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

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Land-use changes are critical for climate policy because native vegetation and soils store abundant carbon and their losses from agricultural expansion, together with emissions from agricultural production, contribute about 20 to 25 per cent of greenhouse gas emissions[1,2]. Most climate strategies require maintaining or increasing land-based carbon[3] while meeting food demands, which are expected to grow by more than 50 per cent by 2050[1,2,4]. A finite global land area implies that fulfilling these strategies requires increasing global land-use efficiency of both storing carbon and producing food. Yet measuring the efficiency of land-use changes from the perspective of greenhouse gas emissions is challenging, particularly when land outputs change, for example, from one food to another or from food to carbon storage in forests. Intuitively, if a hectare of land produces maize well and forest poorly, maize should be the more efficient use of land, and vice versa. However, quantifying this difference and the yields at which the balance changes requires a common metric that factors in different outputs, emissions from different agricultural inputs (such as fertilizer) and the different productive potentials of land due to physical factors such as rainfall or soils. Here we propose a carbon benefits index that measures how changes in the output types, output quantities and production processes of a hectare of land contribute to the global capacity to store carbon and to reduce total greenhouse gas emissions. This index does not evaluate biodiversity or other ecosystem values, which must be analysed separately. We apply the index to a range of land-use and consumption choices relevant to climate policy, such as reforesting pastures, biofuel production and diet changes. We find that these choices can have much greater implications for the climate than previously understood because standard methods for evaluating the effects of land use[4–11] on greenhouse gas emissions systematically underestimate the opportunity of land to store carbon if it is not used for agriculture.

We define a more 'carbon efficient' use of land as one that increases the capacity of global land to store carbon and reduce greenhouse gas emissions (GHGs) overall, while meeting the same global food demand. For example, producing more crops, meat or milk on one hectare of land increases this carbon efficiency by increasing the global capacity to spare forests and other habitats while producing the same quantity of food. Gains in efficiency increase capacity to generate valuable outputs but do not by themselves guarantee how the added capacity will be used—for example, for more carbon or more food—or how other people might react owing to market forces. Yet because land supply is fixed, only increasing its efficiency can allow the world to meet both climate and food goals.

Governments, companies and individuals are making land-use decisions at least partially directed at reducing GHGs. Questions include whether to encourage conversion of cropland to forest or bioenergy, what targets to set for national emissions from land use and how to reduce the carbon footprint of diets or food supply chains. Yet standard evaluation methods, as discussed below and in more detail in Supplementary Information, do not properly reflect the land's opportunity to store carbon if it is not used for agriculture, which we call its carbon storage opportunity cost. They can therefore encourage inefficient results that reduce the global capacity to store carbon.

For example, typical lifecycle assessments (LCAs), which estimate the GHG costs of a food's consumption, only estimate land-use demands in hectares without translating them into carbon costs[4,5]. Other LCAs consider land-use carbon costs only if a food is directly produced by clearing new land[6,7], or only for specific crops, meat or milk, where both that food and agricultural land overall are expanding[8–10]. Such approaches assign no land-use carbon costs to most of the world's food production because previously converted agricultural lands have no carbon storage opportunity cost[12] (Supplementary Information).

Physical optimization models[13,14] can estimate where agricultural expansion should occur to minimize carbon costs, by assuming likely crop yields of every hectare in a study area. Such models can count carbon storage opportunity costs, but they cannot account for the variability in carbon storage or crop yields in real hectares or estimate the effects of changes in their yields, output types or production methods (Supplementary Information).

Economic models provide a common approach to estimating how conversion of cropland to biofuels or forest affects carbon stored elsewhere, called 'leakage' or 'indirect land-use change' (ILUC). However, these models do not calculate the true efficiency of the changes to the hectare analysed (for example, reforesting cropland) because the models also factor in how resulting increases in food prices cause changes on other land, by other people and at others' expense. Such changes may include lower GHGs through reductions in global food consumption and, although disputed, through simulated increases in the yields (efficiencies) of other farmland[15]. Such estimated 'benefits', paid for by global consumers, result from the decline in food production on the hectare whose use was deliberately changed, not from its gain in forest or bioenergy, and would therefore occur even if that hectare became supremely inefficient by producing nothing at all.

To appreciate the distinction, we imagine a possible economic analysis of a strange climate policy banning all cars except petrol-guzzling, expensive, luxury SUVs (sport utility vehicles). The efficiency of driving would decline, increasing emissions per kilometre. However, if the cost of driving rose high enough, an economic model might estimate overall GHG savings by forcing many people to stay at home and others to switch to public transit. Even if these outcomes were real, these switches would not make SUVs more efficient than economy cars.

The actual efficiency of driving matters because governments can reduce GHGs more generally by using fuel taxes and transit subsidies to encourage less travel and higher use of mass transit while also requiring vehicles that are more fuel-efficient. Similarly, if governments wished to use higher prices to reduce food consumption and spur yield gains, they could reduce GHGs more using taxes and subsidies while encouraging only efficient land-use changes (LUCs). To implement such policies, however, governments need to know which LUCs are more efficient in themselves.

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Table 1 | COCs and global PEMs of major crop and livestock products

	COC[a] (kg CO_2 per kg fresh weight)	PEMs (kg CO_2e per kg fresh weight)	Total (kg CO_2e per kg fresh weight)	Total (g CO_2e per kcal[c])	Total (kg CO_2e per kg protein)
Maize	2.1	0.46	2.6	0.82	29
Rice (rough)	2.6	2.17	4.8	2.0	69
Wheat	1.9	0.69	2.6	0.9	23
Cassava	1.7	0.04	1.7	1.6	160
Potato	0.6	0.09	0.7	1.1	38
Soybeans	5.9	0.26	6.1	1.5	17
Pulses	10.5	0.55	11	3.1	47
Vegetable oils	9.7	1.3	11	1.2	Not applicable
Beef[b]	144	44	188	102	1,250
Cow milk	6.2	2.3	8.4	13.1	260
Pork	14	5.5	20	9.4	150
Poultry meat	11	3.7	14	8.4	110

Values are calculated using the carbon loss method and 4% time discounting.
[a]Includes peatland emissions.
[b]Average, including meat from dairy animals.
[c]1 kcal = 4,184 J.

Our carbon benefits index provides such a measure, expressing benefits as kilograms of CO_2 equivalent (CO_2e) emissions per hectare (ha; 1 ha = 10^4 m^2) per year. The index first incorporates the outputs of a hectare that are directly quantifiable in carbon terms. These include any changes in carbon storage on site, as well as net reductions in GHGs from displacing fossil fuels with bioenergy.

The challenge arises in calculating the carbon benefits of producing foods, whose carbon is consumed. The index values them according to the emissions that are avoided from their production elsewhere. The core assumption is that if one hectare did not produce a food, it would be produced elsewhere at its global-average carbon costs. By holding consumption and other production systems fixed, the index calculates only changes in the efficiency of the hectare analysed.

We call the land cost of replacing each food its 'carbon opportunity cost' (COC), and calculate it using two methods. In the first method, the 'carbon loss' method, the COC is equal to the global carbon loss from plants and soils generated by producing each crop to date (the numerator), divided by the global production (the denominator), and is expressed as kilograms of CO_2e per kilogram of crop. For each meat or milk, the COC is equal to the sum of COCs of the feeds needed to produce it (including lost carbon on pasture for ruminants). The COCs of bioenergy feed by-products equal the COCs of the crops that they displace.

The second method is the 'carbon gain' method, in which we estimate the quantity of carbon that could be sequestered annually if the average productive capacity of land used to produce a kilogram of each food globally were instead devoted to regenerating forest. The carbon loss method is generally more appropriate in a world of expanding cropland, but the carbon gain method could apply where increasing yields could only increase carbon by rebuilding forests.

Because carbon losses of native vegetation occur quickly yet food production could continue indefinitely, we calculate a present discount value of both the numerator and denominator. The choice of rate to discount the costs and benefits of changes in the future is a question of climate policy. We use 4% in our central scenario, in part to match the implicit approach of US biofuel policies (Supplementary Information)[15].

Table 1 presents COCs calculated with the carbon loss method for a sample of products using fresh weights, with a fuller list of 64 products in Extended Data Tables 1, 2 (including COCs using dry matter). COCs from the carbon gain method are mostly similar using a 4% discount rate and do not alter the directional results of our examples (Supplementary Tables 5–9). The COCs reflect the different average yields and native carbon stocks of lands used by different crops. For example, soybean COCs are 2.8 times larger than maize COCs because soybean yields are lower, even though the crops use similar lands. However, wheat and maize COCs are similar despite 40% lower wheat yields because wheat is grown overall on land with lower native carbon stocks.

