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Assessing the efficiency of changes in land use for mitigating climate change

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“Assessing the Efficiency of Changes in Land Use for Mitigating Climate Change”

Supplementary Information

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I. ADDITIONAL METHODOLOGICAL EXPLANATIONS

A. Difference between treatment of consumption and production.

The Carbon Benefits Index calculates a carbon cost of different forms of biomass consumption and a carbon benefit of different forms of biomass production. Consumption of biomass is a cost because it comes at the expense of the opportunity to store carbon in vegetation and soils and therefore keep it away from the atmosphere. Production of any form of biomass likely generates carbon benefit because it can directly generate carbon storage, because it can be used to displace fossil fuel emissions, or because it satisfies consumptive demands for food or fiber and therefore frees up other land to focus on carbon storage while the world still meets the same level of consumptive demands.

Isolating the specific consequences of production decisions and consumption decisions requires an assumption that each decision not influence the other. Thus, a change in consumption by one person results in an absolute change in global consumption by that amount. By contrast, a change in production on one hectare of land of a crop or animal product does not alter total consumption of the quantity of crops or animal products consumed, and therefore produced, but only alters where and how they are produced. The quantity of carbon stored in vegetation and soils is a kind of residual, and it adjusts based on these other consumption and production decisions. In the real world, through price effects, changes in production may affect quantities consumed and changes in consumption may affect production systems, but these effects are not only uncertain, they could also in theory be countermanded by tax and other public policies. As discussed in the main text, they also factor in changes not just in the consumption or the production on a single hectare but changes by consumption or production by other people, sometimes on other land, and at other's people's expense. Our separation of consumption and production these effects makes it possible to evaluate the efficiency of consumption and production decisions in and of themselves.

Our assumption of constant consumption applies to food but not to biofuels. We do not apply it to biofuels in part because biofuel GHG benefits can be directly assessed and in part because we assume that decisions to use biofuels are heavily influenced by their estimated greenhouse gas consequences and so are not automatically replaced elsewhere if one user reduces use. If someone wishes to assume a fixed global demand for ethanol, however, the Index could be used to assess the relative efficiency of producing the ethanol in one location versus the global average.

B. Why we base carbon benefits on changes in carbon storage not absolute levels of carbon storage

Our carbon benefits formula for production decisions estimates the benefits of carbon storage (positive or negative) on the hectare of land analyzed only as annualized, time-discounted changes in carbon storage on that land over time. If management of a hectare will not change existing carbon storage, then carbon storage does not alter its benefits.

Conceptually, it could make sense to count existing carbon storage as a benefit as well as changes in carbon storage. However, we do not count existing carbon storage because the purpose of the index is to compare one use or management of land with an alternative use, and in that comparison, existing carbon storage cancels out. For current land use lm_1 the change in carbon storage ΔCS_{lm_1} at time t_2 equals carbon storage at that time $CS_{lm_1}(t_2)$ minus the carbon storage at the initial time $CS_{lm_1}(t_1)$. For a change in management or use from lm_1 to lm_2, the change in carbon storage equals later carbon storage under new management $CS_{lm_2}(t_2)$ minus initial carbon storage under original management $CS_{lm_1}(t_1)$. Because carbon storage at time t_1 is the same for both existing management and changed management, i.e., they both start with today's carbon stock, the existing carbon stocks cancel out and the only difference is the carbon storage at time t_2 beteen lm_2 and lm_1.

It would be possible mathematically to achieve the same result while also counting absolute carbon storage as a carbon benefit. However, some aspects of carbon storage are often unknown, such as carbon stored at depths below one meter although land use change is unlikely to change such carbon storage. For soil carbon, it is often easier to estimate changes in carbon stocks than to estimate entire existing carbon stocks. In addition, for some hectares with large soil storage numbers, using total carbon storage numbers could dwarf the benefits of other outputs as well as the changes in carbon storage, which would make the carbon benefit numbers less intuitive and useful because the purpose is to focus on changes. Finally, using total carbon storage would create challenges for annualizing benefits. For these practical reasons, we therefore use changes in carbon storage.

C. Time Discounting

Because carbon storage is lost quickly but crop production can continue indefinitely, any system for evaluating the carbon costs of land use must in some way address the relative costs of emissions over time. There have been several articles addressing how to deal with emissions from land use change, typically in the biofuel context[1,2]. Much of the discussion focuses on the value of up-front versus later mitigation. In general, this question can be thought as a question about what is the relative value of reducing emissions sooner rather than later, a debate largely present in the integrated assessment literature, both in cost-efficiency and cost-benefit settings[3–7]. The basic value is all the damages that might be avoided if emissions are reduced sooner rather than later. They include not only the damages that are likely to occur in the interim, but also the potential for incurring, long-term persistent or permanent damages due to short-term emissions, which could be permanently avoided by mitigation in the short-term, but which could not be avoided by mitigation only in the longer term.

The option value to adjust the speed of overall mitigation as information becomes available is another source of value for early versus late mitigation[8]. Other important factors include the investment value of money due to overall economic growth, and the benefits of reducing overall mitigation costs, which often occur through the learning and incentives induced by earlier mitigation[9]. Few papers address all of these considerations. Implicit in political commitments to hold warming to a 2 degree threshold is a commitment to early mitigation because later mitigation will not prevent this threshold from being exceeded[10], which explains proposals for large-scale mitigation by 2050.

In our base case, we choose a period of 100 years, a 4% discount rate based on the real return on investment[11], and a constant cost of a ton of emissions over time. In economic terms, this approach in effect assumes a constant, real cost of emissions. Economic climate models can estimate widely different time-dependent changes in the carbon costs of emissions depending on overall emissions trajectory selected, expected costs of mitigation (in optimal emissions trajectories), whether early mitigation is likely to reduce costs of future mitigation[5,12], whether and how they factor in the risk of crossing thresholds[4,6,13–15]. Another factor concerns estimates of the long-term consequences of early emissions and whether they factor in recent science estimating that the warming consequences of early emissions will persist for long-times, notwithstanding traditional estimates of molecular decay or uptake, because of carbon feedback effects, and the persistent effects of increasing ocean temperatures[16–18]. Simple integrated assessment models propose increasing carbon tax profiles[19], however the assumption of a constant carbon cost is more consistent with these more recent estimates of constant warming effects of emissions regardless of when they occur along with a desire to avoid crossing warming thresholds.

Because the choice of a discount rate and a carbon value trajectory is inherently a question of policy, we also select a 4% discount rate for our central scenario because it is roughly consistent with U.S. bioenergy policies. To date, those policies in Europe and the US. have amortized emissions from land use change for 20-30 years against benefits in fossil fuel displacement from bioenergy that occur in those periods[20]. Amortizing emissions from land clearing over 25 years and applying those emissions to a crop or biofuel indefinitely is equivalent to assigning 4% of the emissions indefinitely, or alternatively to applying a 4% interest (or discount) rate to a one-time emission of that amount in the initial year. When further accounting for the time over which carbon decays, which we calculate as described above, rather than treating all emissions as occurring in year one, we find that in general our use of a 4% discount rate generates similar results to 33-year amortization, which is close to the 30-year -year amortization period used by U.S. biofuel policies.

