivation of an "effective" price-yield elasticity value and its assertion that GTAP includes an endogenous price-yield effect is fundamentally incorrect.

During the March 11 workshop, CARB staff stated that there are "two effects of [price-yield elasticity] within the model: exogenous and endogenous." CARB staff asserted that the use of 0.25 as the YDEL input parameter effectively results in an elasticity value of 0.39 in the model because of an "endogenous effect." This suggestion is not accurate. CARB apparently derived the 0.39 figure by dividing the modeled change in crop yields by the change in crop prices. This method is clearly inappropriate because there are several other factors within the model that would cause both yields and prices to change in response to a demand shock. CARB's approach drew a strong rebuke from Prof. Tyner during the workshop:

> The main point I want to make is that [CARB's] yield-price elasticity slides…are basically just incorrect. [The elasticity] is only for the intensive margin, not for the extensive margin. *There is no such thing as an endogenous and exogenous* [effect] if you measure it correctly. So, I think that whole discussion was misleading and I wouldn't want people to leave thinking that represents the state of the art.[16]

Taheripour & Tyner further illuminated this issue in a note to CARB (Appendix B) following the March 11 workshop:

> It is not correct to divide the weighted average of percentage changes in crop yields by the weighted average of percent changes in crop prices as was done in the CARB presentation. This calculation incorporates area changes as

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Approach to Modeling Indirect Land Use from Expanded Biodiesel Production." Center for Agricultural and Rural Development Iowa State University Staff Report 10-SR 105.

[14] ARB Expert Work Group. 2011. "Final Recommendations from the Elasticity Values Subgroup." Available at: http://www.arb.ca.gov/fuels/lcfs/workgroups/ewg/010511-final-rpt-elasticity.pdf

[15] *Id.*

[16] Audio of Prof. Tyner comments are available at: http://domesticfuel.com/2014/03/12/carb-stresses-iluc-update-is-preliminary/. Emphasis added.

> well as yield changes. One must take into account percentage changes in variable costs of production as well. The calculated value from the CARB presentation of 0.39 for yield to price elasticity for US for the corn ethanol expansion *is meaningless because it includes many factors*. …Furthermore, CARB has ignored the fact that the yield to price ratio only cover the percentage change in intensive yield not total yield. In their calculations, percentage changes in total yield instead of intensive yield were used.

f. Based on the latest scientific analyses of long-run yield-price responses, CARB should adopt a range of 0.14-0.53 for the yield-price elasticity.

For its initial ILUC analysis in 2009, CARB used a yield-price elasticity range of 0.20 to 0.40. Seven different cases were evaluated with various yield-price elasticities and the average elasticity value was 0.32. During the EWG process in 2010, CARB staff stated that there were no reliable recent data or analyses to support the continued use of the 0.20-0.40 range or a central value of 0.25 (as recommended by GTAP). CARB attempted to justify this position by emphasizing and promoting the work of Berry & Schlenker.

However, two detailed analyses of the yield-price elasticity have been completed since the EWG process concluded. As referenced above, both studies analyzed recent periods and found a significantly positive medium- or long-run response of yields to price. Goodwin et al. found that "[t]he long-run price-yield elasticities range from 0.15 to 0.43 at the state-level." Meanwhile, Rosas Perez estimated the long-run price-yield elasticity of corn at 0.14-0.53. The range from Rosas Perez includes the entire range from Goodwin et al., as well as the only other recent long-run estimate (0.15 from Huang & Khana). Thus, the lowest long-run estimate from studies examining recent periods is 0.14—this value should be used as the lower bound of CARB's range. The highest long-run value from the recent studies is 0.53—this should be used as the upper bound of the range.

Again, one could argue for an *even higher* upper bound due to the fact that GTAP does not explicitly treat double-cropping. The proposed range of 0.14-0.53 is inclusive of the CARB EWG recommendations (0.25 as a central value and 0.35 as upper bound). We believe CARB should re-run its analysis using the range of 0.14-0.53 and varying the elasticity in increments of 0.05. For the sake of simplicity, the range could be slightly adjusted to 0.15-0.50. Using this range appropriately reflects the best available science, supports the EWG recommendations, properly recognizes that the yield-price effect occurs primarily over the medium or long term, and properly recognizes the effect of double-cropping. The table below and Appendix C provide the basis for the recommended range of 0.14-0.53.

Study[φ]	Period	Elasticity (Corn)	Short-Run Response	Medium- or Long-Run Response
Houck & Gallagher (1976)	1951-1971	0.24-0.76		X
Lyons & Thompson (1981)	1961-1973	0.22		X
Menz & Pardey (1983)	1951-1971	0.61		X
Choi & Helmberger (1993)	1964-1988	0.27		X
Kaufmann & Snell (1997)[x]	1969-1987	0.0002-0.65	X	X
Huang & Khana (2010)	1977-2007	0.15		X
Berry & Schlenker (2011)[°]	1961-2009	<0.10	X	
Goodwin et al. (2012) long-run (aggregate model)	1996-2010	0.15-0.43 (0.19-0.27)		X
Goodwin et al. (2012) short-run	1996-2010	0.006-0.011	X	
Rosas Perez (2012) (mean)	1960-2004	0.14-0.53 (0.29)		X
Range of Medium- or Long-Term Response (midpoint)		**0.14-0.76** (0.45)		X
Range of Medium- or Long-Term, *Recent Period*† (midpoint)		**0.14-0.53** (0.335)		X
EWG Recommendation (central value)		‡-0.35 (0.25)		X
Keeney & Hertel (2008) Recommendation		0.25		X

φ This table includes the same studies as presented in CARB's March 11 literature review (slide 27) with the exception of Smith & Sumner, which could not be located for review. Red values represent short-run responses, which are inappropriate for inclusion in CARB's GTAP analysis.

x CARB's March 11 literature review incorrectly presented the Kaufmann & Snell estimate as "~0", when in fact the authors estimated the elasticity for corn at 0.0002-0.65, which they wrote is "…similar to the range of 0.24-0.76 calculated by Houck and Gallagher."

° CARB's March 11 literature review incorrectly presented the Berry & Schlenker estimate as "0", when in fact the authors estimate the elasticity as being "…no higher than roughly 0.1."

† "Recent Period" refers to study periods that include post-2000 data.

‡ The CARB EWG Elasticities Subgroup did not recommend a specific lower-bound value, but specified that the "lower bound on this elasticity should not be zero because of strong theoretical considerations (input use responds to crop price) and the reality of double cropping."

2. CARB should adopt a higher range of values for the elasticity of yield with respect to area expansion based on empirical evidence and Expert Work Group analysis.

Another important elasticity in the GTAP model governs the productivity of crops on newly converted lands (represented by the code "ETA" in GTAP). This elasticity is essentially meant to represent a ratio of crop yields on newly converted acres to crop yields on existing cropland. The elasticity is governed in recent versions of GTAP by the Terrestrial Ecosystem Model (TEM), which estimates net primary productivity (NPP) as a surrogate for crop yield potential. We agree with CARB that "[t]he use of biophysical models such as the TEM may be a weak substitute for measuring yield potential in GTAP."[17] However, we understand development of a robust methodology to measure actual yield potential takes time and resources and that the TEM approach is currently the best available method. To the extent that CARB continues to rely on the NPP approach, the agency should give strong consideration to recent research published in *PNAS*

[17] CARB Presentation, Slide 37. March 11, 2014. Available at: http://www.arb.ca.gov/fuels/lcfs/lcfs_meetings/iluc_presentation_031014.pdf

showing the productivity of cropland in the central U.S. has been habitually underestimated by conventional NPP methodologies by 40-60% (Appendix E).

Further, where quality data exist to guide the use of this input parameter, we believe CARB should consider integrating it into the analysis. CARB's draft analysis assumes that the ratio of crop yields on newly converted lands to yields on existing cropland will be as low as 0.43 and no higher than 0.90. We note that Tyner et al. (2010) used values in the range of 0.91-1.00—which is outside of CARB's range—for 58% of the AEZ regions in which land is available.[18] In fact, across all AEZ regions, the values selected by CARB for the draft analysis agree with *just 42%* of the values used by Tyner et al. (2010). Without explanation or scientific justification, CARB has deviated from the values used in Tyner et al. and has adopted an artificial upper bound of 0.90. A comparison of the ETA values used by CARB to the values used by Purdue is found in Appendix D.

Common sense and basic economic theory dictate that farmers *will not* convert non-agricultural land to cropland if there is a high likelihood that yields on newly converted acres would be equivalent to just half of the yield on existing cropland. CARB's EWG Elasticities Subgroup highlighted this logical fallacy, stating, "…from a microeconomic perspective, we would hardly expect investments in new areas if the yield of the new crop would be half of the traditional area, as assumed with an elasticity of 0.5 proposed by CARB staff."[19]

But the notion that farmers won't convert unproductive land isn't simply based on microeconomic theory—it is also supported by empirical data and analysis. The EWG Elasticities Subgroup showed that crop yields on converted acreage in the U.S. and Brazil (i.e., where GTAP assigns the bulk of ILUCs) have not been materially different than yields on existing cropland in those countries. With regard to the U.S., Babcock & Carriquiry (2010) examined a time series of county-level acreage and yield data to determine the ratio of crop yields on expanded cropland to crop yields on existing cropland. For 14 major U.S. crops, they found that the ratio of crop yields on expanded lands to the corresponding crop yields on existing cropland was 0.82-1.23. The average ratio for corn was 0.95. The planted area-weighted average across all crops was 0.98, meaning actual crop yields on expanded acreage were nearly identical to actual crop yields on existing acreage. These results are summarized in the EWG Elasticities Subgroup final report.