Our core replacement assumption implies that if the rate of a food's recurring production emissions (PEMs) on one hectare is lower or higher than the global average, the difference decreases or increases global PEMs. When calculating global-average PEMs for all foods (Extended Data Tables 1, 2), we factor that difference into the index. The index can therefore calculate the net GHG effects of altering yields by changing fertilizer or livestock feeds, which alter N_2O and CH_4 emissions.

In summary, the total carbon benefits of a hectare of land is equal to the sum of: (1) the opportunity that its food production provides to store carbon elsewhere (COC × yield), (2) its savings or increase in global PEMs, (3) its annual change in soil and plant carbon storage and (4) any net savings in fossil emissions due to bioenergy generated (see equation (1) in Methods). The efficiency of an LUC depends on the gain or loss in carbon benefits.

The index can also evaluate the carbon efficiency of consumption by assuming that production systems are fixed. One individual's change in consumption therefore alters global consumption and aggregate production by that amount. The cost of a food is equal to its COC plus its PEMs (see equation (2) in Methods).

The index separates the efficiency of consumption from the efficiency of each hectare's production into different analyses. The higher a product's COC, the costlier its consumption, but also the more beneficial its production. For example, consuming a kilogram of beef costs more carbon than consuming a kilogram of soybeans, but producing a kilogram of beef generates more benefits because it frees up more carbon storage capacity elsewhere, assuming fixed demand.

We supply a Carbon Benefits Calculator (provided as Supplementary Data) for users to evaluate the efficiency of changes in real hectares using site-specific information and changes to discount rates, COCs and other parameters. We also apply our index to production and consumption choices that are important to global climate policy in the following examples (see Supplementary Information for full sources of information used in the examples).

First, we consider production changes from Brazil grazing land. In Brazil, because of low yields of beef from extensive cattle grazing, proposals exist either to convert pastures to cropland for soybeans or to sugarcane for ethanol, or to intensify pasture management to help meet the expected increases of about 80% in global beef demand by 2050[1,16]. We consider which changes would produce more carbon benefits. Cardoso et al.[17] categorized beef production in the

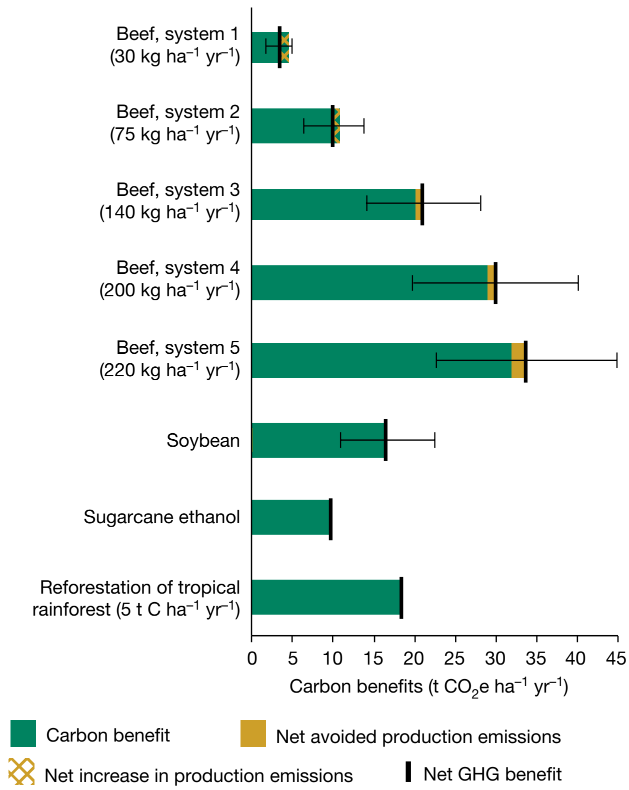

Fig. 1 | Carbon benefits of different potential uses of Brazilian grazing land. Error bars reflect the range of literature estimates of vegetation and soil carbon stocks used in part to derive the COCs.

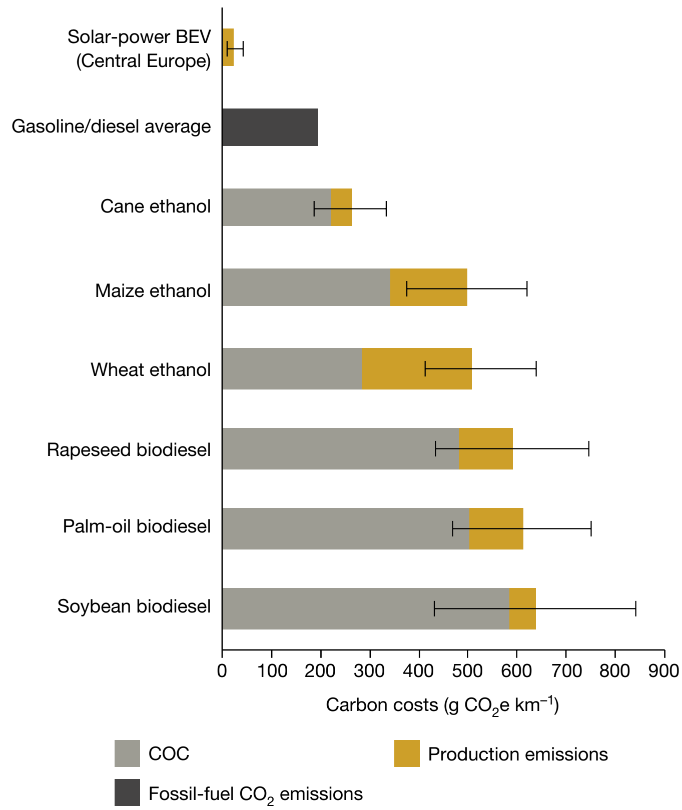

Fig. 2 | Carbon costs of different fuel sources (per kilometre driven) based on the carbon benefits index. Error bars reflect the range of literature estimates of vegetation and soil carbon stocks used in part to derive the COCs. BEV, battery electric vehicles.

Cerrado region in Brazil into five systems with increasing beef yields from 30 kg ha^{-1} yr^{-1} to 220 kg ha^{-1} yr^{-1} on the basis of grazing practices, healthcare, fertilization and replanting frequency, and uses of legumes or crop supplements. We find that for grazing land using system 1 (30 kg ha^{-1} yr^{-1}, carcass weight) shifting to sugarcane ethanol increases carbon benefits (Fig. 1). However, the more commonly used system 2 (75 kg ha^{-1} yr^{-1}) generates roughly the same benefits as sugarcane ethanol, whereas system 3 (150 kg ha^{-1} yr^{-1}) produces much greater carbon benefits[17]. Shifting to soybean production at average Brazilian yields would produce more benefits than grazing system 2, but less than system 3.

By contrast, reforesting pastures at 5 t C ha^{-1} yr^{-1} would increase carbon benefits by a factor of five in the Atlantic Coastal Rainforest region. Grazing system 1 is mostly used in this region at present and pastures are difficult to intensify because they are mainly located on steep terrain.

Factoring in the land's COCs, we find that shifting from system 1 to system 3 increases benefits six times, in contrast to the merely twofold gain[16] from PEMs only. Shifting from grazing system 2 to system 3 provides annual benefits equivalent to those of temperate forest growth (about 3 t C ha^{-1} yr^{-1})[18,19]. Extensive systems that use arid, native grasslands, including nomadic systems, can still be efficient despite producing little beef and few carbon benefits because they also sacrifice little opportunity to store carbon (Supplementary Information).

Second, we consider production changes related to intensification. By examining several plausible examples, we find that increasing crop inputs usually saves more GHGs through reduced land demands than the increase in GHGs because of higher PEMs. Examples include adding 75 kg ha^{-1} yr^{-1} of nitrogen to maize in West Africa using flooded, irrigated rice, rather than upland rice, despite its higher methane emission, and comparing conventional versus organic bean production in Sweden (Extended Data Fig. 1).

Third, we consider production changes related to biofuel production. Carbon benefits from cropland with a rotation of maize and soybeans at average Iowa yields (22 t CO_2e ha^{-1} yr^{-1}) greatly exceed those of ethanol production either from maize (9 t CO_2e ha^{-1} yr^{-1}) or from perennial grasses (17.5 t CO_2e ha^{-1} yr^{-1}) (assuming optimistic grass dry-matter yields[20] of 17 t ha^{-1} yr^{-1} and 0.6 t C ha^{-1} yr^{-1} soil carbon sequestration[21]; Extended Data Fig. 2). For maize ethanol, feed by-products provide two-thirds of the benefits. Perennial grasses for ethanol would have to achieve implausibly high dry-matter yields of 32 t ha^{-1} yr^{-1} to match the benefits of maize–soybean rotations.