In addition to results using 4%, we also show results for COCs using other time discount rates in Supplemental Table 3. The carbon calculator enables a user to specify different discount rates.

D. Dynamic Global Vegetation Models

We provide further information about the LPJmL dynamic global vegetation model (DGVM) used to estimate native carbon stocks and the NPP of native vegetation. LPJmL is a global grid-based dynamic vegetation model[21,22], which builds on process-based representations of key ecosystem processes such as photosynthesis[23], plant and soil respiration, carbon allocation, evapotranspiration and phenology in 9 generic plant functional types (e.g. temperate broadleaved deciduous tree, tropical broadleaved evergreen tree) to represent natural land ecosystems at the level of biomes. The latest updates of the model include a permafrost module and a new hydrology scheme[24]. Competition between different plant functional types for light, space, and water determines vegetation composition within a grid cell. Establishment and mortality of vegetation depend on climatic conditions and plant density. Fires can occur and are more likely under dry conditions and higher fuel loads (i.e. the amount of combustible materials).

LPJmL is driven by monthly fields of temperature, precipitation, cloud cover and number of wet days which are disaggregated according to Gerten et al.[25]. Additional inputs include information on soil properties and annual atmospheric CO_2 concentrations. Here we used observation-based monthly temperature and cloud cover time series provided by the Climatic Research Unit (CRU TS version 3.21)[*], which provides data from 1901 to 2012 (refs. 26,27). These were combined with monthly gridded precipitation data based on the Global Precipitation Climatology Centre (GPCC) Full Data Reanalysis Version 6.0[†] covering the years 1901 to 2010 (refs. 28,29). We applied the CRU methodology to derive the corresponding number of days with rain per month required to distribute monthly precipitation within months[30,31]. For the years up to 1958 we used atmospheric CO_2 concentrations based on ice-core data[32] from the Scripps CO_2 program[‡] and direct observations from the Mauna Loa Observatory[33] for later years from the Global Greenhouse Gas Reference Network[§]. Individual processes in LPJmL have been validated extensively before, e.g. Sitch et al.[21,34] for carbon cycling and plant geography of the natural vegetation, Schaphoff et al.[24] for permafrost, river flow, carbon and water fluxes. The model has also been successfully evaluated against various observational data, such as net primary production[35], vegetation activity measured by leaf area index[36], and pan-tropical forest carbon stocks[37].

We originally intended to use a range of DGVMs to simulate vegetation and soil carbon stocks of potential natural vegetation because of the substantial uncertainties in underlying databases used and in the biophysical processes that drive these models. In addition to LPJmL we analyzed data from three other DGVMs available through the ISIMIP data archive (https://www.isimip.org)): HYBRID, JEDI, and SDGVM. When we analyzed the additional models used to generate native carbon stocks, however, we

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[*] Available at: https://crudata.uea.ac.uk/cru/data/hrg/

[†] Available at: ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata_v6_doi_download.html

[‡] Available at: http://scrippsco2.ucsd.edu/data/atmospheric_co2.html

[§] Available at: https://esrl.noaa.gov/gmd/ccgg/trends/

found not only wide differences in model results but also larger discrepancies overall between the carbon stock estimates of these other DGVMs and average carbon stocks estimates at the biome level reported in the literature[38–42]. Results for above- and belowground vegetation and soil carbon stocks are shown in Supplementary Figure 1.

Vegetation models must attempt to simulate a wide variety of biogeochemical and biophysical processes over time in estimating gains in carbon stocks. Because of the complexity and uncertainty of these processes, we believe DVGM carbon stock results should be considered less reliable than empirically measured carbon stock numbers. Unfortunately, biome carbon stocks cover too large an area to account for differences in the areas used by different crops. For example, all or most of the U.S. grasslands are typically treated as a single biome even though they encompass areas with widely different rainfall patterns and temperatures. Because of these differences, wheat is typically grown in cooler and drier areas more than in the wetter, warmer areas devoted to maize and soybeans. To reflect these differences, we believe the best system is a hybrid between biome estimates and DVGMs, which uses the biomes to set average values and the DVGMs to estimate spatial variation within the biome. Because other DVGMs do a poorer job of matching biome carbon stock estimates, we decided to use only LPJmL for this project.

However, the same preference for measured carbon stocks applies to LPJmL as well. We therefore scaled LPJmL results in each pixel so that the average biome values of our adjusted LPJmL results match those of the reference values for the biome from the literature[38–42]. This procedure preserved the advantage of working with spatially explicit and heterogeneous carbon stock maps of potential natural vegetation while reducing modelling uncertainties at the same time. We then recalculated the average carbon for each crop using this “adjusted LPJmL” data.

E. Accounting for Biofuel PEMs

Although bioenergy by-products could possibly be factored into the carbon benefits analysis at different stages, consistency with the theory behind the Carbon Benefits Index requires that by-products used for feed should be based on the COC and global average PEMs of the crops and crop products they replace, e.g., maize or soybean cake. Their quantities and benefits should therefore be calculated as outputs of land. Electricity biofuel by-products, which can be generated by sugarcane of cellulosic ethanol, are typically factored into lifecycle calculations as a credit against the production emissions of the ethanol. For ease in using these other LCAs, we recommend using that approach for factoring electricity by-products into the production emissions of biofuels and do so in the examples in this paper.

Many biofuel LCAs already provide a credit for by-products in their estimates of biofuel production emissions. When using such an LCA, a user must be careful to avoid double-counting by-product credits. To do this calculation correctly with such a LCA, a user should remove the PEM credits for the feed by-product from the LCA analysis as the PEMs for the feed by-product should be counted in the overall analysis of the outputs of a hectare of land.

F. Determination of potash and phosphorus fertilization for crops missing in data

To determine potash and phosphorus reference application rates when not present in data, we first use classes of similar crops to infer application rates where possible. For crops with application rates still missing, a country-specific ratio of fertilizer use is computed using crops with known application rates, by dividing the country rate by the world average rate using crops with known application rates only. This rescaling factor is then applied to world average application rates to estimate application rates for crops not reported for each country.

G. Sources of information in examples

Land use options Brazil (Figure 1)

Beef: Yield and GHG emissions data from Cardoso et al.[43]. The authors kindly provided additional back-up data for their study to make our full analysis possible.

Gasoline and diesel emissions: GHG emissions data from Edwards et al.[44].

Sugarcane ethanol: Sugarcane yield from FAOSTAT[45]; ethanol yield and GHG emissions data from Edwards et al.[44].

Tropical rainforest: Although there is a large policy focus on potential reforestation of the Atlantic Coastal Rainforest, we found few reported studies of carbon accumulation. Macedo et al.[46] found carbon accumulation rates in soils alone of 1.73 tC/ha/y in deforested and degraded soils of the Atlantic Coastal Rain Forest replanted with nitrogen-fixing trees, but did not measure vegetation carbon. Another study in one part of the region reported carbon accumulation rates in vegetation for experimental plantings in one location in the area ranging from roughly 2 tC/ha/y over only the first seven years for forests planted without any nitrogen-fixing trees to almost 7 tC/ha/y for plantings with 75% nitrogen-fixing trees[47]. More generally, our analysis of average carbon accumulation from tropical forest regeneration of 4.5 tC/ha/y used in the carbon gain method is based primarily on above-ground carbon accumulation rates analyzed in Poorter et al.[48]. This analysis included a wide range of forest types, many of which were far drier than the Atlantic Coastal Rain Forest. Based on these various studies we believe that 5 tC/ha/y is a reasonable and probably conservative estimate for tropical forest regeneration in this ecosystem.