Based on the empirical data, the Elasticities Subgroup suggested using average elasticity values of 0.98 in the U.S. and 0.90-0.95 for Brazil. CARB's reasoning for disregarding this EWG recommendation is unclear, as is the decision to deviate from the Tyner et al. (2010) analysis by choosing an arbitrary limitation of 0.90 for the upper bound. We believe CARB should revisit its elasticity values for each AEZ and region based on the EWG recommendations, the empirical data presented by the Elasticities Subgroup, and the values used in Tyner et al. (2010).

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[18] Tyner, W. E., F. Taheripour, Q. Zhuang, D. Birur, U. Baldos, 2010. "Land use changes and consequent CO2 emissions due to US corn ethanol production: a comprehensive analysis." Department of Agricultural Economics, Purdue University, Final Report (Revised). Table A2.

[19] ARB Expert Work Group. 2011. "Final Recommendations from the Elasticity Values Subgroup." Available at: http://www.arb.ca.gov/fuels/lcfs/workgroups/ewg/010511-final-rpt-elasticity.pdf

3. **The AEZ-EF model appears to be an improvement over the previous approach to emissions factors (i.e., ad hoc use of Woods Hole data). However, CARB should consider additional refinements to the model that would enhance its reliability.**

RFA is still reviewing the AEZ-EF model and the documentation that was posted to the LCFS web site on March 14. Based on an initial review, however, it appears the AEZ-EF represents a considerable improvement over the previous method for assigning emissions factors to ILUCs. Still, the documentation accompanying the AEZ-EF model contains several debatable assumptions and highlights important sources of uncertainty. The most critical issues from our initial review are discussed below.

a. ***AEZ-EF does not include transition of cropland-pasture to (permanent) pasture or forest.***

AEZ-EF estimates the CO2-equivalent emissions released or sequestered when land cover is converted from one class to another. Table 11 of the report shows that eight transitions are included in the model. However, the model does not include transitions from the cropland-pasture class to either the pasture class or forest class. The report explains that "[w]e assume that cropland-pasture is exchanged only with cropland." There is no explanation or scientific basis given for this assumption. Conversion of cropland-pasture to permanent pasture and forest has been observed (e.g., in its latest edition of *Major Uses of Land in the United States*[20], USDA reclassified 36 million acres of previous cropland-pasture as permanent grassland), and thus there is no reason to omit these potential transitions from AEZ-EF.

b. ***The model coarsely assumes emissions from conversion of cropland-pasture to cropland are equivalent to 50% of the emissions from converting pasture to cropland.***

AEZ-EF assumes that conversion of cropland-pasture to cropland results in half the emissions caused by converting pasture to cropland in each region. This is a tenuous assumption in that cropland-pasture is part of an active long-term crop rotation and thus is not sequestering as much carbon as permanent pasture (or even CRP) over the long term. As such, it seems implausible that conversion of cropland-pasture to cropland would result in emissions equivalent to 50% of the emissions from pasture conversion. The AEZ-EF report admits that this assumption "is not empirically-based" and "[u]ncertainty surrounding these estimates is likely quite high." Given that cropland-pasture is typically the first land class to transition to cropland in response to higher crop prices, it is important that CARB establish a more rigorous and defensible method for estimating emissions from conversion of cropland-pasture.

c. ***The model's treatment of harvested wood products (HWP) ignores the fraction of wood harvested and removed for the purposes of energy production.***

The AEZ-EF model assumes 2-36% (depending on region) of above ground carbon remains

[20] Available at: http://www.ers.usda.gov/data-products/major-land-uses.aspx

sequestered in HWP after 30 years. While this estimate is consistent with other estimates of carbon storage in products and landfills, it ignores that some harvested wood products are used for energy production that offsets fossil fuel use. Heath et al. (1996)[21] examined the fate of carbon from wood harvested and removed from U.S. forests from 1900 to 1990. The authors concluded that "…by 1990 approximately 35% of the total C removed is stored in products and landfills, 30% has been returned to the atmosphere through decay or burning without energy production, and 35% has been burned for energy, partially offsetting fossil fuel use." According to the authors, use of this wood to produce energy mitigates increasing atmospheric CO_2 concentrations by offsetting fossil fuel use, and in this respect it is not equivalent to emissions from decay. AEZ-EF should account for harvested wood that is used for bioenergy production.

d. Emissions related to litter and deadwood are extremely uncertain and estimates are not reliable enough for policy decision-making.

Unlike CARB's previous ILUC analysis, the AEZ-EF model includes emissions from dead organic matter (e.g., deadwood and litter). CARB assumes that if not for conversion from forest to some other land class, deadwood and litter carbon stocks would remain in equilibrium and there would be no net emissions from this material. However, this approach ignores the fact that carbon emissions from deadwood and litter would occur in any case. That is, these emissions did not occur as the result of land conversion, and thus should not be charged to the ILUC. Aside from this logical infirmity, the existing estimates of emissions from litter and deadwood are highly uncertain and variable. The authors of the AEZ-EF report acknowledge this dilemma, noting "[l]itter estimates include variability in original data, imperfect mapping to Region AEZs, uncertainty in the ratio of broadleaf to needleleaf forests, and uncertainty whether these estimates represent forests actually converted…" Given the high degree of uncertainty and the fact that these emissions will occur even in the absence of a land conversion, we recommend excluding litter and deadwood emissions from the AEZ-EF.

4. **CARB should continue to resist pressure from certain stakeholders to include a penalty in the ILUC analysis for purported "food consumption effects."**

One stakeholder at the March 11 workshop suggested CARB should penalize biofuels for model-derived "reductions in food consumption." The stakeholder asserted that this additional penalty could be developed by holding food consumption constant in GTAP and assigning the resultant additional ILUCs to biofuels. The suggestion to hold food consumption constant in GTAP (i.e., preventing a general equilibrium model from reaching equilibrium) and adjust biofuel CI scores was neither recommended by the EWG, nor was it discussed in the staff's plan for ILUC updates that was presented and approved at the November 2010 board meeting.

Moreover, the LCFS was intended to address the *carbon intensity* of transportation fuels used within the state, not theoretical economic or social effects potentially occurring in areas outside

[21] L. Heath, R. Birdsey, C. Row, and A. Plantinga. 1996. "Carbon pools and flux in U. S. forest products." In: Forest Ecosystems, Forest Management, and the Global Carbon Cycle, M. Apps and D. Price, eds. NATO ASI Series I: Global Environmental Changes, Volume 40, Springer-Verlag, P. 271-278.

of the state. A decision to address hypothetical food consumption effects within the LCFS regulatory context would set a dangerous precedent and open the door to "policy creep." For example, if ARB were to proceed with a food analysis, it would also need to consider factors like the social, economic, and geopolitical impacts of increased demand for "rare Earth" elements resulting from greater use of electric vehicles. Similarly, CARB would need to examine the economic and social impacts of using natural gas for transportation rather than for home heating or food preparation. In short, introducing broad-ranging, hypothetical impacts unrelated to GHG emissions into the LCFS would be the equivalent of opening Pandora's Box. CARB was right to omit purported "food consumption" effects from its draft analysis, and it should continue to resist pressure from stakeholders to introduce such a factor.

Appendix A

Letter from scientists and researchers to CARB Chair Mary Nichols regarding advancements in ILUC analysis

March 6, 2014

Mary D. Nichols
Chairwoman
California Air Resources Board
Headquarters Building
1001 "I" Street
Sacramento, CA 95812

Dear Chairwoman Nichols,

We, the undersigned scientists and researchers, are writing to encourage the California Air Resources Board (CARB) to strongly consider recent developments in the analysis of indirect land use change (ILUC) when contemplating potential amendments to the Low Carbon Fuel Standard (LCFS). We understand CARB is considering potential changes to the LCFS regulation's current carbon intensity (CI) values, and that these possible adjustments are the subject of an upcoming stakeholder workshop on March 11.

Many of us were members of the CARB-appointed expert work group, which convened in 2010 for the purposes of critically reviewing CARB's ILUC analysis, identifying data gaps and areas in need of additional analysis, and recommending improvements. Upon completion of a year-long deliberative process, the work group recommended that CARB should revise its ILUC estimates using the latest version of Purdue University's GTAP model. Further, many of us have independently conducted additional data analysis and ILUC modeling in the years following the conclusion of CARB's expert work group process. In many cases, the findings from our research have been subjected to peer-review and published in the scientific literature.

While ILUC analysis continues to suffer from a relatively high degree of systematic and data uncertainty, the quality of both the models and input data chosen for use by CARB have substantially improved since the Board formally adopted the LCFS. These improvements have resulted in corn ethanol ILUC emissions estimates that are much lower than CARB's current estimates for the LCFS. The improved ILUC emissions estimates result from the availability of more robust data and enhanced understanding of: 1) the types of land most likely to be converted; 2) the likely location of predicted conversions; 3) crop yields on newly converted lands; 4) crop yield responses to changes in prices; 5) carbon stocks and emissions from land conversion; 6) the feedback effects of animal feed co-products on land use; and 7) crop switching, double-cropping, and cross-commodity effects. Alternative methodologies for accounting for land use change emissions over time (i.e., "time accounting") have also been established.

Many of us continue to believe the use of point-estimate ILUC factors is inappropriate for the purposes of regulation. However, to the extent that CARB continues to rely upon the use of ILUC factors in calculating CI scores for the LCFS, we believe the Board should be familiar with the most recent independent modeling results. In general, our recent work—and analyses conducted by other experts in the field—indicates that CARB's existing CI factors significantly overestimate the GHG emissions associated with potential ILUCs resulting from corn ethanol expansion. Analyses conducted since CARB adopted the LCFS in 2009 show that potential ILUC emissions associated with corn ethanol are more likely in the range of **6-15** grams per megajoule of CO2 equivalent (g/MJ), compared to CARB's estimate of 30 g/MJ. A bibliography of relevant corn ethanol ILUC studies conducted in recent years is provided in the attachment.