Fourth, we consider consumption changes related to biofuels. We estimate that the total GHG costs of consuming biofuels, rather than gasoline or diesel, range from 35% more for sugarcane ethanol to 230% more for soybean biodiesel (Fig. 2). Using Central European solar power to run battery electric vehicles generates only 9% of the GHGs of sugarcane ethanol, mostly through battery production (Supplementary Information). Our biofuel COC estimates are equivalent to ILUC estimates if crops diverted to biofuels (after deducting by-products) are fully replaced at the average global carbon loss per kilogram of crop. Our estimates range from 100 g MJ^{-1} to 300 g MJ^{-1} of CO_2 emissions for biofuels from different feedstocks—higher than gasoline or diesel emissions, even without counting their PEMs (Extended Data Table 3). Our estimates are mostly 6–14 times higher than those of economic models commissioned by California and the European Commission (Supplementary Table 4).

Last, we consider consumption changes related to shifting diets. LCAs have long estimated GHG benefits from diet shifts away from ruminant products (box 8 in ref. [12]), but typically assign little or no GHG costs to land requirements[5,8,22]. By applying the carbon benefits index, we find global-average GHG costs of dairy and beef about 3–4 times higher than previous estimates by the UN Food and Agriculture Organization[8] (Supplementary Information), which only include land-use GHGs from each year's agricultural expansion. We estimate the total GHG costs of average Northern European diets[22] at more than 9 t CO_2 yr^{-1} per capita (Fig. 3). That is about 20 times the

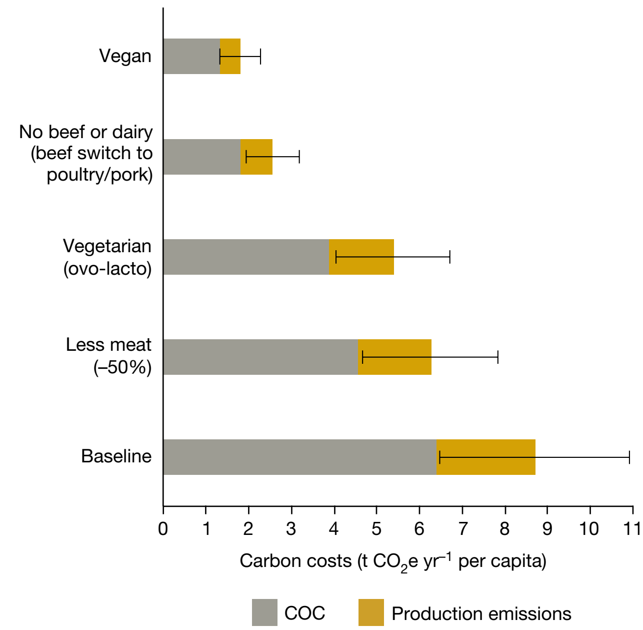

Fig. 3 | Carbon costs of different diets based on the carbon benefits index. Error bars reflect the range of literature estimates of vegetation and soil carbon stocks used in part to derive the COCs.

most-emitting diet estimate in Tilman and Clark[4] and equivalent to GHGs typically assigned to each European's consumption of all goods, including energy[23]. Shifting from beef and dairy would reduce those emissions by 70%. Although animal products offer health benefits for the food-insecure[24], we estimate much larger climate benefits than others if the wealthy consume less beef and dairy.

As these examples illustrate, our analysis finds that consumption and LUCs can have many times larger implications for climate change than often calculated. By undercounting the carbon storage opportunity costs of land, LCAs and economic models can greatly overvalue mere shifts in land uses—for example, shifting croplands or pasture to forest or bioenergy—and undervalue both increases in pasture or crop productivity and reductions in demand—such as shifts to diets low in beef and milk.

By using average global costs as a benchmark, our method evaluates the comparative carbon advantage of different land uses. Even between two inefficient land uses, the less inefficient one will generate more benefits. As yields and farming areas change, COCs must change.

Despite many estimation uncertainties (Supplementary Information), implications for policy appear to be insensitive to them. Varying COCs on the basis of native carbon estimates that are ±20% of our estimates for vegetation and ±30% for soils and changing discount rates to 2% and 6% (Supplementary Table 3) do not alter the directions of our examples (Supplementary Tables 5–9). Because of scientific uncertainties, however, our index does not incorporate biophysical effects of LUC (for example, albedo), which could be substantial.

Our index assumes that food would be replaced at global-average, rather than marginal, costs. In the real world, marginal carbon costs could differ through price effects or because a food's replacement land physically differs from the global average. (Our calculator does allow a user to select marginal COCs as a lower or higher percentage of average COCs.) We therefore suggest the following uses for our index.

First, our index can be used to evaluate shifts from agriculture to forest or bioenergy. Efforts to deliberately replace food production with forests or bioenergy for climate purposes could require sizable carbon benefits as one core criterion. Regardless of whether price effects alter consumption or the productivity of other farms, the world is unlikely to achieve the ultimate climate goals through LUCs that reduce the global capacity to store carbon. In addition, changing the production of one hectare of land to try to lower GHGs by reducing food consumption is probably inefficient and inequitable, as suggested by the SUV example. Other farmers would probably replace most of the production, and higher prices would typically depress consumption by the poor more than by the rich owing to the greater price-sensitivity of the former[25]. To reduce inefficient consumption, targeted taxes or other demand strategies could be more efficient and equitable.

Second, our index can be used in attributional LCAs to assign land-use carbon costs to consumption choices, as we show in our diet examples. Those LCAs also use average GHG costs of production, rather than some estimate of marginal costs, and similarly assume that one person's change in consumption equally alters global consumption.

Third, our index can be used as a benchmark for evaluating predictive models. Accurately projecting marginal, rather than average, consequences of one hectare's changes would still have value. Doing so requires economic models, but results greatly vary by model or assumption[3,11,26,27]. Only a small number of the demand and supply elasticities required by global models have been econometrically estimated. Missing critical estimates include almost all cross-price elasticities, almost all medium-to-long-term elasticities, and supply elasticities of different pasture systems, although pasture occupies two-thirds of all agricultural land (Supplementary Information). Our view is that global land sparing is powerful[15], although often hidden, because gains in local yields can increase competitiveness and encourage local expansion[1]. Although our index cannot by itself answer these questions, the COC provides a useful benchmark to evaluate model results. For example, California's estimates of ILUC from maize ethanol[28] are about 10% of the average global loss of carbon generated by producing the required maize (using California's amortization period and after accounting for by-products). By providing this average cost, our index helps to evaluate a model's justification for estimating greatly different marginal costs.

Last, where some conversion of natural vegetation to agriculture is inevitable, such as for oil palm in Southeast Asia[29] or for staple foods in Africa[14], our index could help to determine the most efficient lands and crops to choose. For policy reasons, however, we advise great caution in using the index to justify conversion of native vegetation based on claims of high food yields. Because climate strategies require quick elimination of emissions from LUCs, clearing land in one location does not provide a general solution, even if clearing elsewhere would be worse. Strategies to reduce LUCs require strong policies to discourage expansion, so farmers intensify instead. It may be tempting to exaggerate likely yields on lands proposed for conversion, and promises of intensive management cannot justify conversions if the same investment could generate equal yields on existing cropland. However, these kinds of conversion also have high potential to harm biodiversity and other ecosystem values, which our index does not measure and which must be evaluated separately.

Overall, the concept of 'carbon benefits' offers an alternative to the concept of 'leakage', which assumes that land benefits the climate only by sequestering carbon or producing biofuels. Our approach recognizes that all increases in efficiency generate climate benefits.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of data availability and associated accession codes are available at https://doi.org/10.1038/s41586-018-0757-z.

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Author contributions All authors contributed to all features of the paper. In addition, T.D.S. conceived the idea for the research and wrote the paper. S.W. programmed our spreadsheet model. T.B. performed global vegetation modelling and spatial analysis. P.D. estimated product-specific PEMs.

Competing interests The authors declare no competing interests.

Additional information
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METHODS

Calculating COCs using the carbon loss method. *Basic method for crops.* The COC for each crop equals the aggregate, time-discounted carbon lost from native vegetation and soils on land used to produce the crop globally (the numerator) in kilograms, divided by the aggregate, time-discounted annual production for that crop in kilograms. The result is multiplied by 3.67 to be expressed as kilograms of CO_2e per kilogram of crop.