To illustrate the likely effects of extensive grazing on arid, native grasslands, we used the carbon benefits index to estimate the carbon benefits of grazing on the Campos in Uruguay at 5.9 tCO2/ha/y. We also estimated that removal of grazing and allowing regrowth of the Campos vegetation would generate 1.5 tCO2/ha/y.

Crop products (Extended Data Figure 1)

Iowa maize: Yield data is from USDA NASS statistics**, and GHG emissions data from Edwards et al.[44]. The marginal emissions from additional nitrogen fertilizer input in Iowa was based on data generated about crop yield response to additional nitrogen by actual farmers analyzed by the Iowa Soybean Associated reported in the Supplementary Material for Searchinger[49] and emission factors used by this study for the Carbon Benefits Index.

West Africa maize: Yield response data is from Fischer et al.[50], and GHG emissions data estimated from emissions factors used for the Carbon Benefits Index.

Rice: Yield data from dataset in this study (SPAM database), and GHG emissions data estimated from Bryngelsson et al.[51]. Estimates of the portion of farms in different countries using single or multiple, mid-season drawdowns were adjusted based on improved professional opinion as reflected in Adhya et al.[52].

Organic and conventional wheat: Yield data is statistics from Swedish Board of Agriculture[53]. GHG emissions data for conventional wheat is from Flysjö et al.[54]; for organic wheat estimated from ALBIO model in Bryngelsson et al.[51] assuming manure input instead of nitrogen fertilizer. (The ALBIO model uses nitrous oxide emission rates that are the same as those used in Globagri.)

Organic and conventional beans: Yield data comes from statistics of the Swedish Board of Agriculture[53]. GHG emissions data for conventional beans is from Flysjö et al.[54]; for organic beans estimated from ALBIO model in Bryngelsson et al.[51] assuming manure input instead of nitrogen fertilizer.

Different fuel sources (Figure 2) and "ILUC"

Solar-cell-powered battery-electric vehicle (BEV): COC for land requires that we assume an alternative land use. For this calculation, we assumed solar cell modules to be located on clear-cut forest that would otherwise be allowed to regrow with a COC corresponding to 3.1 ton C/ha/y based on Lind[55], which provides average carbon sequestration rates of Northern European coniferous forest. In fact, the carbon cost of the actual land use demands for solar panels is a small fraction of the emissions from the solar option, which is dominated by emissions from battery and solar panel construction. Our forest assumption is equivalent to a land use cost of 11.4 tCO_2/ha/y. Assuming solar panels replaced land used for beans or wheat, the annual loss of carbon benefits would rise to 15.7-17 tCO_2/ha/y. As this land use cost is such a small part of the costs of this alternative, we did not do overall sensitivity analyses with these alternatives.

** https://www.nass.usda.gov

Module efficiency of 16% is a conservative number based on Green et al.[56] and performance ratio is from NREL[57], and GHG emissions in solar panel production from Louwen et al.[58]. Energy use in BEV battery production was taken from Dunn et al.[59] with emissions per unit energy based on Peters et al.[60]. Fuel economy, and battery capacity and specific energy are 2017 Chevrolet Bolt specifications.

To account for the varying solar radiation and module output over the year, which necessitates backup supply in winter, as well as that energy demand in BEV battery production increasingly is met through solar electricity (cf. the Tesla battery plant in Nevada), we did a set of additional calculation variants. As to the varying solar radiation, we simplistically assumed that the modules deliver a surplus power output during the four brightest summer months but runs an equally large power deficit during the four darkest months. Since the CO_2 intensity of European power supply generally is higher in winter than summer, we assumed that the CO_2 intensity of winter power supply exceeds that of summer supply by 300 gCO_2/kWh (this corresponds roughly to the difference between coal power and gas power in CO_2 intensity). As to energy use for battery manufacturing, we did a low CO_2 variant where we assumed all energy being met by solar power that carries a CO_2 cost in module manufacturing of 30 gCO_2/kWh (based on Louwen et al.[58]). The error bar in Fig. 2 shows the range of the permutations of the additional calculations described here.

Biofuel powertrains: Carbon opportunity costs and emissions per unit of fuel estimated as described in the main text and methods. Fuel economy data based on Swedish Energy Agency[61].

As discussed in the main text, the COCs of biofuels are based on the COCs of their feedstock after subtracting the COCs of their by-products. In the case of vegetable oil feedstocks, we allocate the COCs of the oilseed crops between vegetable oil and oilseed meals or other by-products based on energy content.

Biofuel COCs are equivalent to estimates of indirect land use change if the crop devoted to the biofuel were replaced at the global average carbon cost. For a proper comparison with California estimates of ILUC from maize-based ethanol, reported in Searchinger et al.[20], we did not apply our time discounting but followed the California method of amortizing ILUC emissions over 30 years.

Iowa land use options (Extended Data Figure 2)

Maize-soybean: Maize data as from above (see “Crop products”). Soybean yield data from USDA NASS statistics[62], and GHG emissions data from Edwards et al.[44].

Maize ethanol: Maize yield from USDA NASS; ethanol yield, DDGS yield and GHG emissions data from Edwards et al.[44]. DDGS credited as described in the methods.

Grass ethanol: Grass yield from Hudiburg et al.[63]; ethanol yield (375 l/t DM) and GHG emissions from Evans et al.[64]

Human diets (Figure 3)

Diet data from Bryngelsson et al.[51]. Refers to consumption measured at whole-sale level, i.e. before losses in retail, restaurants, households, etc.; hence, we factor in these losses, but not those that occur up-stream of whole-sale, such as harvest losses. Carbon opportunity costs and emissions per food unit from the global average data set in this study (see Extended Data Tables 1, 2).

H. Sensitivities

We analyzed the effect on COCs of 30% variations in global soil carbon stocks and 20% variations in native vegetation carbon stocks as explained in the methods discussion. We also analyzed COCs using the carbon loss method for 2% and 6% discount rates. The results for COCs are set forth in Supplementary Table 3 and the potential implications for the examples we analyze are set forth in Supplementary Tables 5-9.

There are other uncertainties in the analysis including precise locations and areas of production of individual crops, soil carbon loss rates due to cropping, global pasture area estimates, and feeds consumed by different livestock. There are also uncertainties in production emission rates. We believe there is not enough high-quality data to model these uncertainties both quantitatively and rigorously in a truly meaningful way.