Nearly three and a half years have passed since the Board adopted resolution 10-49, which directed CARB staff to prepare amendments to the LCFS by the spring of 2011. Among the amendments directed by the Board were CI revisions that would reflect "[u]pdates to the land use values for corn ethanol, sugarcane ethanol, and soy biodiesel, and other feedstocks…" Given this directive and CARB's commitment to using the "best available science" to "determin[e] the total direct and indirect emissions associated with…all fuels,"[1] we believe CARB staff should give serious consideration to immediately adopting a lower ILUC factor for corn ethanol based on the studies included in the attachment.

Sincerely,

Steffen Mueller, PhD
Principal Research Economist
Energy Resources Center
University of Illinois at Chicago
CARB Expert Work Group Member

Blake A. Simmons, PhD
Vice-President
Deconstruction Division
DOE Joint BioEnergy Institute
Sandia National Laboratories
CARB Expert Work Group Member

[1]California Air Resources Board, Staff Report: Initial Statement of Reasons, Proposed Regulation to Implement the Low Carbon Fuels Standard: Vol. I (March 5, 2009), Page IV-48

Jesper Kløverpris, PhD
Sustainability Manager
Novozymes A/S
CARB Expert Work Group Member

Richard G. Nelson, PhD
President
Enersol Resources Inc.
(Former Associate Professor at Kansas State University)
CARB Expert Work Group Member

Mark D. Stowers, PhD
Vice President and Head
Global Research and Development
HM.Clause
CARB Expert Work Group Member

Harvey W. Blanch, PhD
Merck Professor of Biochemical Engineering
Department of Chemical & Biomolecular Engineering
University of California Berkeley

Jay D. Keasling, PhD
University of California, Berkeley
Lawrence Berkeley National Laboratory
Director, DOE Joint BioEnergy Institute
Synthetic Biology Engineering Research Center

Bruce E. Dale, PhD
University Distinguished Professor
Department of Chemical Engineering and Materials Science
DOE Great Lakes Bioenergy Research Center
Michigan State University

C. Gregg Carlson, PhD
South Dakota State University
Professor, Plant Science

David E. Clay, PhD
South Dakota State University
Professor, Plant Science and Director South Dakota Drought Center

Timothy Donohue, PhD
University of Wisconsin-Madison
Professor of Bacteriology
Director, DOE Great Lakes Bioenergy Research Center

Seungdo Kim, PhD
Associate Professor
Department of Chemical Engineering and Materials Science
Michigan State University

Jon Magnuson, PhD
Director of Fungal Biotechnology
DOE Joint BioEnergy Institute

Stefan Unnasch
Managing Director
Life Cycle Associates, LLC

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Appendix B

Note from Taheripour & Tyner to CARB staff
following March 11 workshop

Discussion of the Yield Price Elasticity in GTAP

Farzad Taheripour and Wallace E. Tyner
Purdue University

At the March 11, 2014 CARB meeting, there was considerable interest in the yield to price elasticity parameter in GTAP. There also seemed to be a good bit of confusion on what it does and does not do. The purpose of this note is to provide an explanation of the role of this parameter in GTAP, explain why it is there, and to explain other reasons why yields can change in GTAP.

First, the basic idea behind the parameter is that over the medium to long term (the time horizon of GTAP), one would expect the agricultural sector to respond to increases in net returns to crops with appropriate investments in improving yields of crops with growing returns. This investment is certainly not limited to on-farm investment. In fact, a major portion of it may occur off-farm. It could include investments by seed companies to produce higher yielding seeds, investments in chemical companies to produce better herbicides/pesticides, investments by farm equipment companies to produce more efficient machinery for cultivation and harvest, investments by farmers to improve drainage and other soil properties, and other productivity enhancing investments. In other words, this parameter attempts to capture responses throughout the agricultural sector to higher returns in given crops.

The yield to price elasticity does not measure changes over one crop year. In fact, any estimate done over one year would be totally inappropriate for GTAP and should be excluded from consideration in determining appropriate values for the parameter.

What is the precise definition of the yield to price elasticity (YDEL)? YDEL is the *percentage change in intensive yield* over the percentage changes in *relative price of a crop over input prices*. In other words it is the intensive yield change with respect to change in variable returns to a crop. If the YDEL value is 0.25, and the change in variable returns of a crop is 10%, then the change in intensive yield would be 2.5%. It is very important to emphasize that the parameter YDEL only governs changes in intensive yield due the changes in net return. Other factors can affect crop yields as well.

How else can yields change in GTAP? Yields are affected by changes on the intensive and extensive margins. As noted in Hertel et al. (2010), there are *two* important sources which affect the extensive margin of yields. The first source is due to *shifting among crops*. For example, shifting from corn-soybean rotation to corn-corn rotation could affect yield. The second source of change in extensive yield is due to land conversion from forest or pasture to cropland. In the first case, if there is a corn ethanol shock applied to the model, more corn will be demanded, and there likely will be both

crop switching and land cover changes to accommodate the higher demand for corn. With crop switching, there will be more acres of corn and fewer acres of other lower yielding crops. Thus, when one calculates the weighted average yields after the shock, the average likely would be higher. For example, consider typical corn, soybean, and wheat yields of 4.5, 1.2, and 1.7 tons/ac respectively. If the post shock crop mix has more corn acreage, the post shock weighted average yields can be higher even if YDEL were zero. That is simply because corn has a higher mass yield per acre.

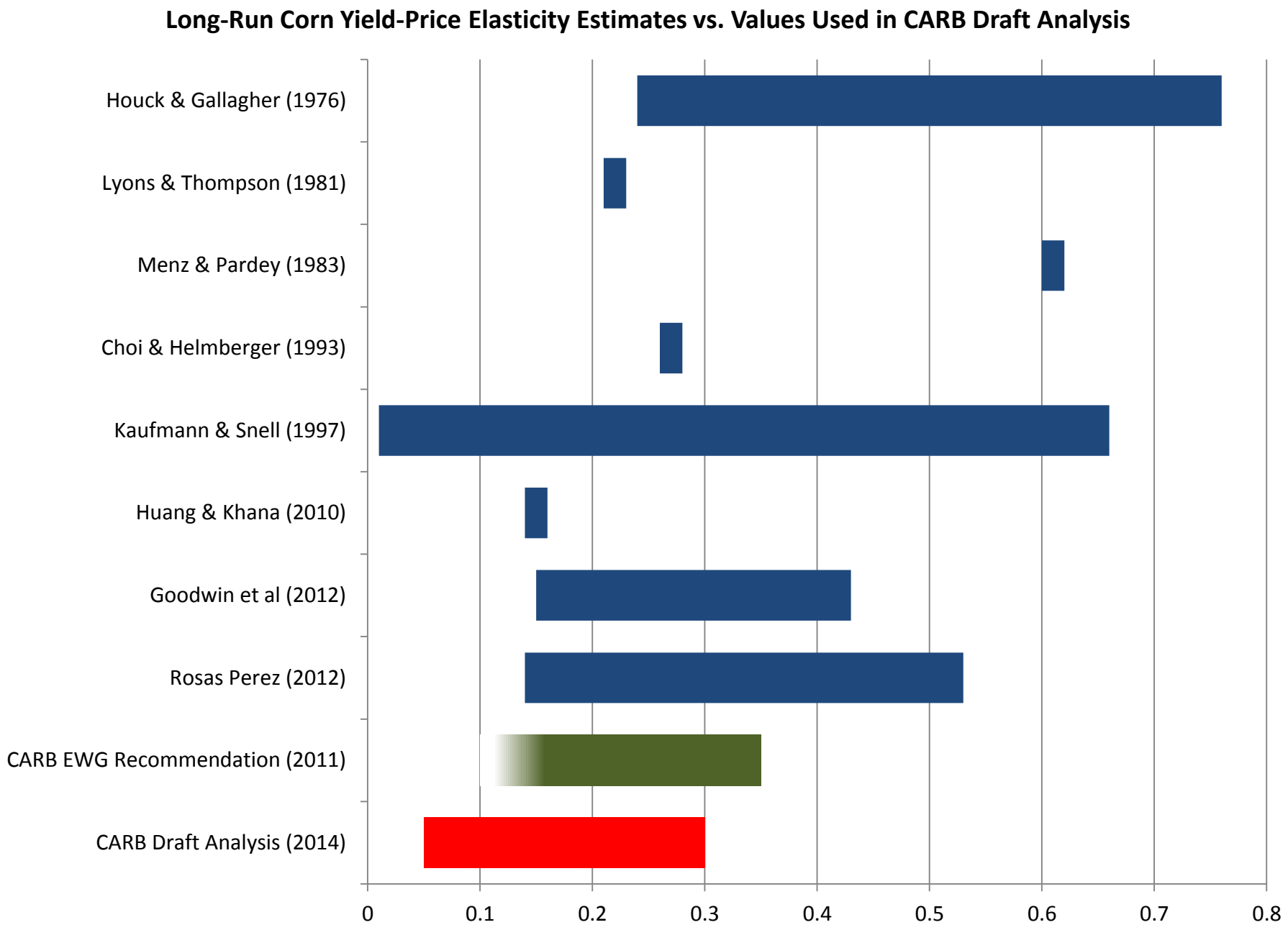
Yields can also change when more or less productive acres come into corn from other uses. Crop switching can result in higher or lower productivity. However, land cover changes from pasture or forest typically tends to reduce yields because new land could be lower productivity. The productivity of converted land is affected by the ETA parameter.

Since GTAP is a CGE model, yields can also be influenced by a myriad of other changes such as changes in relative price of variable inputs. The bottom line is that while yields can be and are affected by many factors working in GTAP, the YDEL parameter is only designed to capture the incentive to invest over the medium term in crops with increasing returns.

It is not correct to divide the weighted average of percentage changes in crop yields by the weighted average of percent changes in crop prices as was done in the CARB presentation. This calculation incorporates area changes as well as yield changes. One must take into account percentage changes in variable costs of production as well. The calculated value from the CARB presentation of 0.39 for yield to price elasticity for US for the corn ethanol expansion is meaningless because it includes many factors. If we follow the CARB approach and calculate the same measure for Brazil due to the US corn ethanol shock, we get a yield to price elasticity of -0.16 for Brazil, which obviously does not make sense. Furthermore, CARB has ignored the fact that the yield to price ratio only cover the percentage change in intensive yield not total yield. In their calculations, percentage changes in total yield instead of intensive yield were used.