To estimate native carbon stocks of both vegetation and soils of existing cropland (Extended Data Figs. 3, 4), we employ a combination of vegetation modelling and biome estimates. We use the Lund–Potsdam–Jena managed land (LPJmL) dynamic global vegetation model (DGVM)[30,31] to estimate native carbon stock in each 0.5° × 0.5° grid cell, but we scale the LPJmL results in each pixel so the average biome values of our adjusted LPJmL results match those of average reference values for the biome from the literature[32–36]. After analysing estimates of native carbon stocks available from three other DGVMs and determining that many of their estimates were too implausible to use (as discussed extensively in Supplementary Information), we chose LPJmL because its average estimates at the biome level match literature estimates fairly well.

Although some previous efforts used average carbon stocks for entire biomes to estimate stocks for each crop[13,37], these biomes are large and include lands with very different native carbon stocks and productivities used differently by different crops; so they cannot properly distinguish among crops. Our method uses empirical measures to adjust our DGVM results at the biome level to match empirical estimates but preserves the higher spatial resolution of the DGVM, so that carbon stocks within a biome can reflect major physical differences, such as rainfall. This method also implicitly incorporates the effects of disturbance, for example, from fire and wind, because they are automatically incorporated into biome estimates.

To identify the locations of different crops, we use maps provided by the Spatial Production Allocation Model (SPAM) for 42 crops in the year 2005[38] and estimate carbon losses on all cropland used by each crop separately. The loss represents the difference between vegetative carbon in native vegetation (including both above- and below-ground parts) and the average carbon stock of the crop. For crop carbon stocks, we use data from ref. 39 for perennial crops. For annual crops we assume annual average carbon stocks of 25% of the peak values and a whole-plant multiplier of 2.5 from the carbon in harvested crops. For conversion to cropland, we also assume loss of 25% of soil carbon within the top metre of soils, consistent both with several other global studies[39,40] and with a range of new meta-analyses[41–45]. For global crop production, we use data from the FAOSTAT database[46]. For products that are only a portion of crops, such as vegetable oils, we apportion crop output based on energy content.

Time discounting. Conversion of land from forest to cropland loses carbon relatively quickly whereas the benefits of crop production for food or bioenergy extend over time. To reflect the values of earlier emissions reductions, we apply a discount rate both to the stream of carbon losses in the numerator of the COC and to the stream of production in the denominator. For vegetation losses in the numerator, we estimate the annual stream of losses using exponential decay functions from ref. 47, which vary by type of vegetation and climatic regions. For soil carbon losses we consider these rates[47] to be too fast, and instead follow the exponential carbon response function from ref. 48. For the conversion of forests to cropland, it implies the loss of 98% of the volatile soil organic carbon (SOC) stock (25% of the SOC in the upper 1 m of the soil) within 20 years and is therefore consistent with the default period of the Intergovernmental Panel on Climate Change (IPCC). We apply similar discounting to the stream of crop production in the denominator.

In our base case, we use a 4% discount rate over 100 years for reasons that we explore more thoroughly in Supplementary Information. The choice of discount rate should be solely a question of climate policy for valuing mitigation over time, reflecting, among other matters, the cost of short-term as well as long-term damages, risks of crossing thresholds, and the time value of money. In general, a 4% discount rate is consistent with a 4% real return on investment[49] and a constant cost of a tonne of emissions over time. It also produces results roughly equivalent to the implicit treatment of time discounting by USA federal and California biofuel policies, which use a 30-year amortization period for carbon lost from land conversion owing to biofuels.

Calculating carbon loss from organic soils. Because the LPJmL model does not include detailed representations of peatland development and distribution, we use a global map of peatland regions[50] to estimate emissions from organic soils under croplands. We determine shares of peatland soils for all SPAM crop distribution maps[38] and apply emission factors from ref. 51 (using a rate of 15 t C ha^{-1} yr^{-1} for oil palm). We also assume 8 Mha of drained peatland for pasture[52] and emission rates equal to half of cropland emission rates because of lower need for drainage.

Calculating COCs using the carbon gain method. To calculate COCs with the carbon gain method, we assume that if increasing yields result in a reduction in agricultural land, the productive potential of the land no longer used for crops can be restored to forest. We base this productive potential on the net primary productivity of the native vegetation (NPP_{nat}) of global hectares devoted to each crop, expressed in tonnes of carbon per hectare per year (t C ha^{-1} yr^{-1}). Although land management can increase or decrease this productive potential, this native productivity (which reflects rainfall, solar radiation, temperature and soil type, among other factors) provides a reasonable measure of inherent productive potential. We use LPJmL to estimate and map NPP_{nat} (Extended Data Fig. 5) and then use the SPAM 2005 v3.2 cropland maps to estimate the average NPP_{nat} of the land used for each type of crop. This average NPP_{nat} per hectare, divided by the average yield of that crop, generates the amount of NPP_{nat} used to produce a tonne of each crop, which can be converted to kilograms CO_2 per kilogram of crop.

To determine how much potential carbon sequestration would be generated on average by devoting one tonne of NPP_{nat} to reforestation, we need to determine both the NPP_{nat} of forests that have become cropland and the average carbon sequestration rate on croplands modified to regenerate forest. We estimate the average NPP_{nat} of all tropical croplands that were originally forest to be 9.7 t C ha^{-1} yr^{-1}. We then use the mean of three recent meta-analyses of carbon fluxes in forests to estimate average carbon sequestration in regenerating tropical forests[18,19,53,54] over 100 years at 4.1 t C ha^{-1} yr^{-1} in vegetation and soils. Dividing the output (4.1 t C ha^{-1} yr^{-1}) by NPP_{nat} produces a ratio of 0.42 t C ha^{-1} yr^{-1} for every tonne of NPP_{nat} available, which equals 1.5 kg CO_2 (kg CO_2 NPP_{nat})$^{-1}$ for the tropics.

Extending our analysis to originally forested croplands in both the tropics and the temperate zone, we estimate the NPP_{nat} at 8.5 t C ha^{-1} yr^{-1} from LPJmL, and the average annual carbon sequestration rate for regrowing forests[18,19,54] is 3.6 t C ha^{-1} yr^{-1}. Although both figures are lower than those obtained for the tropics alone, they generate the same ratio of 0.42 t C ha^{-1} yr^{-1} sequestration for every tonne of NPP_{nat} available. As the vast majority of the world's croplands are located in temperate to tropical regions[55], we use this benchmark.

For each crop, the COC calculated using this method equals that crop's ratio of NPP_{nat} to crop output in kilogram of CO_2 per kilogram of crop, multiplied by this 1.5 kg CO_2 (kg CO_2 NPP_{nat})$^{-1}$, which generates kilograms of CO_2 per kilogram of crop.

Calculating COCs of livestock products. The global-average COC of livestock products (meat, dairy and eggs) equals the global-average COC of feeds, including portions of crops, such as oilseed meals, used to produce them. We estimate the global-average feed use per unit of livestock output based on the few publications available on global feed use[56–58]. We calibrated these data against FAOSTAT data on forage production and FAOSTAT feed use data for cereals, tubers, oil crops, pulses, brans, molasses and oil meals, so our total global feed use equals that in the FAOSTAT data. We treated fibrous, low-value by-products, such as crop residues and straw, as land-free sources of feed (that is, they have no COC), which applies to roughly 20% of global feed use in dry matter[56].

Because ruminants heavily rely on grasses, we estimate the COC of permanent grazing land and apportion this COC to the forage from permanent grasslands for beef, bovine milk, and mutton based on global estimates of their relative consumption of grasses[58,59].

To estimate carbon losses on pasture, we use the HYDE 3.2 land-use map[60], which estimates 2.8 billion hectares of grazing land. We overlay pastures with our estimate of native vegetation carbon stocks described above. Changes in SOC following the conversion of forests or grasslands into pastures remain disputed. Because effects in the tropics vary from negative to positive depending on grazing practices[42,61,62], we assume no change in soil carbon for tropical pastures. Relying on a recent meta-analysis for temperature pastures, we assume a 10% loss of carbon in temperate pastures[63].

For grazing lands that were naturally grassland (tree canopy cover less than 10%), we also assume no loss of vegetative carbon. For grazing lands that were naturally forested (more than 60% tree cover), we estimate a loss of all tree carbon and replacement by grass carbon assuming that such areas must be cleared to show up as grasslands in land cover classifications from satellite data. For grazing lands that were naturally some kind of woody savanna, we assume 75% loss of vegetation carbon for woody savannas (30%–60% canopy cover) and 50% loss of vegetation carbon for savannas (10%–30% canopy cover), also based on assumptions about satellite data. On average for all grassland, these assumptions imply a 92% loss of vegetation carbon. Because this carbon loss is dominated by the loss of dense forests, assumptions for carbon losses on native grasslands and woody savannas have little consequence (see Supplementary Table 2).