One additional uncertainty involves the biophysical effects of land cover change. Such biophysical effects are highly complex and debated. For example, the the combined effects of albedo and transpiration changes on regional temperatures due to changes in European forest cover are still debated – compare Alkama & Cescatti[65] and Naudts et al.[66]. For an estimate of different results of U.S. forests, see Zhao & Jackson[67]. There are some uncertainties regarding direct solar reflection at the terrestrial surface, but the big uncertainties involve transpiration and cloud cover. Alkama & Cescatti[65] estimate that albedo changes from deforestation are amplifying the consequences of increased CO_2 concentrations while Bright & Jackson[68] conclude the opposite. Transpiration also influences seasonal and diurnal fluctuations in cloud cover, which may also reduce climate effects. Unfortunately, the science on these issues is still very much evolving.

Second, because of the effect on cloud cover and a variety of other feedback effects, the effects of land use change on albedo cannot be calculated on a hectare by hectare basis. They can therefore not be incorporated into a global analysis of our type.

We also do not factor biophysical changes into the carbon benefits index because their effects cannot be calculated on a hectare-by-hectare basis because of the effects of multiple hectares working together on cloud cover and a variety of other feedback effects. When and if biophysical changes can be accurately analyzed with confidence, our analysis would still be useful for the effects of GHG emissions alone.

II. SUPPLEMENTARY TABLES & FIGURES

Supplementary Table 1: Global percentage deviation of carbon pools simulated by DGVMs from reference values at the biome level based on results shown in Supplementary Figure 1.

	LPJmL	HYBRID	JEDI	SDGVM
Vegetation carbon	6	78	13	-24
Soil carbon	-14	-37	-27	33

Supplementary Table 2: Extent and native-vegetation carbon stocks of global permanent grasslands (area numbers from HYDE 3.2 (ref. 68); carbon stocks from LPJmL model).

	Area		**Estimated losses of native-vegetation plant and soil C stocks**		
	Mha	% of total	Pg C	% of total	tC per ha
Originally forested	908	32.1%	187	66.6%	206
Originally woody savanna (30-60% tree cover)	300	10.6%	35	12.3%	115
Originally savanna (10-30% tree cover)	163	5.8%	14	5.0%	86
Originally grassland (5-10% tree cover)	1461	51.6%	46	16.2%	31
TOTAL	2832		282		99

Supplementary Table 3: COC's under sensitivity based on variations in native vegetation and soil carbon content and discount rates.

Category	Product	Carbon opportunity cost*								
		Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant	
		kg CO_2e/ kg fresh weight	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base
Cereals										
	Maize grains	2.1	1.6	-22%	2.6	22%	1.4	-35%	2.9	35%
	Rice grains (rough)	2.6	2.1	-20%	3.1	20%	1.7	-35%	3.5	34%
	Wheat grains	1.9	1.5	-23%	2.3	23%	1.2	-34%	2.5	33%
	Barley grains	2.6	2.0	-22%	3.1	22%	1.7	-33%	3.4	32%
	Sorghum grains	4.4	3.4	-22%	5.4	22%	2.9	-34%	5.9	33%
	Millet grains	4.9	3.9	-20%	5.8	20%	3.4	-30%	6.3	29%
Tubers										
	Cassava tubers	1.7	1.3	-20%	2.0	20%	1.1	-34%	2.2	34%
	White potato tubers	0.6	0.5	-22%	0.76	22%	0.4	-35%	0.8	34%
	Sweet potato tubers	1.2	1.0	-21%	1.5	21%	0.8	-35%	1.6	35%
	Yam tubers	1.5	1.2	-20%	1.8	20%	1.0	-34%	2.0	34%
Sugar crops										
	Sugar cane stems	0.2	0.2	-23%	0.25	23%	0.13	-34%	0.3	33%
	Sugar beet roots	0.2	0.1	-23%	0.23	23%	0.12	-34%	0.3	33%
Oil crops										
	Soybean seeds	5.9	4.6	-22%	7.1	22%	3.8	-35%	7.9	35%
	Oil palm fruit (bunches)	2.2	1.8	-19%	2.6	19%	1.6	-28%	2.8	28%
	Canola seeds	5.8	4.6	-21%	7.0	21%	3.9	-33%	7.7	32%
	Sunflower kernels	4.9	3.7	-24%	6.0	24%	3.2	-36%	6.6	35%
	Groundnut pods	6.0	4.7	-22%	7.3	22%	3.9	-35%	8.0	35%
	Coconuts	2.8	1.9	-33%	3.8	33%	2.0	-29%	3.5	25%
Pulses										
	Common beans	14.2	11.1	-22%	17.3	22%	9.0	-36%	19.3	36%
	Chickpeas	3.7	2.7	-26%	4.7	26%	2.3	-38%	5.0	36%
	Cowpeas	13.1	10.5	-20%	15.7	20%	9.0	-31%	17.0	30%
	Pigeon peas	7.5	5.6	-25%	9.3	25%	4.6	-38%	10.2	37%
	Lentils	5.9	4.5	-22%	7.2	22%	3.9	-33%	7.7	32%

Category	Product	Carbon opportunity cost*								
		Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant	
		kg CO_2e/ kg fresh weight	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base
Fruits										
	Banana	1.1	0.9	-21%	1.4	21%	0.7	-35%	1.5	34%
	Plantains	3.1	2.4	-21%	3.7	21%	2.0	-35%	4.2	35%
	Other fruit - temperate	0.9	0.7	-22%	1.1	22%	0.6	-35%	1.3	35%
	Other fruit - tropical	1.0	0.8	-21%	1.2	21%	0.7	-35%	1.3	34%
Vegetables										
	Vegetables	0.71	0.6	-22%	0.9	22%	0.5	-35%	1.0	35%
Vegetable oils										
	Soybean oil	10.8	8.4	-22%	13.2	22%	7.0	-35%	14.5	35%
	Palm oil	9.3	7.5	-19%	11.0	19%	6.7	-28%	11.8	28%
	Palm kernel oil	9.3	7.5	-19%	11.0	19%	6.7	-28%	11.8	28%
	Canola oil	8.9	7.1	-21%	10.7	21%	6.0	-33%	11.7	32%
	Sunflower oil	7.5	5.7	-24%	9.3	24%	4.8	-36%	10.1	35%
	Groundnut oil	12.9	10.1	-22%	15.7	22%	8.3	-35%	17.3	35%
	Maize oil	5.0	3.9	-22%	6.1	22%	3.2	-35%	6.7	35%
	Cotton oil	3.3	2.5	-23%	4.1	23%	2.1	-36%	4.5	35%
Sugars										
	Cane white sugar	1.9	1.4	-23%	2.3	23%	1.2	-34%	2.5	33%
	Beet white sugar	0.9	0.7	-23%	1.1	23%	0.6	-34%	1.2	33%
Meat, dairy and eggs										
	Beef and buffalo meat**	144	113	-21%	175	21%	94	-35%	194	35%
	Sheep and goat meat**	186	146	-21%	225	21%	121	-35%	250	35%
	Cow and buffalo milk	6.2	4.9	-21%	7.5	21%	4.0	-35%	8.3	35%
	Sheep and goat milk	19.9	15.6	-21%	24.1	21%	12.9	-35%	26.8	35%
	Pork^	14.3	11.2	-22%	17.5	22%	9.3	-35%	19.3	34%
	Poultry meat^	10.7	8.3	-22%	13.1	22%	6.9	-35%	14.4	35%
	Eggs	10.7	8.3	-22%	13.0	22%	6.9	-35%	14.3	35%
Livestock feeds										
	Soybean meal	4.9	3.8	-22%	6.0	22%	3.2	-35%	6.6	35%
	Palm kernel meal	4.3	3.5	-19%	5.2	19%	3.1	-28%	5.5	28%
	Canola meal	4.0	3.1	-21%	4.8	21%	2.7	-33%	5.2	32%
	Sunflower meal	3.3	2.5	-24%	4.1	24%	2.1	-36%	4.5	35%