Appendix C

Comparison of YDEL values used by CARB to long-run yield-price elasticities from the literature


Long-Run Corn Yield-Price Elasticity Estimates vs. Values Used in CARB Draft Analysis
Houck & Gallagher (1976)
Lyons & Thompson (1981)
Menz & Pardey (1983)
Choi & Helmberger (1993)
Kaufmann & Snell (1997)
Huang & Khana (2010)
Goodwin et al (2012)
Rosas Perez (2012)
CARB EWG Recommendation (2011)
CARB Draft Analysis (2014)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

Appendix D

Comparison of ETA values used by CARB to values from Tyner et al. (2010)

Comparison of ETA values used by CARB to ETA values used by Tyner et al. (2010)

Top row in each AEZ shows values used in Tyner et al. (2010)

Bottom row in each AEZ shows values used by CARB for 2014 draft analysis

RED denotes CARB use of a value lower than corresponding Tyner et al. value; GREEN denotes CARB use of the same value as Tyner et al.

AEZ/Region	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19
AEZ1	0.00	0.00	0.91	0.00	0.00	0.00	0.93	1.00	0.95	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.68	0.61	1.00
	0.00	0.00	0.90	0.00	0.00	0.00	0.90	0.90	0.90	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.68	0.61	0.90
AEZ2	0.00	0.00	0.92	0.00	0.00	0.00	0.89	1.00	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.59	1.00	1.00
	0.00	0.00	0.90	0.00	0.00	0.00	0.89	0.90	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.59	0.90	0.90
AEZ3	0.00	0.00	0.93	0.00	0.00	0.00	0.86	1.00	0.90	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.89	0.74
	0.00	0.00	0.90	0.00	0.00	0.00	0.86	0.90	0.90	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.90	0.89	0.74
AEZ4	0.00	1.00	0.89	0.00	0.00	1.00	0.93	1.00	0.88	0.00	0.88	0.89	1.00	0.00	0.00	0.00	0.86	0.92	0.92
	0.00	0.90	0.89	0.00	0.00	0.90	0.90	0.90	0.88	0.00	0.88	0.89	0.90	0.00	0.00	0.00	0.86	0.90	0.90
AEZ5	0.00	0.00	0.93	0.00	0.00	0.90	0.98	0.88	0.90	0.00	0.90	0.91	0.98	0.00	0.00	0.00	0.00	1.00	0.96
	0.00	0.00	0.90	0.00	0.00	0.90	0.90	0.88	0.90	0.00	0.90	0.90	0.90	0.00	0.00	0.00	0.00	0.90	0.90
AEZ6	0.00	0.00	0.91	0.00	0.00	0.88	0.98	0.97	0.85	0.00	0.88	0.95	0.78	0.00	0.00	0.00	0.00	1.00	0.88
	0.00	0.00	0.90	0.00	0.00	0.88	0.90	0.90	0.85	0.00	0.88	0.90	0.78	0.00	0.00	0.00	0.00	0.90	0.88
AEZ7	0.73	0.00	0.00	0.89	0.00	0.80	0.90	0.59	1.00	1.00	0.00	0.00	0.43	1.00	0.98	0.00	0.46	0.80	0.65
	0.73	0.00	0.00	0.89	0.00	0.80	0.90	0.59	0.90	0.90	0.00	0.00	0.43	0.90	0.90	0.00	0.46	0.80	0.65
AEZ8	0.71	0.90	0.00	0.91	0.00	1.00	0.71	0.72	0.90	1.00	0.00	0.00	0.60	0.84	0.84	0.00	0.71	0.79	0.86
	0.71	0.90	0.00	0.90	0.00	0.90	0.71	0.72	0.90	0.90	0.00	0.00	0.60	0.84	0.84	0.00	0.71	0.79	0.86
AEZ9	1.00	1.00	0.00	0.85	1.00	0.98	0.88	1.00	0.91	1.00	0.00	0.00	1.00	0.94	0.82	0.00	0.77	0.84	0.93
	0.90	0.90	0.00	0.85	0.90	0.90	0.88	0.90	0.90	0.90	0.00	0.00	0.90	0.90	0.82	0.00	0.77	0.84	0.90
AEZ10	0.93	0.96	0.88	0.88	0.96	0.84	1.00	0.89	1.00	0.93	0.00	1.00	0.92	0.89	0.89	0.87	0.98	0.88	0.92
	0.90	0.90	0.88	0.88	0.90	0.84	0.90	0.89	0.90	0.90	0.00	0.90	0.90	0.89	0.89	0.87	0.90	0.88	0.90
AEZ11	0.96	0.83	1.00	1.00	0.94	0.95	0.90	1.00	0.87	0.84	0.00	1.00	0.79	0.89	1.00	0.00	0.00	0.77	0.96
	0.90	0.83	0.90	0.90	0.90	0.90	0.90	0.90	0.87	0.84	0.00	0.90	0.79	0.89	0.90	0.00	0.00	0.77	0.90
AEZ12	0.89	0.86	0.91	0.00	0.95	0.92	0.90	1.00	0.84	0.00	0.00	1.00	1.00	0.00	0.89	0.00	0.00	1.00	0.98
	0.89	0.86	0.90	0.00	0.90	0.90	0.90	0.90	0.84	0.00	0.00	0.90	0.90	0.00	0.89	0.00	0.00	0.90	0.90
AEZ13	0.92	1.00	0.00	0.55	0.00	1.00	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.63	0.97	0.00	0.00	0.00	0.00
	0.90	0.90	0.00	0.55	0.00	0.90	0.90	0.00	0.90	0.90	0.00	0.00	0.90	0.63	0.90	0.00	0.00	0.00	0.00
AEZ14	0.51	0.89	0.00	0.80	0.00	0.92	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.90	1.00	0.95	0.00	0.00	0.00
	0.51	0.89	0.00	0.80	0.00	0.90	0.90	0.00	0.90	0.90	0.00	0.00	0.90	0.90	0.90	0.90	0.00	0.00	0.00
AEZ15	0.71	0.90	0.00	0.83	1.00	1.00	1.00	0.00	0.64	1.00	0.00	1.00	1.00	0.90	1.00	0.87	0.00	0.00	1.00
	0.71	0.90	0.00	0.83	0.90	0.90	0.90	0.00	0.64	0.90	0.00	0.90	0.90	0.90	0.90	0.87	0.00	0.00	0.90
AEZ16	1.00	0.89	0.00	1.00	0.00	1.00	1.00	0.00	0.92	0.00	0.00	1.00	1.00	0.85	1.00	1.00	0.00	0.00	1.00
	0.90	0.89	0.00	0.90	0.00	0.90	0.90	0.00	0.90	0.00	0.00	0.90	0.90	0.85	0.90	0.90	0.00	0.00	0.90
AEZ17	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.90
AEZ18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix E

L. Guanter et al. 2014. “Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence.” PNAS 2014, published ahead of print March 25, 2014.

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Global and time-resolved monitoring of crop photosynthesis with chlorophyll fluorescence

Luis Guanter[a,1,2], Yongguang Zhang[a,1], Martin Jung[b], Joanna Joiner[c], Maximilian Voigt[a], Joseph A. Berry[d], Christian Frankenberg[e], Alfredo R. Huete[f], Pablo Zarco-Tejada[g], Jung-Eun Lee[h], M. Susan Moran[i], Guillermo Ponce-Campos[i], Christian Beer[j], Gustavo Camps-Valls[k], Nina Buchmann[l], Damiano Gianelle[m], Katja Klumpp[n], Alessandro Cescatti[o], John M. Baker[p], and Timothy J. Griffis[q]

[a]Institute for Space Sciences, Freie Universität Berlin, 12165 Berlin, Germany; [b]Department for Biogeochemical Systems, Max Planck Institute for Biogeochemistry, 07745 Jena, Germany; [c]Laboratory for Atmospheric Chemistry and Dynamics (Code 614) National Aeronautics and Space Administration Goddard Space Flight Center, Greenbelt, MD 20771; [d]Department of Global Ecology, Carnegie Institution for Science, Stanford, CA 94305; [e]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91109; [f]Plant Functional Biology and Climate Change Cluster, University of Technology Sydney, Sydney, 2007, Australia; [g]Instituto de Agricultura Sostenible, Consejo Superior de Investigaciones Científicas, 14004 Córdoba, Spain; [h]Geological Sciences, Brown University, Providence, RI 02912; [i]Southwest Watershed Research, Agricultural Research Service, US Department of Agriculture, Tucson, AZ 85719; [j]Department of Applied Environmental Science and Bolin Centre for Climate Research, Stockholm University, 10691 Stockholm, Sweden; [k]Image Processing Laboratory, Universitat de València, 46980 València, Spain; [l]Agricultural Sciences, Eidgenössiche Technische Hochschule Zurich, 8092 Zurich, Switzerland; [m]Sustainable Agro-ecosystems and Bioresources Department, Research and Innovation Centre, Fondazione Edmund Mach, 38010 San Michele all'Adige, Italy; [n]Grassland Ecosystem Research Unit, Institut National de la Recherche Agronomique, Clermont-Ferrand, France 63122; [o]Institute for Environment and Sustainability, Joint Research Centre, European Commission, 20127 Ispra, Italy; [p]Soil and Water Management Research, Agricultural Research Service, US Department of Agriculture, St. Paul, MN 55108; and [q]Department of Soil, Water, and Climate, University of Minnesota, St. Paul, MN 55108

Edited by Gregory P. Asner, Carnegie Institution for Science, Stanford, CA, and approved February 25, 2014 (received for review October 24, 2013)