Calculating COCs using the carbon gain method. For the carbon gain method, we estimate the NPP_{nat} of grazing lands using LPJmL. Because grazing lands maintain native vegetation carbon stocks to a varying degree, we assign some NPP_{nat} to the maintenance of these carbon stocks using complementary numbers to those for vegetation carbon loss (see previous paragraph). Hence, for natural grasslands we assume 100% for forests, 25% for woody savannas, 50% for less-woody savannas and 0% for grasslands that were originally forests.

We follow the same approach to time-discounting COCs for livestock and pasture feeds as described above for crops.

Estimating PEMs for crops and crop products. We estimate the global-average PEMs for each crop for which we derived COCs based on sources (listed below) that ultimately rely on the IPCC Tier 1 or Tier 2 methods. These emissions were built into a global agriculture emissions accounting model (GlobAgri-WRR; developed by CIRAD, the World Resources Institute, Princeton University and INRA (Institut National de la Recherche Agronomique) for the World Resources Report of the World Resources Institute[12]) that uses the same methodology for agricultural product balances and similar livestock data as those used in studies by CIRAD and INRA[64,65]. Although this model contains many other features, for the purposes of this study, the model essentially provides a spreadsheet that adds up the emissions in the production process for crops in each region where they are produced and divides them by the total production. Sources of emissions are as follows.

Emissions from nitrogen use. Nitrogen balance, harvested nitrogen, nitrogen fixation and use of fixed nitrogen, in addition to legumes needs of following crops, are based on data used in the analysis of ref. [59], with manure nitrogen rescaled using data from ref. [58]. Emissions from nitrogen in the form of nitrous oxide are based on IPCC Tier 1 emission factors for direct and indirect emissions. Emissions from the manufacture and transport of nitrogen are based on analysis by the US Environmental Protection Agency (EPA)[66]. To compute N_2O nitrogen residue emissions, we apply a factor of N_2O emissions per harvested nitrogen, obtained by dividing the FAOSTAT total residue N_2O emission by the total harvested nitrogen for each country.

Rice methane. Rice methane emissions rates are based on a spreadsheet model[67], adjusted to match expert opinions of mid-season drainage or multiple drainages[68].

Emissions from potash and phosphorus consumption. Quantities of potash and phosphorus used per crop are based on estimates for 2003 and 2007 data originally compiled by the International Fertilizer Institute and completed by FertiStat[69]. We use methods described in Supplementary Information to estimate application rates for crops not represented in the initial data. Country-level fertilizer consumption from FAOSTAT is then used to rescale over time the rates per crop per unit area. Emissions are based on estimates of those associated with phosphate and potash extraction in the analysis of EPA[66].

Pesticides emissions. Pesticide quantities are taken from FAOSTAT and emissions per kilogram of active ingredients in pesticides are based on the analysis of EPA[66].

Direct on-farm energy use. Emissions for energy used directly on farms are taken from FAOSTAT[46]. To allocate emissions to individual crops, we first deduct a global number for livestock PEMs based on previous estimates[8] and on the hypothesis of a constant coefficient for emissions per energy content of livestock product. Then we allocate the remainder to crops using professional judgment supported by different lifecycle calculations.

We use 100-year global warming potentials of 298 for N_2O and 34 for CH_4 based on recommendations in the latest assessment report by the IPCC[70].

Estimating PEMs for livestock products. Although GlobAgri-WRR estimates livestock PEMs that rely heavily on ref. [58], we do not use GlobAgri-WRR for this purpose, in part because it uses the ruminant model to estimate methane emissions from enteric fermentation, which is not easily accessible by others for use in estimating methane emissions for individual farms. We therefore use IPCC Tier 2 methods to estimate methane from enteric fermentation based on the feed use estimates obtained in this study. Non-enteric livestock emission sources are estimated on the basis of GLEAM model results[8,71,72]. To be consistent with our crop production estimates, PEMs for feed (which contribute to livestock PEMs) are based on GlobAgri-WRR, as described above. For emissions of nitrous oxide from pasture, we use estimates of nitrogen applied to pasture generated from ref. [59].

Biofuel and biofuel by-product COCs and PEMs for estimating GHG costs of consumption. As in the case of livestock products, the global-average COC of biofuels equals the global-average COC of the feedstock (that is, crop products) used to produce them. Process yields and GHG emission data are based on ref. [73], except in the case of grass-based ethanol, where they are based on ref. [74], which assumed conversion of biomass to ethanol of 375 litres per tonne of dry matter, which we use as well. In both studies[73,74], the GHG savings due to electricity by-products from sugarcane or cellulosic ethanol production are allocated to the biofuel, which reduces its nominal PEMs. To account for the land and GHG-sparing value of feed co-products from maize and wheat ethanol (distillers' dried grains with solubles, DDGS) we use the substitution method. We estimate the specific crops that the DDGS would replace based on ref. [75]. We then apply the COC values of the crops substituted. (Despite uncertainty about DDGS uses, the analysis[75] generally values DDGS for its protein value, which increases by-product values compared to use for calories.)

Equation for calculating carbon benefits of production. The carbon benefits (CB; in kg $CO_2e\ ha^{-1}\ yr^{-1}$) are calculated as

$$\mathrm{CB} = \mathrm{COC_s} + \mathrm{PEM_{bfits}} + \mathrm{CARBST_{ch}} + \mathrm{FOS_{sav}} \tag{1}$$

with

$$\mathrm{COC_s} = \boldsymbol{Y} \cdot \mathbf{COC}$$
$$\mathrm{PEM_{bfits}} = \boldsymbol{Y} \cdot (\mathbf{PEM_{avg}} - \mathbf{PEM_h})$$
$$\mathrm{CARBST_{ch}} = \frac{\mathrm{PDV_{cs\text{-}ch}}}{\mathrm{PDV_{ha\text{-}yr_{1\rightarrow100}}}}$$
$$\mathrm{FOS_{sav}} = \mathbf{BIOFY} \cdot (\mathbf{FOSEF} - \mathbf{BIOFEF})$$

$\mathrm{COC_s}$ is the total COC (kg $CO_2e\ ha^{-1}\ yr^{-1}$), $\boldsymbol{Y}$ is a vector of yield(s) of agricultural product(s) (including any biofuel feed by-products; kg product $ha^{-1}\ yr^{-1}$) and **COC** is a vector of the COC(s) of agricultural product(s) (kg CO_2e per kg product). $\mathrm{PEM_{bfits}}$ is the total benefits (or costs) from PEMs on the hectare (kg $CO_2e\ ha^{-1}\ yr^{-1}$), where $\mathbf{PEM_{avg}}$ is a vector of the global-average PEMs for each agricultural product (kg CO_2e per kg product) and $\mathbf{PEM_h}$ is the PEMs on the hectare analysed (kg CO_2e per kg product). This equation applies to all crop and animal outputs other than biofuels and includes biofuel by-products used for feed or food, whose value is based on the crop products that they substitute. $\mathrm{CARBST_{ch}}$ is the time-discounted benefit from the annual change in carbon storage in vegetation and soils (kg $CO_2e\ ha^{-1}\ yr^{-1}$) where $\mathrm{PVD_{cs\text{-}ch}}$ is the present discounted value of the expected change in carbon storage (kg CO_2e) and $\mathrm{PDV_{ha\text{-}yr_{1\rightarrow100}}}$ is the present discounted value of each hectare, each year, over 100 years (ha yr). (Discounting the stream of hectare years is equivalent for carbon-stock changes to discounting the stream of crop production in the denominator of the COC.) $\mathrm{FOS_{sav}}$ is the total fossil fuel savings (net; kg $CO_2e\ ha^{-1}\ yr^{-1}$), where **BIOFY** is a vector of biofuel yield(s) (MJ $ha^{-1}\ yr^{-1}$), **FOSEF** is a vector of fossil fuel emission factor(s) (production and combustion, but not LUC; kg $CO_2e\ MJ^{-1}$) and **BIOFEF** is a vector of biofuel PEMs factor(s) (production only, not combustion or LUC; kg $CO_2e\ MJ^{-1}$). **BIOFEF** is partially a function of the agricultural practices on a particular parcel of land and partially a function of the emissions involved downstream in the conversion and transportation processes. When evaluating biofuels, the PEM applied to the biofuel by-product should allocate total farm PEMs between that by-product and the biofuel.