Category	Product	Carbon opportunity cost*								
		Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant	
		kg CO_2e/ kg fresh weight	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base	kg CO_2e/ kg fresh weight	% change from base
	Groundnut meal	6.3	5.0	-22%	7.7	22%	4.1	-35%	8.5	35%
Livestock feeds										
	Cotton meal	3.3	2.5	-23%	4.1	23%	2.1	-36%	4.5	35%
	DDGS (maize-ethanol)	2.7	2.1	-22%	3.3	22%	1.7	-35%	3.6	35%
	DDGS (wheat-ethanol)	2.6	2.0	-22%	3.2	22%	1.7	-35%	3.5	35%
Other										
	Coffee beans (green)	31.1	24.5	-21%	37.8	21%	20.0	-36%	42.1	35%
	Tea leaves (dried)	14.9	11.7	-22%	18.1	22%	9.5	-36%	20.2	36%
	Cocoa beans (dried)	40.4	31.6	-22%	49.2	22%	25.7	-36%	54.8	36%
	Cotton lint	3.0	2.3	-23%	3.7	23%	1.9	-36%	4.0	35%
Bioethanol										
	Maize ethanol	4.4	3.9	-22%	4.9	22%	3.4	-36%	5.3	36%
	Wheat ethanol	4.3	3.9	-24%	4.8	24%	3.4	-34%	5.0	32%
	Sugarcane ethanol	2.8	2.5	-23%	3.1	23%	2.2	-34%	3.3	33%
Biodiesel										
	Soy methylester	10.6	9.4	-22%	11.8	22%	8.1	-35%	12.8	35%
	Palm oil methylester	8.7	7.8	-19%	9.6	19%	7.0	-28%	10.1	28%
	Canola methylester	8.9	8.0	-21%	9.8	21%	7.0	-33%	10.6	32%

*Carbon "loss" method (see text). Includes organic soil emissions.
**Average including meat from dairy animals. GE: gross energy; LHV: lower heating value
^Refers to whole carcass weight including bone and fatty tissue

Supplementary Table 4: Comparison of our Biofuel COCs with Economic Modeling for the European Commission and the California Air Resources Board (gCO_2/MJ).

Biofuel	Carbon Benefits (COCs)	GLOBIOM-EU	GTAP-CAL
Wheat ethanol	140	23	
Corn ethanol	200	9	22
Sugarcane ethanol	110	11	14
Soybean Biodiesel	330	100	27
Rapeseed Biodiesel	270	43	13
Palm oil Biodiesel	260	230	71

Results are solely from land use change and do not include production emissions.

To assure consistent comparison, all results are adjusted to amortize total emissions from land use change over 30 years reflecting California practice.

GLOBIOM-EU results are modeling results using the GLOBIOM model prepared for the European Commission and taken from ref. 69 (Fig. 3) and GTAP-CAL results are model results using the GTAP model used the California Air Resources Board and taken from ref. 70 (Table ES-2).

Supplementary Table 5: Sensitivity analysis results for data in Brazilian land use example (cf. Figure 1)

Example	**Net GHG benefit (carbon benefit + differences in PEM and soil sequestration)**										
	Base variant	**"Low" variant**		**"High" variant**		**"2% discounting" variant**		**"6% discounting" variant**		**"Gain" method***	
	Mg CO_2e/ ha/ yr	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base
Beef Brazil Cardoso Syst. 1 (30 kg CW/ha/yr)	3.4	2.5	-28%	4.4	28%	1.9	-46%	5.0	45%	4.1	21%
Beef Brazil Cardoso Syst. 2 (75 kg CW/ha/yr)	10.0	7.7	-23%	12.3	23%	6.2	-38%	13.7	37%	11.7	17%
Beef Brazil Cardoso Syst. 3 (140 kg CW/ha/yr)	21.0	16.7	-20%	25.2	20%	13.9	-34%	27.9	33%	24.1	15%
Beef Brazil Cardoso Syst. 4 (200 kg CW/ha/yr)	29.9	23.7	-21%	36.1	21%	19.8	-34%	39.9	34%	34.5	15%
Beef Brazil Cardoso Syst. 5 (220 kg CW/ha/yr)	33.7	26.9	-20%	40.4	20%	22.6	-33%	44.7	33%	38.7	15%
Soybean Brazil	16.3	12.7	-22%	19.9	22%	10.5	-36%	22.0	35%	15.2	-7%
Sugarcane ethanol Brazil	9.6	9.6	0%	9.6	0%	9.6	0%	9.6	0%	9.6	0%

CW: carcass weight

*Estimate using the carbon "gain" method (see section 1.2 in Supplementary methods)

Supplementary Table 6: Sensitivity analysis results for data in crop production example (c.f. Extended Data Figure 1).

Example	Net GHG benefit (carbon benefit + differences in PEM and soil sequestration)										
	Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant		"Gain" method*	
	Mg CO_2e/ ha/ yr	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from gain
Maize Iowa											
2013-15 avg yield	23.8	18.6	-22%	29.0	22%	15.5	-35%	32.1	35%	27.3	15%
Higher yield (+ 1 ton/ha/y)	24.7	19.0	-23%	30.4	23%	15.7	-37%	33.8	37%	28.5	15%
Maize West Africa											
Current (unfertilized)	4.5	3.7	-19%	5.4	19%	3.2	-30%	5.9	30%	5.1	13%
Fertilized (100 kg N/ha/y)	13.6	10.8	-21%	16.5	21%	9.2	-33%	18.1	33%	15.5	14%
Rice (rough) global averages											
Upland rainfed	14.2	12.5	-12%	15.9	12%	11.4	-20%	17.0	19%	13.7	-4%
Lowland irrigated	21.7	17.5	-19%	25.9	19%	14.7	-32%	28.6	32%	20.4	-6%
Organic and conventional winter wheat Sweden - 2013-15 avg yields											
Conventional	14.1	11.3	-20%	17.0	20%	9.9	-30%	18.2	29%	19.0	34%
Organic	7.8	6.3	-19%	9.3	19%	5.6	-28%	10.0	28%	10.4	33%
Organic and conventional peas Sweden - 2013-15 avg yields											
Conventional	14.3	10.8	-24%	17.8	24%	9.2	-35%	19.1	34%	33.6	135%
Organic	9.5	7.2	-24%	11.8	24%	6.2	-35%	12.7	34%	22.4	135%

*Estimate using the carbon "gain" method

Supplementary Table 7: Sensitivity analysis results for data in fuel source example (cf. Figure 2).