Photosynthesis is the process by which plants harvest sunlight to produce sugars from carbon dioxide and water. It is the primary source of energy for all life on Earth; hence it is important to understand how this process responds to climate change and human impact. However, model-based estimates of gross primary production (GPP, output from photosynthesis) are highly uncertain, in particular over heavily managed agricultural areas. Recent advances in spectroscopy enable the space-based monitoring of sun-induced chlorophyll fluorescence (SIF) from terrestrial plants. Here we demonstrate that spaceborne SIF retrievals provide a direct measure of the GPP of cropland and grassland ecosystems. Such a strong link with crop photosynthesis is not evident for traditional remotely sensed vegetation indices, nor for more complex carbon cycle models. We use SIF observations to provide a global perspective on agricultural productivity. Our SIF-based crop GPP estimates are 50–75% higher than results from state-of-the-art carbon cycle models over, for example, the US Corn Belt and the Indo-Gangetic Plain, implying that current models severely underestimate the role of management. Our results indicate that SIF data can help us improve our global models for more accurate projections of agricultural productivity and climate impact on crop yields. Extension of our approach to other ecosystems, along with increased observational capabilities for SIF in the near future, holds the prospect of reducing uncertainties in the modeling of the current and future carbon cycle.

crop productivity | carbon fluxes | Earth observation | carbon modeling | spaceborne spectroscopy

The rapidly growing demand for food and biofuels constitutes one of the greatest challenges for humanity in coming decades (1). It is estimated that we must double world food production by 2050 to meet increasing demand (2), but the once rapid growth seen in the "green revolution" has stalled, and even past advances are threatened by climate change (3–5). Much of past yield improvement has focused on increases in the harvest index and resistance to pests. However, all else being equal, the quantity of photosynthesis places an upper limit on the supply of food and fuels from our agricultural systems.

Ironically, we currently have very limited ability to assess photosynthesis of the breadbaskets of the world. Agricultural production inventories provide important information about crop productivity and yields (6–8), but these are difficult to compare between regions and lag actual production. Carbon cycle models, based on either process-oriented biogeochemistry or semiempirical data-driven approaches, have been used to understand the controls and variations of global gross primary production (GPP, equivalent to ecosystem gross photosynthesis) (9) and to investigate the climate impact on crop yields (10). However, uncertainty associated with inaccurate input data and much simplified process descriptions based on the plant functional type concept severely challenge the application of these models to agricultural systems. Recent model intercomparisons conducted as part of the North American Carbon Project found that GPP estimates for crop areas varied by a factor of 2 (11). The best available estimates of GPP of crop systems are from direct measurement of carbon dioxide exchange by so-called flux towers over agricultural fields (12). However, these generally sample small areas (<1 km^2) and are concentrated in North America and Europe.

Remote sensing of reflectance-based vegetation parameters has been used in the last decades to monitor agricultural

Significance

Global food and biofuel production and their vulnerability in a changing climate are of paramount societal importance. However, current global model predictions of crop photosynthesis are highly uncertain. Here we demonstrate that new space-based observations of chlorophyll fluorescence, an emission intrinsically linked to plant biochemistry, enable an accurate, global, and time-resolved measurement of crop photosynthesis, which is not possible from any other remote vegetation measurement. Our results show that chlorophyll fluorescence data can be used as a unique benchmark to improve our global models, thus providing more reliable projections of agricultural productivity and climate impact on crop yields. The enormous increase of the observational capabilities for fluorescence in the very near future strengthens the relevance of this study.

Author contributions: L.G., Y.Z., M.J., and J.A.B. designed research; L.G., Y.Z., M.V., A.R.H., P.Z.-T., J.-E.L., M.S.M., and G.P.-C. performed research; L.G., Y.Z., M.J., J.J., C.B., G.C.-V., N.B., D.G., K.K., A.C., J.M.B., and T.J.G. contributed new reagents/analytic tools; L.G., Y.Z., J.J., M.V., and C.F. analyzed data; and L.G., Y.Z., J.A.B., C.F., and A.R.H. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

[1]L.G. and Y.Z. contributed equally to this work.

[2]To whom correspondence should be addressed. E-mail: luis.guanter@wew.fu-berlin.de.

This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1320008111/-/DCSupplemental.

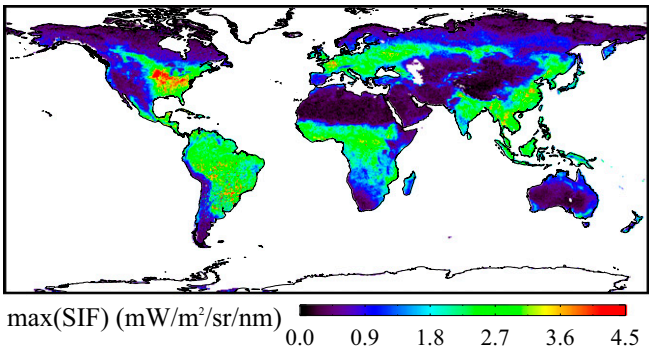

Fig. 1. Global map of maximum monthly sun-induced chlorophyll fluorescence (SIF) per 0.5° grid box for 2009. SIF retrievals are performed in a spectral window centered at 740 nm (see *Materials and Methods* and *SI Appendix, SIF Retrievals*). This maps illustrates the outstanding SIF signal detected at the US CB, which shows the highest SIF return of all terrestrial ecosystems. The maximum SIF over the largest part of the US CB region is detected in July.

resources (e.g., refs. 13, 14). The signal of the so-called spectral vegetation indices convolves leaf chlorophyll content, biomass, canopy structure, and cover (15, 16), such that estimating actual productivity from vegetation indices requires additional data and modeling steps, both associated with considerable uncertainty. Complementing reflectance-based indices, global space-based estimates of sun-induced chlorophyll fluorescence (SIF) became available recently. SIF is an electromagnetic signal emitted in the 650- to 850-nm spectral window as a by-product of photosynthesis (e.g., refs. 17–19). The first global maps of SIF were derived using data from the Greenhouse Gases Observing Satellite (GOSAT) (20–23). Despite the complicated photosynthesis-SIF relationships and the convolution of the signal with canopy structure (16), SIF retrievals showed high correlations with data-driven GPP estimates at global and annual scales (21, 22), as well as intriguing patterns of seasonal drought response in Amazonia (24, 25). Recently, a global SIF data set with better spatial and temporal sampling than that from GOSAT was produced using spectra from the Global Ozone Monitoring Experiment-2 (GOME-2) instrument onboard the MetOp-A platform (26) (see *SI Appendix, SIF Retrievals*).

Our attention is drawn to the remarkably high SIF returns from the US Corn Belt (CB) region (Fig. 1). This highly productive area (Fig. 2*D*) accounts for >40% of world soybean and corn production (30). We hypothesize that the high SIF indicates very high GPP for this area and report here on studies that compare SIF retrievals to GPP models and flux tower data with the aim of gaining a unique global perspective on crop photosynthesis.

Results and Discussion

Looking at the spatial patterns of the maximum monthly gross carbon uptake from model results in the north temperate region (Fig. 2), we find a generally good agreement between the data-driven approach (27), that relies on data from a global network of micrometeorological tower sites (FLUXNET) (12), and the median of 10 state-of-the-art global dynamic vegetation models from the Trendy ("Trends in net land-atmosphere carbon exchange over the period 1980–2010") project (28, 29), the former showing somewhat larger values in a small region of the US CB (Fig. 2 *A* and *B*) (see *SI Appendix, Model-Based GPP Data*). It must be stated that the Trendy models do not include explicit crop modules, so the results from our comparisons with process-based models are intended to illustrate the potential impact of such crop-specific modules on simulations over agricultural regions. The SIF measurements, on the other hand, show large differences between the US CB and the cropland and grassland areas in Western Europe, with much enhanced SIF in the US CB (Fig. 2*C*). This pattern is roughly consistent with the distribution of C4 crops in the area, predominantly corn fields (Fig. 2*D*). Is the photosynthesis signal in the SIF retrievals disturbed by other factors, or is the US CB indeed much more productive than any area in Western Europe, which is not captured by the carbon models?

We compare year-round monthly means of flux tower-based GPP estimates at cropland and grassland sites in the United States and Europe with SIF retrievals, GPP estimates from carbon models, and spectral reflectance indices (Figs. 3 and 4 and *SI Appendix, Comparison of Flux Tower-Based GPP with Model GPP, SIF and Vegetation Indices*). Data-driven model GPP data are from the statistical model developed at the Max Planck Institute for Biogeochemistry (MPI-BGC) (27) (Fig. 3*B*) and the semiempirical moderate resolution imaging spectroradiometer (MODIS) MOD17 GPP model (31) (*SI Appendix*, Fig. S4). The same ensemble of 10 land surface models (28, 29) is used to evaluate the performance of process-based models (Fig. 3*C*). We present the comparisons in Fig. 3 without including the European cropland sites, as we want to illustrate the strong differences