Equation for calculating carbon costs of consumption. The carbon cost of consumption (CCC; kg CO_2e) is

$$\mathrm{CCC} = \mathbf{CONSUM} \cdot (\mathbf{COC} + \mathbf{PEM}) \tag{2}$$

where **CONSUM** is the consumption of a product(s) in kilograms, and the COC and PEM of each product is expressed in kilograms CO_2e per kilogram product.

Sensitivity calculations. We perform sensitivity analysis for COCs by varying soil and vegetation carbon estimates across all areas. We used an uncertainty of ±30% for soil carbon, based on a review of differential soil carbon estimates[76], and ±20% for vegetative carbon, based on our assumption that their uncertainties are substantially lower. We generate high and low COCs based on this range and on alternative discount rates of 2% and 6% (Supplementary Table 3). We show the effects of these assumptions on all examples analysed here in Supplementary Tables 5–9. The results show no directional changes in land-use comparisons, except for a few uses that have very similar carbon benefits or carbon costs in our central scenario and that can shift modestly from one side to another.

Uncertainties and certain data advantages of our approach. Our approach has one inherent technical advantage over modelling approaches that attempt to estimate likely carbon losses from land conversion by estimating the precise locations where land conversion will occur. To estimate where conversion will occur and the resulting carbon losses, such approaches require overlapping multiple spatial datasets, each of which has its own random errors. Even maps of cropland versus other lands have large discrepancies and substantial errors[77,78]. Overlapping the maps will produce errors wherever any individual map has errors; for example, a correct yield estimate combined with an incorrect carbon estimate will generate an incorrect result. More problematically, many cells with such errors will probably stand out as most likely or beneficial for conversion because of such errors.

Because the carbon benefits index estimates carbon loss per kilogram of crop by averaging critical parameters across all cells devoted to each crop worldwide—although opportunities for systematic errors remain—the method provides many opportunities to average out random errors. At the same time, although the COC is based on this global average, the user can use better site-specific information about the precise parcel undergoing change. Supplementary Information contains a fuller discussion of additional uncertainties.

Code availability. The carbon benefits index model, which shows the calculation of COCs and PEMs, is available for download from Pangea at https://doi.org/10.1594/PANGAEA.893761. The LPJmL model code is available at https://github.com/PIK-LPJmL/LPJmL. The Carbon Benefits Calculator, which facilitates calculation of carbon benefits using COCs and PEMs for specific parcels of land, is included as Supplementary Data, and future revisions will be available at https://www.princeton.edu/~tsearchi.

Data availability

LPJmL modelling results, in the form of global carbon and native net primary productivity maps, are available at https://doi.org/10.1594/PANGAEA.893761. The different datasets used to run LPJmL for this study are publicly available and described in Supplementary Information along with links. Any other materials generated for this study are available from the corresponding author on reasonable request.

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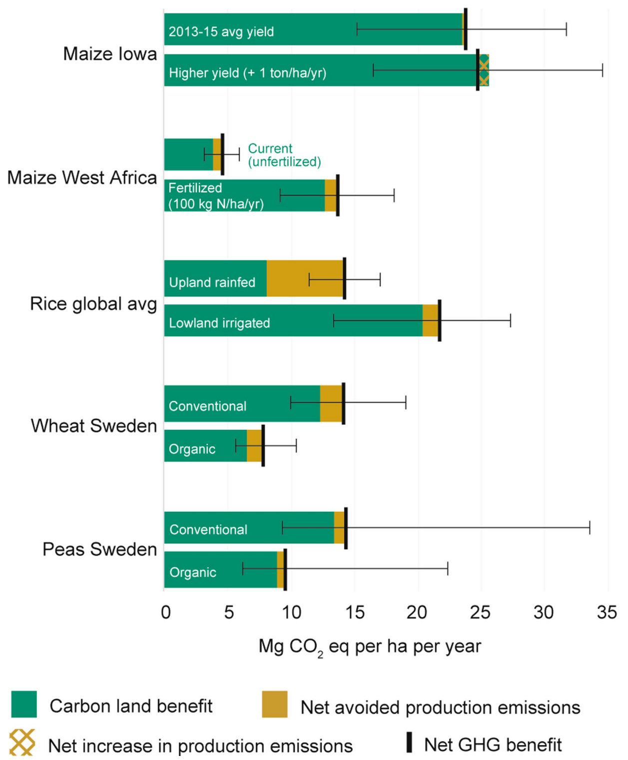
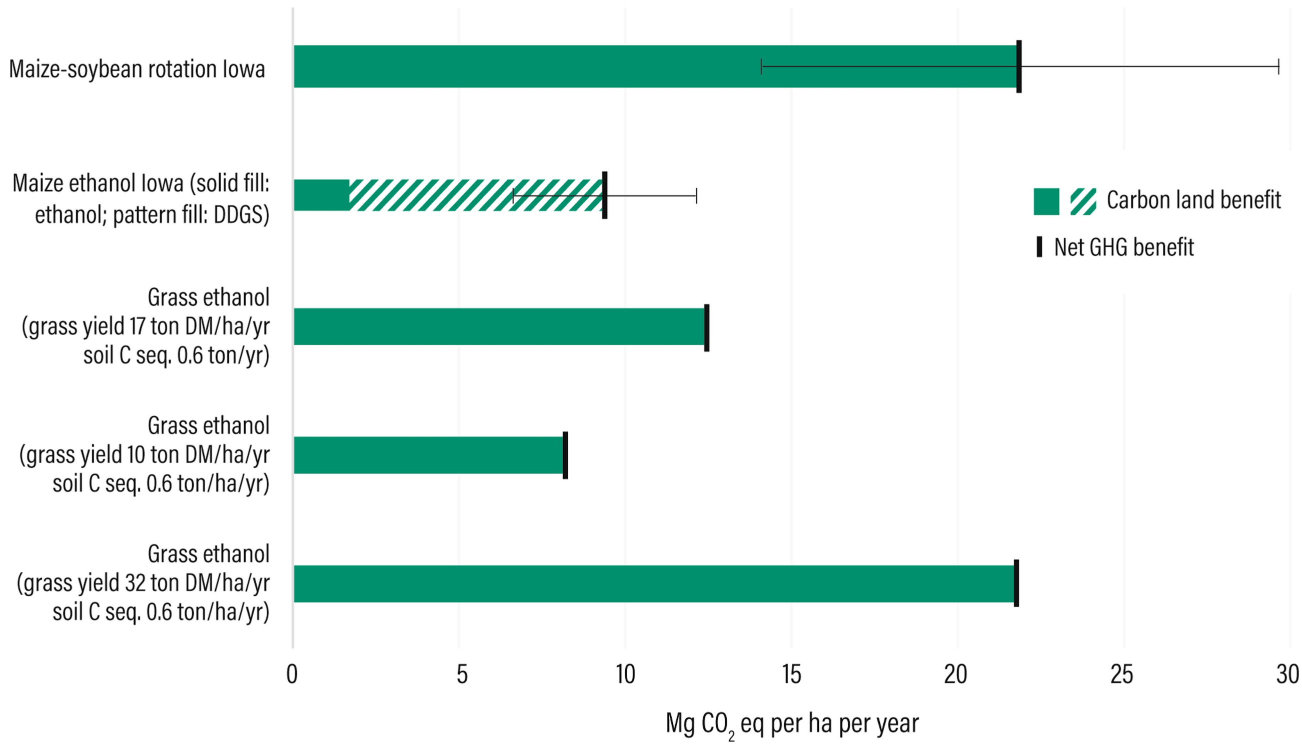
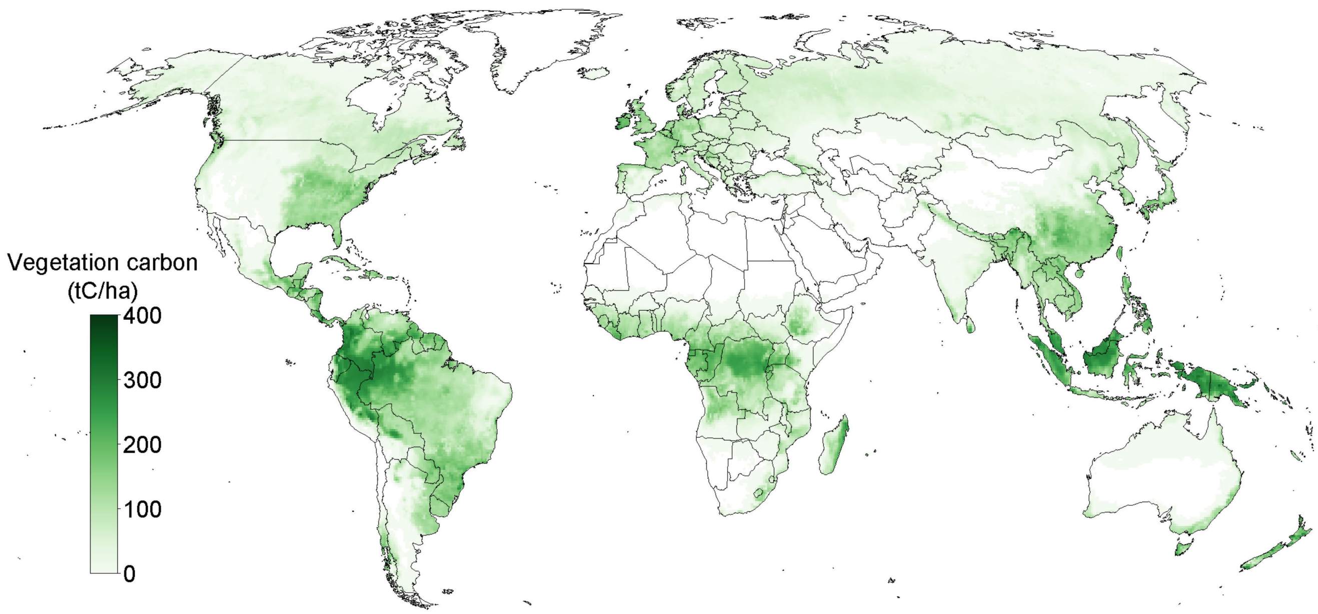