Example	COC and emissions per distance (mid-sized car)										
	Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant		"Gain" method*	
	g CO_2e/ km	g CO_2e/ km	% change from base	g CO_2e/ km	% change from base	g CO_2e/ km	% change from base	g CO_2e/ km	% change from base	g CO_2e/ km	% change from gain
Solar power BEV	22.4	22.4	0%	22.4	0%	22.4	0%	22.4	0%	22.4	0%
Cane ethanol	261	211	-19%	312	19%	187	-29%	334	28%	276	6%
Wheat ethanol	507	440	-13%	575	13%	412	-19%	598	18%	639	26%
Maize ethanol	498	421	-15%	574	15%	376	-25%	620	25%	522	5%
Palm-oil biodiesel	611	517	-15%	706	15%	469	-23%	750	23%	528	-14%
Rapeseed biodiesel	592	492	-17%	692	17%	435	-27%	746	26%	575	-3%
Soybean biodiesel	639	510	-20%	768	20%	432	-32%	842	32%	600	-6%

*Estimate using the carbon "gain" method

Supplementary Table 8: Sensitivity analysis results for data in Iowa land use example (cf. Extended Data Figure 2).

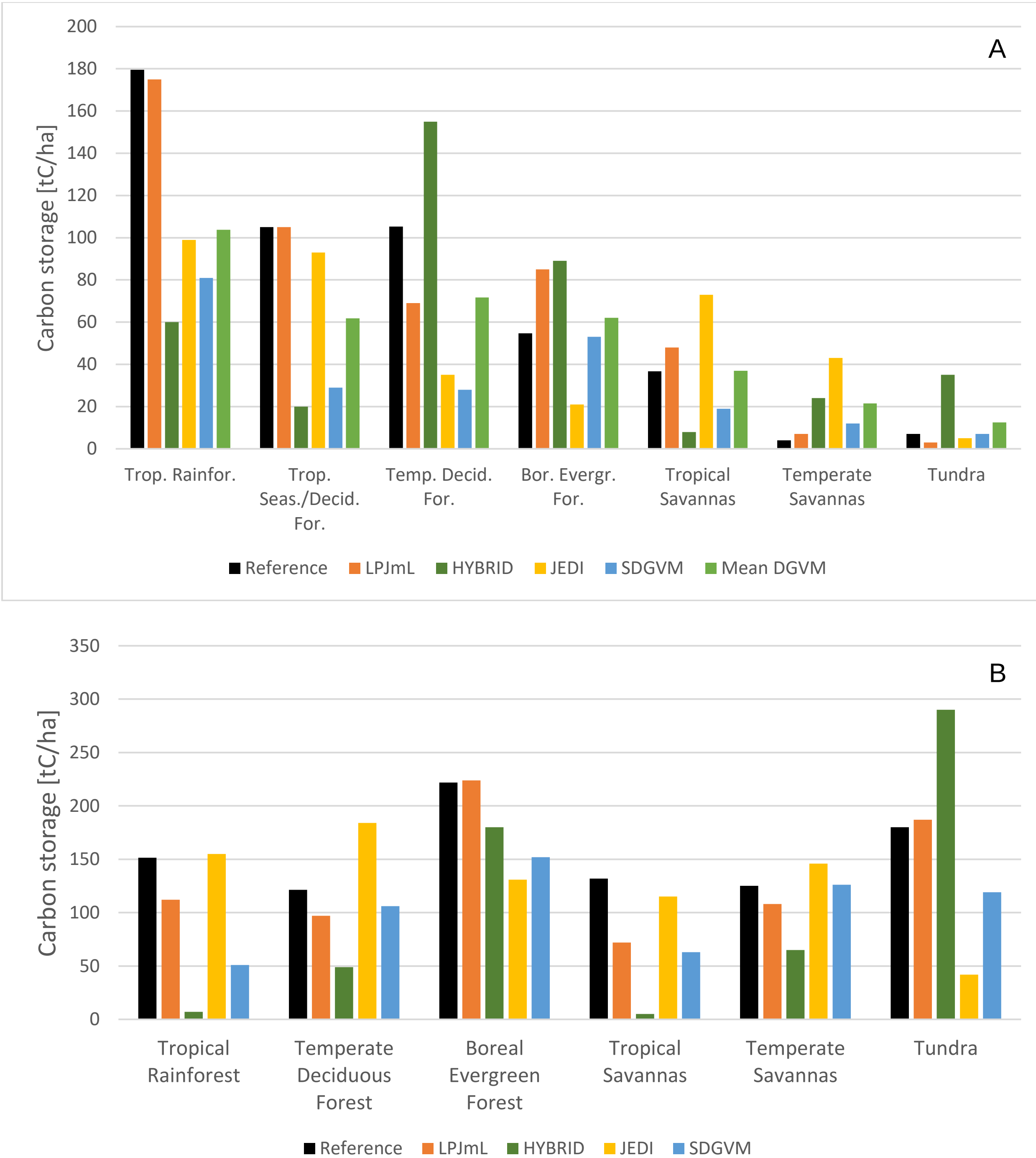
Example	Net GHG benefit (carbon benefit + differences in PEM and soil sequestration)										
	Base variant	"Low" variant		"High" variant		"2% discounting" variant		"6% discounting" variant		"Gain" method*	
	Mg CO_2e/ ha/ yr	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from base	Mg CO_2e/ ha/ yr	% change from gain
Maize-soybean rotation Iowa	21.8	17.0	-22%	26.6	22%	14.1	-36%	29.5	35%	22.9	5%
Maize ethanol Iowa	9.4	7.7	-18%	11.1	18%	6.7	-29%	12.0	28%	11.7	25%
Grass ethanol (grass yield 17 ton DM/ha/yr soil C seq. 0.6 ton/yr)	12.5	12.5	0%	12.5	0%	12.5	0%	12.5	0%	12.5	0%

*Estimate using the carbon "gain" method

Supplementary Table 9: Sensitivity analysis results for data in human diets example (cf. Figure 3).

Example	**COC and emissions per capita (Norther European diets)**										
	Base variant	**"Low" variant**		**"High" variant**		**"2% discounting" variant**		**"6% discounting" variant**		**"Gain" method***	
	Mg CO_2e/ cap/yr	Mg CO_2e/ cap/yr	% change from base	Mg CO_2e/ cap/yr	% change from base	Mg CO_2e/ cap/yr	% change from base	Mg CO_2e/ cap/yr	% change from base	Mg CO_2e/ cap/yr	% change from base
Baseline (year 2050)	8.7	7.3	-16%	10.1	16%	6.5	-26%	10.9	25%	9.7	11%
Less meat (- 50%)	6.3	5.3	-16%	7.2	16%	4.7	-25%	7.8	25%	6.9	11%
Vegetarian (ovo-lacto)	5.4	4.5	-16%	6.2	16%	4.0	-25%	6.7	25%	6.0	11%
No beef or dairy (pork & poultry at baseline level)	2.6	2.2	-16%	3.0	16%	1.9	-25%	3.2	24%	2.8	9%
Vegan	1.8	1.5	-17%	2.1	17%	1.3	-27%	2.3	26%	2.0	12%

*Estimate using the carbon "gain" method



Supplementary Figure 1: Comparison of modeled carbon stocks of native vegetation from LPJmL, HYBRID, JEDI, and SDGVM with reference values for different biomes taken from Trumper et al.[42], Malhi et al.[40], and Jobbágy et al.[39]. "A" is vegetation carbon and "B" is soil organic carbon.