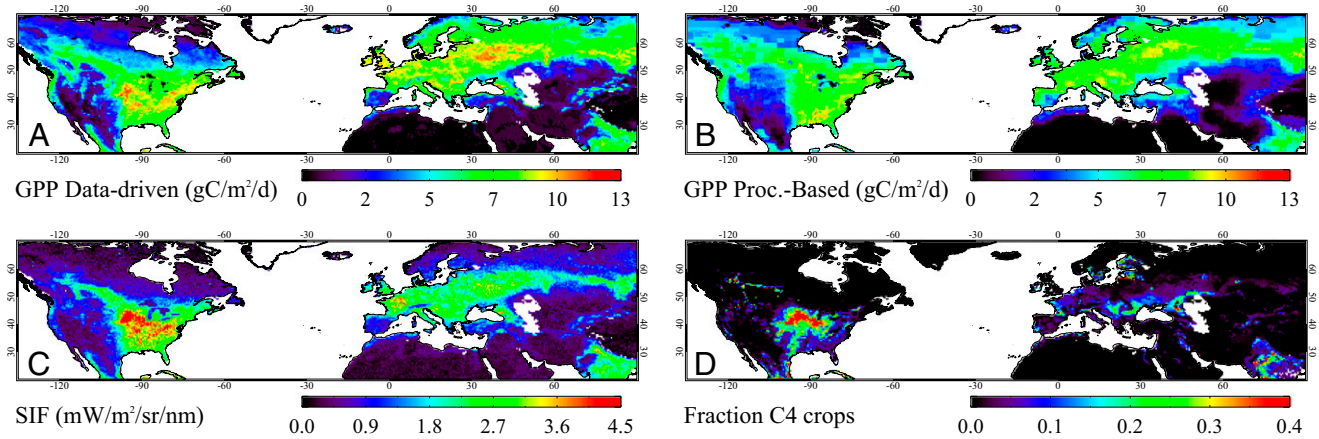

Fig. 2. Spatial patterns of maximum monthly gross primary production (GPP) per 0.5° grid box for 2009 from data-driven (*A*) and process-based (*B*) models together with maximum monthly SIF at 740 nm (*C*). The fraction of C4 crop area (mostly corn in this region) depicts the approximate area of the US Corn Belt (*D*). The data-driven GPP data correspond to the MPI-BGC model (27), the process-based GPP corresponds to the median of an ensemble of 10 global dynamic vegetation models from the Trendy ("Trends in net land-atmosphere carbon exchange over the period 1980–2010") project (28, 29), and SIF was retrieved from GOME-2 satellite measurements (26). The fraction of C4 crop data are described in Ramankutty et al. (6).

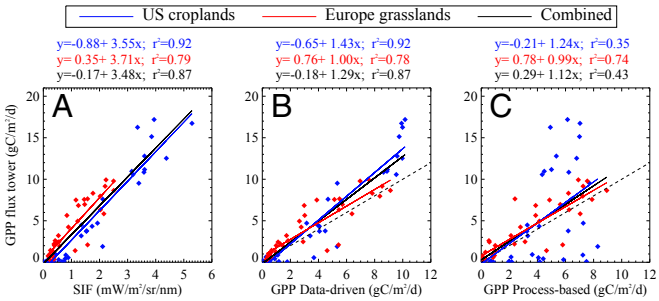

Fig. 3. Comparison of monthly mean GPP estimates at cropland flux tower sites in the US Corn Belt and grassland sites in Western Europe. Flux tower GPP estimates are compared with sun-induced fluorescence (SIF) observations at 740 nm (*A*) and with GPP estimates from the MPI-BGC data-driven model (27) (*B*) and from process-based models [median of an ensemble of 10 dynamic global vegetation models (28, 29)] (*C*). Each symbol depicts a monthly average for a 0.5° grid box and those months in the 2007–2011 period for which flux tower data were available (see *SI Appendix*, Table S1). The *P* value is <0.01 in all of the comparisons. The dashed line in *B* and *C* represents the 1:1 line. Similar comparisons but including also Western Europe cropland sites are provided in *SI Appendix*, Fig. S4.

between cropland and grassland GPP over the most homogeneous ecosystems (the European cropland sites are highly fragmented, which may not be properly sampled by the 0.5° resolution at which we can grid the GOME-2 SIF retrievals; see *SI Appendix, SIF Retrievals*). The comparison including all types of cropland and grassland sites is provided in *SI Appendix*, Fig. S4.

We find that the peak monthly mean GPP derived from the flux tower data in some of the US CB sites is very high (>15 $gC{\cdot}m^{-2}{\cdot}d^{-1}$), whereas for the grassland sites, monthly mean GPP never exceeds 10 $gC{\cdot}m^{-2}{\cdot}d^{-1}$ (Fig. 3). Process-based GPP estimates compare well with the tower-based estimates over the grassland sites but show a poor correlation over the US CB (Fig. 3*C*). Concerning the data-driven models, there is a clear nonlinear relation between flux tower and model GPP, showing that models strongly underestimate GPP at cropland sites with high fluxes. A piece-wise linear approximation reveals that deviations from the linear relation appear at GPP > 10 $gC{\cdot}m^{-2}{\cdot}d^{-1}$ for the MPI-BGC estimates (Fig. 3*B*) and at GPP > 8 $gC{\cdot}m^{-2}{\cdot}d^{-1}$ for the MODIS MOD17 (*SI Appendix*, Fig. S4). We observe that data-driven models produce similar peak GPP values for both grasslands and croplands, and that grasslands have even a higher GPP than croplands in results from the process-based models, which is not reflected by tower-based estimates. We find that SIF values exhibit a much stronger linear relationship with tower GPP at these cropland and grassland sites (Fig. 3*A*), and that a single linear model is able to link SIF with GPP for both croplands and grasslands. On the other hand, the good agreement between the model- and tower-based GPP estimates at grassland sites, including similar peak values, suggests that the direct comparison of flux tower data (typical footprint of <1 km^2) with SIF retrievals and model data at 0.5° is acceptable for these sites.

Hence, the comparisons in Fig. 3 support the following claims: (*i*) SIF captures high photosynthetic signals that are observed from flux towers in the US CB, and (*ii*) the models underestimate crop GPP, in particular for the highly productive crop sites at the US CB. The low correlation between the crop GPP estimates by the process-based models at the US CB sites may be explained by the lack of specific crop modules in the Trendy model ensemble. Concerning the underestimation of crop GPP by data-driven models, it can be argued that these cannot capture the complex dynamics required to link stable and structurally driven vegetation indices derived from remote sensing data with a highly variable physiological measure such as crop photosynthesis. On the other hand, those reflectance-based indices usually underestimate "greenness" for very dense crop canopies with high green biomass levels, such as cultivars with high fertilizer levels. This can lead to the underestimation of GPP by the data-driven models constrained by those vegetation indices.

The same flux tower-based GPP data set is compared with SIF retrievals and the enhanced vegetation index (EVI) extracted from the MODIS MOD13C2 product (15) in Fig. 4. This comparison illustrates that spectral reflectance indices, similar to the GPP models, do not scale linearly with GPP for these biomes despite the good representation of the temporal patterns: The highest EVI values for grassland sites are close to the values for some of the cropland sites, whereas GPP is very different. On the other hand, it is difficult to find a global baseline value for EVI to indicate the total absence of green vegetation activity. The minimum EVI value depends on the soil nature and especially on the presence of snow (32), which can be observed in the relatively high variability of EVI in the months in which no photosynthetic activity is observed (Fig. 4 *C* and *D*). This poses a problem for the identification of start- and end-of-season times in phenological studies based on reflectance-based remote sensing data (32). The SIF observations, in turn, drop to zero following photosynthesis, which provides an unambiguous signal of photosynthetical activity.

The linear relationship between SIF data and flux tower GPP observed in Fig. 3*A* may be rationalized by considering that

$$\mathrm{GPP} = \mathrm{PAR} \times \mathrm{fPAR} \times \mathrm{LUE_P}, \quad [1]$$

where PAR is the flux of photosynthetically active radiation received, fPAR is the fractional absorptance of that radiation, and $\mathrm{LUE_P}$ is the efficiency with which the absorbed PAR is used in photosynthesis (33). SIF may be similarly conceptualized as

$$\mathrm{SIF}(\lambda) = \mathrm{PAR} \times \mathrm{fPAR} \times \mathrm{LUE_F}(\lambda) \times f_{esc}(\lambda), \quad [2]$$

where λ is the spectral wavelength (~740 nm in our GOME-2 retrievals; see *Materials and Methods* and *SI Appendix, SIF Retrievals*), $\mathrm{LUE_F}$ is a light-use efficiency for SIF (i.e., the fraction of absorbed PAR photons that are re-emitted from the canopy as SIF photons at wavelength λ), and $f_{esc}(\lambda)$ is a term accounting for the fraction of SIF photons escaping from the canopy to space. These equations can be combined making the dependence on light implicit,

$$\mathrm{GPP} \approx \mathrm{SIF}(\lambda) \times \frac{\mathrm{LUE_P}}{\mathrm{LUE_F}(\lambda)}, \quad [3]$$

where we assume $f_{esc}(\lambda) \approx 1$ because of the low absorptance of leaves in the near-infrared wavelengths at which we perform the

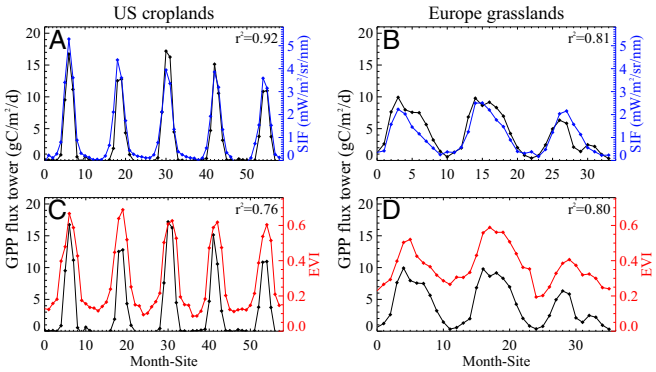

Fig. 4. Time series of flux tower-based GPP compared with SIF retrievals (*A* and *B*) and the MODIS MOD13C2 EVI (*C* and *D*) for the same cropland and grassland sites and spatiotemporal averages as in Fig. 3 (monthly averages in 0.5° grid boxes and the 2007–2011 period). SIF and EVI are plotted with the same vertical scale for cropland and grassland sites.

SIF retrievals and the relatively simple plant structure and high leaf area index of grasses and crops (34).