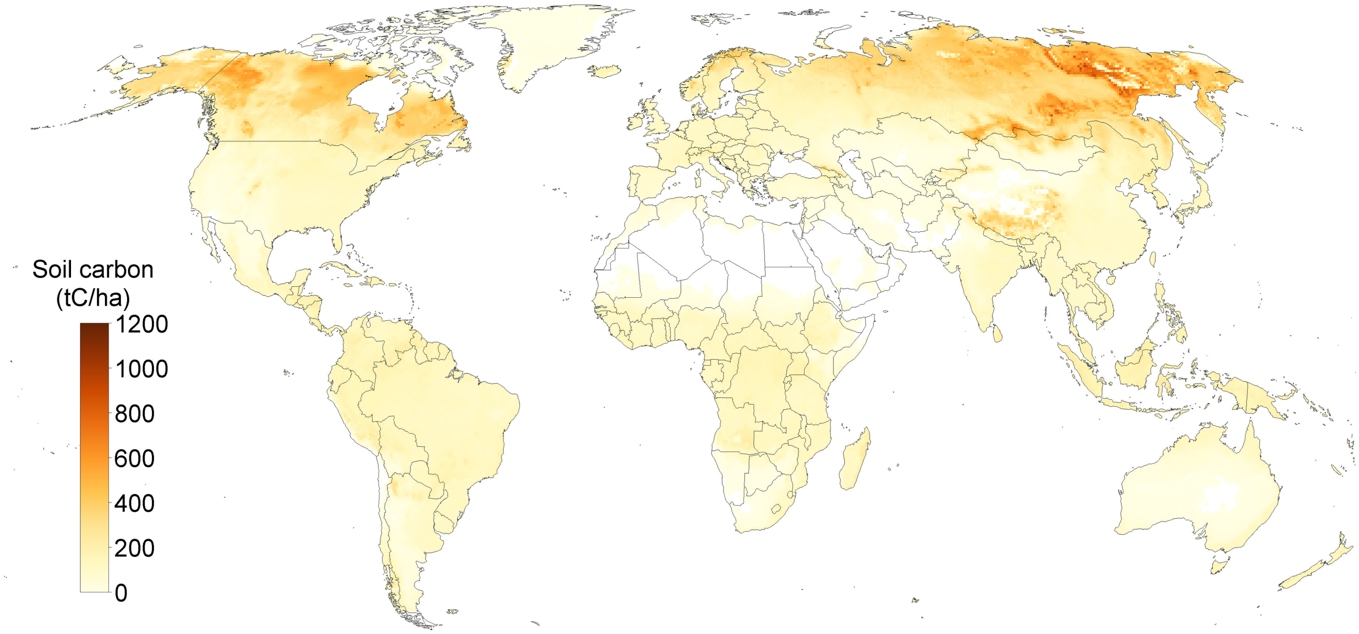
Extended Data Fig. 1 | Carbon benefits of different crop production systems based on the carbon benefits index. Error bars reflect the range of literature estimates of vegetation and soil carbon stocks.



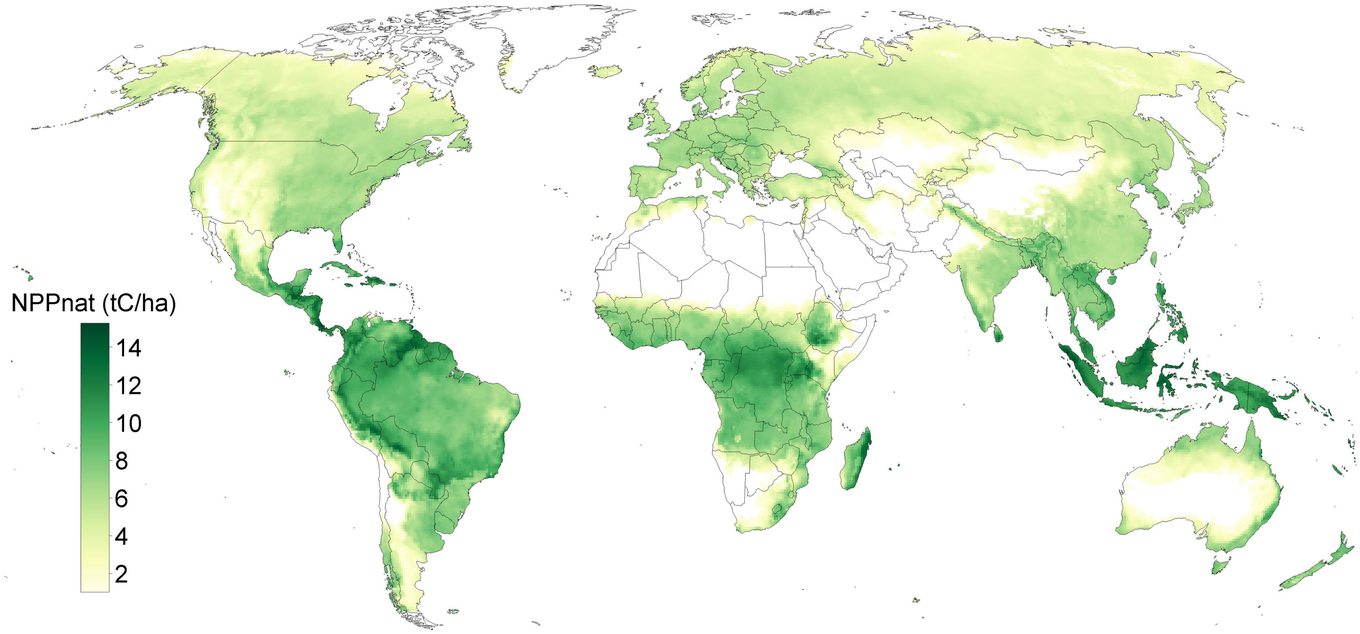
Extended Data Fig. 2 | Carbon benefits of different potential Iowa cropland uses based on the carbon benefits index. Error bars reflect the range of literature estimates of vegetation and soil carbon stocks.



Extended Data Fig. 3 | Above- and below-ground carbon stocks of potential natural vegetation under current climate, used to derive COCs with the carbon loss method. Data simulated with the LPJmL model and adjusted at the biome level according to reference values from the literature (see Supplementary Information).



Extended Data Fig. 4 | Soil carbon stocks of potential natural vegetation under current climate used to derive COCs with carbon loss method. Data simulated with LPJmL and adjusted at the biome level according to reference values from the literature (see Supplementary Information).



Extended Data Fig. 5 | Annual net primary productivity of potential native vegetation under current climate used to derive COCs with carbon gain method. Data simulated with LPJmL.