III. SUPPLEMENTARY DISCUSSION

A. How treatment of land use in other LCAs means most crops have little or no land use cost.

The most obvious examples of inadequate other methods are lifecycle calculations for food or agricultural GHG calculators that do not attempt to assign greenhouse gas costs to land use demands[71,72]. They may separately calculate land use demands, but those results cannot be factored directly into GHGs. Other greenhouse gas calculators assign land use costs only if the agricultural change directly converts native lands. The Ex-Act tool developed by the UN FAO[73] is one example.

To illustrate the consequences, if a farm adopts more fertilizer and thereby increases production emissions per hectare or per kilogram of food, these tools will calculate that change as a greenhouse gas increase regardless of the yield gain and the potential land savings. Similarly, if a farm reduces inputs and yields, it will likely measure that change as good for the climate despite implicit increases in land use demands to feed people. Measured this way, farms in Africa with low yields but also few inputs will generally appear desirable from a greenhouse gas perspective – and preferable to alternatives with more inputs – regardless of whether keeping farms this way will result in tens of millions of hectares of clearing of forests and savannas and resulting large losses in carbon (as well as biodiversity).

LCAs like Gerber et al.[74] assign LUC emissions to specific food products only based on the LUC emissions that are occurring recently and that they associate with these food products. Thus, if soybeans are derived from Brazil, soybeans are expanding in Brazil and land use change is occurring in Brazil, the LCAs attribute some expansion of land to soybeans and then average the resulting emissions over all the soybeans produced in Brazil. By contrast, if, e.g., either soybeans are not expanding or net cropland is not increasing in the U.S., U.S. soybeans have no land use cost. Some other LCAs follow a similar approach but focus on global expansion of a particular crop and global expansion of cropland[75]. Even for this approach, individual crops can have zero, low or high land use costs depending on whether demand for that crop is expanding more rapidly than yield. (Different LCA approaches are discussed in Schmidinger & Stehfest[76]).

LCAs that follow these general approaches do not focus on the opportunity costs of land but only attempt to assign responsibility for ongoing land use change emissions. If land area is not expanding for a crop because there is no increasing demand or because yield growth is keeping up with growing demand, then a crop is viewed as having no land use emissions at all. The same is true if area is expanding for a crop, but high yield growth or declining demand for other crops results in no net land use change.

This approach also averages responsibility for LUC emissions across all consumers. It does not focus on the consequences of each person’s individual demand. If one were interested in the marginal effect of each ton of product demand, then the analysis should focus only on the LUC caused by that additional ton of product demand. The rationale in these other LCAs appears to be to apportion responsibility for LUC to each consumer in proportion to the share of consumption. Because land use change occurs only when yield growth cannot keep pace with increases in demand, the marginal consequences of each person's demand should instead be the additional land use required to produce that additional consumption.

The Carbon Benefits Index approach, by focusing on opportunity costs, is essentially a form of marginal analysis of food demand (although it uses average land use conversion costs to measure the effects of that marginal increase in demand). If land use change is occurring to meet growing demand, then increases in demand add to growing land use change, and the carbon loss method is an appropriate benchmark estimate of the costs. Similarly, production on one hectare helps avoid that much LUC elsewhere. If agricultural expansion would not occur, then consumption by one person keeps land in production, and the carbon gain method is a more appropriate measure of the carbon costs of consumption and the carbon benefits of production.

B. Physical optimization models

Several physical land use models optimize areas for agricultural expansion in ways that would meet specified targets for food production while minimizing emissions from land conversion, including Johnson et al.[77] who focused on global crop production, and other papers that focused on national crop production[78–80]. Such models are inherently focused on efficiency, and they can help guide development decisions. In theory, each cell could be ranked based on its estimated likely carbon-efficiency.

These models also have limitations that preclude their uses to make most decisions regarding individual hectares. For a simulation, such a model must specify the key characteristics of all land in the world or country analyzed, including such factors as caloric crop yields, carbon stock and loss rates from conversion. The model must also assumes one alternative for all this land, which is typically to hold its native or existing carbon stock. Because analyzing these land use characteristics on a global basis is hard, such a model must make broad assumptions, e.g., in Johnson et al. (2014) all new cropland in a region will have the same yields as existing cropland and all carbon stocks are the same within each biome (not just in their native state but today).

Unfortunately, real hectares differ. That is in part because global assumptions about vast land areas are inherently crude (yields and carbon stocks vary from hectare to hectare), and also because there are many parameters that people can control that are not accounted for in models of this type, such as the Johnson model, and realistically could not be included. In the real world, people can generate different yields, different production emissions, and changes in carbon stocks on the same land. In addition, in the real world, many potential areas of land expansion do not hold full, native carbon stocks — many lands are already disturbed. These kind of optimization models are not able to handle these deviations of land in the real world from the model's fixed assumptions, which limits their utility for analyzing individual, real hectares. Although valuable for many purposes, models such as the Johnson model cannot be used to evaluate the effects of any of the following on real hectares: changes to management, yield or type of crop on existing cropland, changes from cropland to forest, bioenergy production or pasture, changes in consumption, or changes in production emissions.

C. Estimation challenges of global economic land use change models

Here we elaborate on some of the challenges global economic land use change models face in estimating the consequences of changes in one hectare on carbon storage by others.

Own-price elasticities: Models must estimate responses of changed supply of one food one hectare and resulting effects on prices on the demand for and supply of all other foods globally. Doing so requires large numbers of explicit or implicit supply and demand elasticities. Because only a few such elasticity have typically been estimated in any form, modelers tend to borrow elasticities from other crops and other countries. In addition, to determine a true causal relationship between a change in price and changes in supply and demand, elasticities cannot properly be calculated just by regressing changes in quantity demanded or supplied as a function of price. These changes could be caused by unexplained variables that influence both supply and demand, and the simultaneous influence of supply and demand on each other also defeats analysis using this simple relationship. Proper analyses therefore require analyses driven by changes in “exogenous instruments”. Only a limited number of the own price supply or demand elasticities that exist at all are based on proper econometric methods.

Cross-price elasticities: The land use consequences of a change in production of one crop on one hectare depend not just on how much supply or demand for a food changes with price, but how much of those changes result in shifts to other foods, which have their own land use demands. For example, as a diversion of maize to bioenergy reduces supply for food, a portion of the own price elasticity occurs not because of an absolute increase in agricultural production or due to a decrease in demand for all crops but instead occurs because of a shift of production and consumption away from one crop to another. It is the sizes of the ultimate increases or decreases in all crops that determine the change in overall agricultural land.

One of the potential theoretical advantages of global economic models is that they can estimate the extent to which increased demand or reduced production of one crop leads farmers and consumers to switch from one crop to another. But there are so few econometric estimates of cross-price supply or demand elasticities that no model to our awareness relies on them. Models instead typically produce cross-price elasticities through functional forms. Because the cross-price elasticities are not known, the true sizes of these increases or decrease in land demands also cannot be known.