Empirical studies at the leaf and canopy scale indicate that the two light-use efficiency terms tend to covary under the conditions of the satellite measurement (35–37). Hence, the SIF data should provide information on both the light absorbed and the efficiency with which it is being used for photosynthesis. Vegetation indices derived from reflectance measurements from spaceborne instruments such as MODIS (15) and knowledge of the solar angle and atmospheric condition can be used to estimate PAR × fPAR (Eq. **1**), but LUE_P is a free parameter. These data from the CB are consistent with LUE_P being much higher for intensively managed crops than for native grasslands or less managed crops.

Based on the linear relationship obtained from the comparison of SIF with tower-based GPP at all of the US and Western Europe cropland and grassland flux tower sites [GPP(SIF) = −0.10 + 3.72 × SIF; see *SI Appendix, Comparison of Flux Tower-Based GPP with Model GPP, SIF and Vegetation Indices* and *Derivation of Spatially-Explicit Crop GPP Estimates*], we have produced unique global estimates of annual crop GPP. Even though tower data outside the US CB and Western Europe were not available for the derivation of the empirical GPP–SIF relationship, we assume it to hold for all of the ecosystems in which GPP is driven by canopy chlorophyll content such as croplands and grasslands (14). We have compared our SIF-based crop GPP estimates with the GPP predicted by ensembles of state-of-the-art data-driven (9) and process-based (28, 29) biogeochemistry models (see *SI Appendix, Model-Based GPP Data*). We evaluate the consistency of the different GPP estimates with the agricultural yield statistics from the National Agriculture Statistics Service of the US Department of Agriculture (USDA NASS) (38) (only North America, years 2006–2008) and the data set by Monfreda et al. (7) (global coverage, year 2000). These inventories provide large-scale cropland net primary production (NPP, biomass production by plants) estimates by combining national, state, and county-level census statistics with maps of cropland areas (see *SI Appendix, NPP Data from Agricultural Inventories*).

The comparison between our annual crop GPP estimates and the NPP from the USDA NASS inventory at the US CB shows that SIF-based GPP estimates are, similar to the flux tower comparisons, more linearly related to the inventory-based NPP than the model GPP (Fig. 5). Again, data-driven GPP estimates show a strongly nonlinear relationship with the inventory-based NPP, whereas the comparison with the process-based GPP estimates presents more scatter compared with the SIF-based and the data-driven estimates. The same conclusions hold for the comparison of the different GPP estimates over the US CB and Western Europe with the NPP data set from Monfreda et al. (7) (see *SI Appendix, NPP Data from Agricultural Inventories*). Assuming that annual GPP and NPP covary linearly across the entire US CB area, this result confirms our initial statement that GPP models substantially underestimate the photosynthetic uptake of highly productive crops. However, it is challenging to relate GPP and yield-based NPP estimates in a quantitative way, as it is difficult to account for heterogeneous land cover given the coarse resolution of current SIF retrievals. For example, much of Northern Europe is a mosaic of forests (which have low SIF) and agricultural fields. This may partly explain the apparently lower productivity of European agricultural regions.

Continuing the comparison of model estimates to SIF-based crop GPP over the globe (Figs. 6 and 7 and *SI Appendix, Derivation of Spatially-Explicit Crop GPP Estimates*), spatial patterns of SIF-based crop GPP estimates differ from data-driven models by 40–60% in the US CB area and by 50–75% in some regions of the Indo-Gangetic Plain, the North China Plain, and the Sahel belt in Africa. Smaller differences within 0–10% are found in Europe. In terms of area-integrated annual GPP estimates (*SI Appendix*, Table S2), the largest differences are found in the US CB region (+43% for the data-driven models and +18% for the process-based models) and the Indo-Gangetic Plain (+55% and +39%, respectively). A remarkable difference of −38% is also obtained

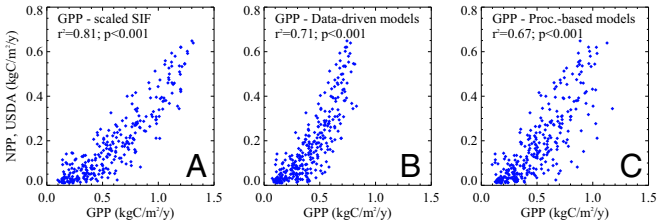

Fig. 5. Comparison of net primary production (NPP) estimates over the US Corn Belt (35°N–50°N, 80°W–105°W) from the USDA agricultural inventory (8) with crop GPP estimates from SIF retrievals (*A*) and data-driven and process-based model ensembles (*B* and *C*). Points correspond to 1° grid boxes with fraction of cropland area higher than 20%. GPP and NPP values are given in per-total-area units (see *SI Appendix, NPP Data from Agricultural Inventories*). The squared Pearson's correlation coefficient r^2 and the *P* value of the comparisons are shown. An analogous comparison with the inventory-based NPP from Monfreda et al. (7), which also includes Western Europe, can be found in *SI Appendix, NPP Data from Agricultural Inventories*.

between the SIF- and the process-based model estimates in the cropland areas between Brazil and Argentina. This area is often specified in biogeochemistry models as C4 grasslands, which have higher productivity than the C3 grasslands. Despite the relatively important local differences, the global cropland GPP estimated from SIF is in excellent agreement with the data-driven models (17.04 ± 0.19 $PgC{\cdot}y^{-1}$ and 17 ± 4 $PgC{\cdot}y^{-1}$, respectively), whereas a difference about −12% is found with the process-based models (global cropland GPP of 20 ± 9 $PgC{\cdot}y^{-1}$). These annual GPP numbers must be compared with the 14.8 $PgC{\cdot}y^{-1}$ given by Beer et al. (9) for croplands, and 123 $PgC{\cdot}y^{-1}$ for the total of all biomes.

Time series of SIF- and model-based crop GPP over some selected agricultural regions give insight into the differences observed in the annual GPP estimates (Fig. 7). The variation range of the monthly GPP estimates from SIF observations agrees well with the estimates from data-driven models in all of the selected cropland regions, which supports the consistency of our approach of scaling SIF to GPP using direct comparisons between GOME-2 SIF data and flux tower-based GPP. Also, the seasonal variations of data-driven and SIF-based GPP estimates are in general very consistent in all regions, and especially in Western Europe and China (Fig. 7 *B–D*). Estimates over the US CB and the Indo-Gangetic Plain also show the same phenological trends, but the SIF-based GPP estimates over the US CB are systematically higher than data-driven estimates by about 20% throughout the year (Fig. 7*A*). Over India, both GPP estimates coincide for the so-called *Rabi* crops sown in winter and harvested in the spring, but SIF-based GPP is about 40% higher than data-driven GPP for the *Kharif* or monsoon crops sown around June and harvested in autumn (Fig. 7*C*). This large difference in the estimated crop GPP over India in autumn explains the time shift of the global SIF-based crop GPP with respect to the data-driven models (Fig. 7*F*). On the other hand, the tested process-based models from the Trendy ensemble compare very well with data-driven models and SIF over the Western Europe region despite the lack of crop-specific modules in the Trendy models. We hypothesize that this is due to the fact that West European crops mostly follow the seasonality of grasslands, by which crops are often represented in the models. However, these models fail to describe crop phenology at the other regions and, more significantly, the multiple cropping in China and India. A time shift of the peak GPP estimates at the US CB with respect to SIF-based and data-driven GPP can be explained by modeling uncertainties associated to irrigation and also by the fact that sowing and harvesting time in the US CB is different from the lifetime of natural grassland (peak in June), as opposed to Western Europe. Also, process-based models substantially underestimate the peak GPP values for the US CB, India, and China regions, and tend to overestimate GPP in South America, which explains the