Extended Data Table 1 | Global-average COCs, PEMS and GHGs for a selection of food, feed and fibre items, calculated using the carbon loss method and 4% time discounting

Product category	Product	Carbon opportunity cost ("loss" method)			COC ("gain" method)	Production emissions	TOTAL*			
		Vegetation & mineral soils	Organic soils emissions	Total						
		kg CO2/ kg fresh weight	kg CO2e/ kg fresh weight		kg CO2/ kg fresh weight	kg CO2e/ kg fresh weight	kg CO2e/ kg fresh weight	kgCO2e/ kgDM	kg CO2e/ MJ human kcal†	kg CO2e/ kg protein
Cereals										
	Maize grains	2.0	0.1	2.1	2.3	0.5	2.6	2.9	0.8	29
	Rice grains (rough)	2.4	0.2	2.6	2.2	2.2	4.8	5.5	2.0	69
	Wheat grains	1.8	0.1	1.9	2.5	0.7	2.6	2.9	0.9	23
	Barley grains	2.4	0.2	2.6	3.3	0.5	3.1	3.5	1.0	29
	Sorghum grains	4.0	0.4	4.4	6.8	0.4	4.9	5.5	1.6	55
	Millet grains	3.9	0.9	4.9	7.2	0.5	5.4	6.1	1.8	68
Tubers										
	Cassava tubers	1.5	0.2	1.7	1.3	0.0	1.7	4.9	1.6	160
	White potato tubers	0.6	0.0	0.6	0.6	0.1	0.7	3.4	1.1	38
	Sweet potato tubers	1.2	0.1	1.2	0.9	0.1	1.3	4.5	1.4	90
	Yam tubers	1.4	0.2	1.5	1.2	0.0	1.5	5.1	1.4	100
Sugar crops										
	Sugar cane stems	0.19	0.0	0.2	0.2	0.0	0.2	0.9	0.7	59
	Sugar beet roots	0.17	0.0	0.2	0.2	0.1	0.2	1.0	0.5	29
Oil crops										
	Soybean seeds	5.7	0.2	5.9	5.3	0.3	6.1	6.7	1.5	17
	Oil palm fruit (bunches	1.6	0.5	2.2	1.3	0.1	2.3	4.3	1.2	120
	Canola seeds	5.2	0.6	5.8	5.0	1.0	6.8	7.4	1.6	32
	Sunflower kernels	4.7	0.2	4.9	7.2	0.8	5.6	6.1	1.0	28
	Groundnut pods	5.6	0.4	6.0	6.8	0.3	6.3	6.8	1.7	36
	Coconuts	2.4	0.5	2.8	3.5	0.1	2.9	6.4	2.1	210
Pulses										
	Common beans	13.6	0.6	14.2	15.3	0.6	14.8	16.5	4.4	69
	Chickpeas	3.7	0.0	3.7	9.1	0.5	4.2	4.6	1.2	20
	Cowpeas	10.6	2.5	13.1	18.3	0.5	13.5	15.4	4.2	57
	Pigeon peas	7.5	0.0	7.5	14.2	0.5	8.0	8.9	2.4	37
	Lentils	5.2	0.7	5.9	9.3	0.5	6.3	7.0	2.0	26
Fruits										
	Banana	1.0	0.1	1.1	0.9	0.1	1.2	4.9	2.0	160
	Plantains	2.9	0.2	3.1	2.3	0.1	3.2	9.1	3.8	450
	Other fruit - temperate	0.9	0.0	0.9	1.1	0.2	1.2	6.5	2.7	180
	Other fruit - tropical	0.9	0.1	1.0	0.9	0.1	1.1	6.0	2.5	170
Vegetables										
	Vegetables	0.68	0.0	0.7	0.6	0.2	0.9	11.4	3.7	76

*Includes organic soil emissions.
†To convert to grams CO_2e per megajoule, divide by 4.18.

Extended Data Table 2 | Global-average COCs, PEMS and GHGs for a selection of food, feed and fibre items, calculated using the carbon loss method and 4% time discounting (continued from Extended Data Table 1)

Product category	Product	Carbon opportunity cost ("loss" method): Vegetation & mineral soils (kg CO2/ kg fresh weight)	Carbon opportunity cost ("loss" method): Organic soils emissions (kg CO2e/ kg fresh weight)	Carbon opportunity cost ("loss" method): Total	COC ("gain" method) (kg CO2/ kg fresh weight)	Production emissions (kg CO2e/ kg fresh weight)	TOTAL*: kg CO2e/ kg fresh weight	TOTAL*: kgCO2e/ kgDM	TOTAL*: kg CO2e/ MJ human kcal†	TOTAL*: kg CO2e/ kg protein
Vegetable oils										
	Soybean oil	10.5	0.3	10.8	9.8	0.8			1.3	
	Palm oil	7.0	2.3	9.3	5.5	1.8			1.2	
	Palm kernel oil	7.0	2.3	9.3	5.5	1.8			1.2	
	Canola oil	8.0	0.9	8.9	7.7	1.7			1.2	
	Sunflower oil	7.3	0.2	7.5	10.9	1.3			1.0	
	Groundnut oil	12.1	0.8	12.9	14.7	0.8			1.5	
	Maize oil	4.7	0.3	5.0	5.5	1.1			0.7	
	Cotton oil	7.2	0.2	7.4	10.2	2.9			1.2	
Sugars										
	Cane white sugar	1.7	0.2	1.9	1.8	0.3			0.6	
	Beet white sugar	0.8	0.1	0.9	1.0	0.3			0.3	
Meat, dairy and eggs										
	Beef and buffalo meat††	135	9.1	143.9	165.3	44.2	188.2	448.0	102.2	1300
	Sheep and goat meat††	174	11.3	185.7	212.8	42.1	227.7	555.5	112.1	1600
	Cow and buffalo milk	5.8	0.4	6.2	7.1	2.3	8.4	67.0	13.1	260
	Sheep and goat milk	19	1.2	19.9	22.8	4.7	24.6	163.9	25.7	490
	Pork^	14	0.8	14.3	15.1	5.5	19.8	48.3	9.4	150
	Poultry meat^	10	0.5	10.7	11.5	3.7	14.4	36.0	8.4	110
	Eggs	10	0.5	10.7	11.4	3.6	14.3	44.6	10.7	130
Livestock feeds										
	Soybean meal	4.8	0.1	4.9	4.5	0.3				11
	Palm kernel meal	3.3	1.1	4.3	2.6	0.8				31
	Canola meal	3.5	0.4	4.0	3.4	0.7				12
	Sunflower meal	3.2	0.1	3.3	4.9	0.6				11
	Groundnut meal	5.9	0.4	6.3	7.2	0.4				15
	Cotton meal	3.2	0.1	3.3	4.6	1.3				11
	DDGS (maize-ethanol)	2.5	0.1	2.7	3.4	0.5				12
	DDGS (wheat-ethanol)	2.5	0.1	2.6	3.3	0.5				12
Other										
	Coffee beans (green)	29	1.7	31.1	24.9	1.2				
	Tea leaves (dried)	15	0.3	14.9	11.0	1.0				
	Cocoa beans (dried)	39	1.9	40.4	34.4	0.7				
	Cotton lint	2.9	0.1	3.0	4.1	1.2				

*Includes organic soil emissions.
†To convert to grams CO_2e per megajoule, divide by 4.18.
††Average, including meat from dairy animals (refers to whole-carcass weight, including bone and fatty tissue).
^Refers to whole-carcass weight, including bone and fatty tissue (see Methods for sources).

Extended Data Table 3 | Consumption GHG costs for a selection of biofuels

Product category	Product	Carbon opportunity cost ("loss" method)			COC ("gain" method)	Production emissions	Net with gasoline/ diesel substitution*		
		Vegetation & mineral soils	Organic soils emissions	Total			CO2 savings	Net GHG balance	
		g CO2/ MJ GE (LHV)	g CO2e/ MJ GE (LHV)	g CO2e/ MJ GE (LHV)	g CO2/ MJ GE (LHV)	g CO2e/ MJ GE (LHV)	g CO2e/ MJ GE (LHV)	g CO2e/ MJ GE (LHV)	kg CO2e/ liter
Bioethanol									
	Maize ethanol	150	8,2	160	160	72	86	140	3,1
	Wheat ethanol	123	8,2	130	180	104	86	150	3,2
	Sugarcane ethanol	93	9,0	100	100	19	86	35	0,7
Biodiesel									
	Soy methylester	287	8,4	300	270	27	88	230	7,8
	Palm oil methylester	192	60	250	150	50	88	220	7,3
	Canola methylester	218	26	240	210	55	88	210	7,0

GE, gross energy; LHV, lower heating value. See Methods for sources.
*For COC data calculated with the carbon loss method.