Ruminant Livestock: Ruminant livestock production heavily uses grazing land, which is a large majority of all agricultural land, and a proper agricultural land use model would need to estimate how changes in feed prices lead to changes in ruminant production methods (for example, influencing the extent of reliance on pasture or crop residues versus crops, and on one type of crop-based feed versus another). Such estimates should also predict changes in the country of production. Similarly, these models must estimate how production loss due to crop conversion of pasture leads to changes in production and therefore land use demands elsewhere. But global analysis of production methods and production costs for ruminant livestock is crude. Few models even attempt any significant, disaggregated representation of the ruminant livestock sector.

Effective yield elasticities: Many economic models attempt to estimate the effect of higher prices on increases in effective crop yields and attempt to do so for all crops and in all countries. These higher crop yields reduce the amount of land use change and therefore emissions attributable to the biofuel. Unfortunately, there is no reason that the intensification effect for any one crop in any one country should be the same or even similar to the effect for other crops or for other countries. Farmers should choose to intensify if and when the costs of boosting production by increasing cropland or pasture is higher than the costs of increasing yields by increasing the share of other inputs such as fertilizer or labor. That calculation will depend on the agronomy of each crop and on the amount, cost of access and productivity of additional potential cropland in a country. In general, however, there are extremely few estimates of yield responses to price, even fewer with proper econometric methods, and most are focused on maize or soybeans in the United States[20,81]. Some models apply numbers ultimately derived from analysis of maize in the U.S. to all other crops and to all other countries even though these numbers should greatly vary[82].

Estimating land use change emissions and yields of new cropland: Consequential economic models attempt to estimate which lands or types of land will be converted for new crops in each country where cropland conversion occurs. Doing so requires difficult estimates of where land use changes will occur within a country and the carbon contents of these lands. These calculations therefore depend not merely on average carbon stock estimates around the world but on precise carbon stock estimates of particular locations despite the difficulty of inferring precise cell-by-cell information from satellite-based maps or scattered field measurements. Models must also in one form or another make assumptions about the yields of these new croplands, which are based little evidence. Models can seek out areas as likely candidates for conversion precisely where relationships among parameters unexpectedly diverge. For example, if a cell is claimed to have high yield potential but today stores little carbon or is cheap, a model might select it as prime candidate for conversion. However, if any one of these overlapping maps map has an error, that error may make the cell seem like a promising candidate for conversion. As a result, models may estimate conversion will occur areas precisely because of random data errors.

The Carbon Benefits Index does not face these challenges precisely because it does not attempt to estimate the marginal costs of replacing a food product but instead uses average costs. That means it cannot offer these kinds of marginal predictions but can offer more robust estimates of average costs.

D. How consequential economic models attribute global intensification gains and reductions in consumption as GHG benefits to biofuels or reforestation of agricultural land.

Searchinger et al.[20] provide extensive discussion and illustration of how consequential economic models attribute global consumption and intensification changes to biofuels. The effect can be calculated in two conceptually different but mathematically equivalent ways. The simplest conceptual way is that when biofuels reduce supply of crops for food, both intensification on other croplands and reduced consumption of food lead to less land use change to replace the crops. The reduction in land use change, typically treated as ILUC, results in lower GHG costs for biofuels. In this type of analysis, the modeling systems ignore the carbon emitted by fermentation and burning of the biomass itself and instead attribute biogenic carbon losses to the biofuel only that result from indirect land use change. In calculations of "leakage" due to reforestation of agricultural land, reductions in food consumption work to reduce leakage in the same way.

This calculation, however, is an indirect way of counting the actual changes in flows of carbon to and from the atmosphere. Physically, fermenting biomass into ethanol and burning any biofuel do release carbon into the atmosphere. This carbon is a GHG emission. This carbon also has the potential to be offset by reduced food consumption, which reduces the amount of carbon released from the consumption of food and feed directly through respiration and wastes by people and/or livestock. These emissions may also be offset by increased plant growth, which absorbs more carbon, and which can result from increased crop yields. As shown in Searchinger et al.[20], another way to understand these LCAs is that they are counting these carbon gains implicitly as offsets for the carbon emitted by fermentation and burning of the biomass as a fuel.

E. Biodiversity and "land sharing versus land sparing"

Land use decisions should consider effects on biodiversity, water and other environmental services of land in addition to carbon. Maximizing global carbon and GHG benefits will often increase other ecosystem services[83], and the failure to appreciate the carbon costs of many ecosystems, such as woody savannas, has sometimes led to proposals to convert them in ways that would also seriously harm biodiversity[84]. Yet, carbon enhancement could sometimes harm biodiversity. For example, planting dense forests on woody savannas would store more carbon but with serious implications for biodiversity and water supplies[85].

Unlike carbon, evaluating biodiversity and many other ecosystem services requires a local approach because each hectare's value depends on the composition of land around it. For example, if a hectare of forest is contiguous with other hectares of forest, it will typically have far more biodiversity value than if it is isolated, yet in some cases, small refugia of forest may have disproportionate value. Some watershed areas with relatively low biodiversity may be critical to the preservation of downstream ecosystems[84]. There is no scientifically valid way to examine values per hectare in isolation. Carbon benefits, however, could be incorporated into physical optimization exercises described above.

One of the substantial debates in conservation biology involves the extent to which biodiversity strategies should focus on “land sparing” versus “land sharing”[86]. “Land sparing” typically implies intensifying agricultural production to be able to avoid clearing larger, intact landscapes. “Land sharing” can sometimes refer to agricultural practices that enable use of the crop-production land itself as habitat, e.g., trees or ephemeral ponds, and sometimes implies preserving non-agricultural landscape features, such as hedgerows or vegetated wetlands, within agricultural landscapes.

Efforts to reduce land use demands or the greenhouse gas effects of agricultural production can sometimes reduce habitat. As just some examples, leveling farm fields can boost yields but eliminate ephemeral ponds used by migratory birds, and increasing fertilizer can have offsite adverse effects on aquatic habitats. For these reasons, some efforts that boost carbon benefits on agricultural land could have negative effects on its habitat values even if doing so helps to spare land elsewhere.

The Carbon Benefits Index, however, also factors in changes in carbon storage on agricultural lands. Although there is academic debate about the viability of different “climate smart agriculture” practices claimed to build soil carbon[87,88], the index will count as a carbon benefit any practices that do build carbon in either soil or vegetation. Some practices, such as silvopastoral systems, claim gains both in soil carbon and food outputs[89]. The Carbon Benefits Index does not avoid the need to evaluate land use changes separately based on effects on biodiversity and other ecosystem values, but it will recognize the climate benefits of efforts to enhance carbon on agricultural lands.

F. Why the index does not yet include forest product COCs

Our analysis does not at this time estimate COCs for the uses of wood products. One key factor is the efficiency of wood harvest, i.e., the ratio of wood harvested to forest carbon losses. This factor must be known worldwide, and to differentiate wood products, for different types of wood. Because this data is not available, developing a COC for wood products therefore depends on further work. Our analysis of forests therefore presently focuses only the carbon storage value of forests.

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