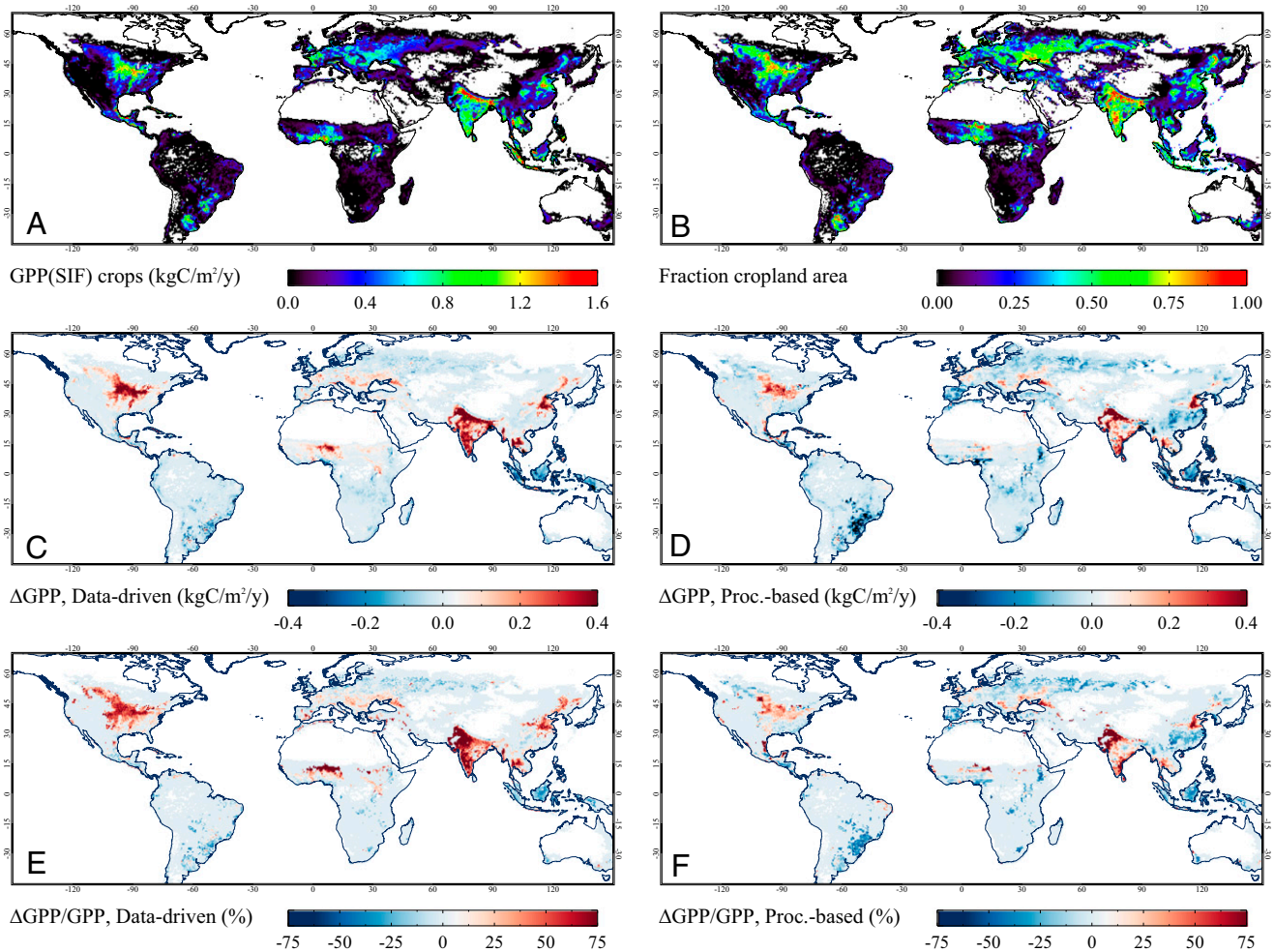

Fig. 6. Spatial details of the annual SIF-based crop GPP estimates over cropland areas (*A*), fraction of cropland area per grid box (*B*), and absolute and relative differences between annual SIF-based crop GPP estimates and the output of data-driven models (*C* and *E*) and process-based models (*D* and *F*). Spatially explicit GPP is derived through the scaling of SIF retrievals with the relationship GPP(SIF) = −0.10 + 3.72 × SIF (see *SI Appendix, Derivation of Spatially-Explicit Crop GPP Estimates*). Cropland GPP is given in per-total-area units. The absolute difference ΔGPP is calculated as GPP(SIF) − GPP(model), and the relative difference is calculated as ΔGPP over GPP(model).

spatial patterns observed in the annual GPP comparisons in Fig. 6. These results illustrate the need for specific crop modules in global dynamic vegetation models.

Considering the growing pressure on agricultural systems to provide for an increasing food and biofuel demand in the world, a global, time-resolved, and accurate analysis of crop productivity is critically required. Crop-specific models or improved process-based biogeochemistry models including explicit crop modules could provide projections of agricultural productivity and climate impact on crop yields (e.g., refs. 39–41). However, local information such as meteorology, planting dates and cultivar choices, irrigation, and fertilizer application are needed. In this

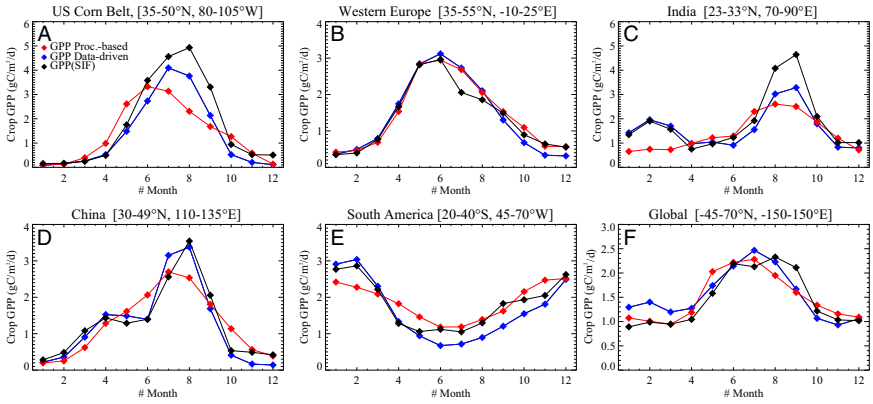

Fig. 7. (*A*–*F*) Time series of monthly crop GPP derived from SIF retrievals, process-based models, and data-driven models over different cropland regions in 2009. GPP area averages are weighted by the fraction of cropland area per grid box. Data-driven GPP corresponds to the MPI-BGC data-driven model (27). Process-based GPP estimates are calculated as the median of the monthly GPP estimates from the Trendy process-based model ensemble (28, 29) (see also *SI Appendix*, Table S2).

work, we have demonstrated that spaceborne SIF retrievals can provide realistic estimates of photosynthetic uptake rates over the largest crop belts worldwide without need of any additional information. This finding indicates that SIF data can help us improve our current models of the global carbon cycle, which we have shown to substantially underestimate GPP in some large agricultural regions such as the US CB and the Indo-Gangetic Plain. The launch of the Orbiting Carbon Observatory-2 and the Sentinel 5-Precursor satellite missions in 2014 or 2015 will enormously improve the observational potential for SIF, up to a 100-fold increase in spatiotemporal resolution (42, 43). This will especially benefit measurements over the typically fragmented agricultural areas, which suggests that SIF-based estimates of crop photosynthesis will soon become a unique data set for both an unbiased monitoring of agricultural productivity and the benchmarking of carbon cycle models.

Materials and Methods

We have used monthly averages of SIF retrievals (26) from the GOME-2 instrument onboard the MetOp-A platform to produce unique estimates of global cropland GPP. GOME-2 SIF retrievals are performed in the 715- to 758-nm spectral window. Single retrievals are quality-filtered and aggregated in a 0.5° grid. The GOME-2 SIF data set used in this study covers the 2007–2011 time period (see *SI Appendix, SIF Retrievals*).

Ensembles of process-based and data-driven biogeochemistry models have been analyzed to assess the ability of global models to represent crop GPP (see *SI Appendix, Model-Based GPP Data*). The process-based model ensemble comprises the 10 global dynamic vegetation models (CLM4C, CLM4CN, HYLAND, LPJ, LPJ-GUESS, OCN, Orichidee, SDGVM, TRIFFID, and VEGAS) included in the Trends in net land carbon exchange over the period 1980–2010 (Trendy) project (28, 29). It must be noted that these models do not include explicit crop modules. The data-driven model ensemble consists of the MTE1, MTE2, ANN, KGB, and LUE models used by Beer et al. (9). In addition, monthly GPP estimates from the MPI-BGC data-driven model (27), which corresponds to the MTE1 in the data-driven model ensemble, and the MODIS GPP product (MOD17) (31) have been compared with monthly flux tower-based GPP over croplands and grasslands to evaluate the ability of data-driven models to reproduce GPP at those biomes. Cropland GPP is calculated from the SIF observations and the model ensembles as the product of the total GPP in each 0.5° grid box by the fraction of cropland area given by Ramankutty et al. (6) (see *SI Appendix, Derivation of Spatially-Explicit Crop GPP Estimates*). EVI data in Fig. 4 and *SI Appendix, Comparison of Flux Tower-Based GPP with Model GPP, SIF and Vegetation Indices*, have been extracted from the MODIS MOD13C2 product (15).

Flux tower-based GPP estimates covering the 2007–2011 period were extracted from 14 sites in Midwest United States and Western Europe. Sites correspond to the Ameriflux and the European Fluxes Database networks. Only the most spatially homogeneous sites have been selected to enable direct comparisons with the SIF observations and the GPP model outputs available in 0.5° grid cells. The relationship GPP = −0.1 + 3.72 × GPP derived from the comparison of GOME-2 monthly SIF composites with flux tower GPP data has been used to scale SIF to GPP (see *SI Appendix, Comparison of Flux Tower-Based GPP with Model GPP, SIF and Vegetation Indices*).

Large-scale NPP estimates have been derived from the USDA-NASS (38) and Monfreda et al. (7) agricultural inventory data sets. The USDA inventory covers North America and the 2006–2008 period. It is based on a statistical method to upscale county-level crop NPP data from the USDA National Agricultural Statistics Service (8, 38). The inventory by Monfreda et al. (7) is for 2000. It is based on the aggregation of 175 crop classes in a 5 min by 5 min grid. Inventory-based NPP is converted from per-harvested-area to per-total-area units through scaling by the fraction of harvested area, following Monfreda et al. (7) (see *SI Appendix, NPP Data from Agricultural Inventories*).

ACKNOWLEDGMENTS. We thank T. Meyers (National Oceanic and Atmospheric Administration Air Resources Laboratory), D. Cook and R. Matamala (Argonne National Laboratory), A. Suyker (University of Nebraska), C. Bernhofer (Technische Universität Dresden), Z. Nagy (Szent István University), M. Aubinet (Université de Liège), W. Kutsch (Johann Heinrich von Thuenen Institut), and K. Schneider (University of Cologne) for kindly providing eddy covariance data. We acknowledge C. Monfreda (Arizona State University), P. H. Verburg (Vrije Universiteit University Amsterdam), and N. Ramankutty (McGill University) for the crop fraction and NPP data sets and/or advice on their use, Eumetsat for the GOME-2 data, the Trendy project for the process-based model runs, and the USDA NASS for their agricultural inventory data. We also thank the two anonymous reviewers and Dr. Asner for their valuable suggestions and comments. MODIS MOD17 GPP data were downloaded from the server of the Numerical Terradynamic Simulation Group at the University of Montana, MODIS MOD13 data were obtained from the MODIS Land Processes Distributed Active Archive Center archive, and MERIS-MTCI from the Infoterra Ltd server. This work used eddy covariance data acquired by AmeriFlux and GHG-Europe. The work by L.G., Y.Z., and M.V. has been funded by the Emmy Noether Programme (GlobFluo project) of the German Research Foundation. J.J. is supported by the National Aeronautics and Space Administration (NASA) Carbon Cycle Science program (NNH10DA001N) and G.P.-C. is supported by NASA Soil Moisture Active Passive Science Definition Team (08-SMAPSDT08-0042). We also thank the W. M. Keck Foundation for funding the New Methods to Measure Photosynthesis from Space workshop held at the Caltech Keck Institute for Space Studies.

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