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Maximizing tree carbon in croplands and grazing lands while sustaining yields

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Abstract

Background Integrating trees into agricultural landscapes can provide climate mitigation and improves soil fertility, biodiversity habitat, water quality, water flow, and human health, but these benefits must be achieved without reducing agriculture yields. Prior estimates of carbon dioxide (CO_2) removal potential from increasing tree cover in agriculture assumed a moderate level of woody biomass can be integrated without reducing agricultural production. Instead, we used a Delphi expert elicitation to estimate maximum tree covers for 53 regional cropping and grazing system categories while safeguarding agricultural yields. Comparing these values to baselines and applying spatially explicit tree carbon accumulation rates, we develop global maps of the additional CO_2 removal potential of Tree Cover in Agriculture. We present here the first global spatially explicit datasets calibrated to regional grazing and croplands, estimating opportunities to increase tree cover without reducing yields, therefore avoiding a major cost barrier to restoration: the opportunity cost of CO_2 removal at the expense of agriculture yields.

Results The global estimated maximum technical CO_2 removal potential is split between croplands (1.86 $PgCO_2\ yr^{-1}$) and grazing lands (1.45 $PgCO_2\ yr^{-1}$), with large variances. Tropical/subtropical biomes account for 54% of cropland (2.82 $MgCO_2\ ha^{-1}\ yr^{-1}$, SD = 0.45) and 73% of grazing land potential (1.54 $MgCO_2\ ha^{-1}\ yr^{-1}$, SD = 0.47). Potentials seem to be driven by two characteristics: the opportunity for increase in tree cover and bioclimatic factors affecting CO_2 removal rates.

Conclusions We find that increasing tree cover in 2.6 billion hectares of agricultural landscapes may remove up to 3.3 billion tons of CO_2 per year – more than the global annual emissions from cars. These Natural Climate Solutions could achieve the Bonn Challenge and add 793 million trees to agricultural landscapes. This is significant for global climate mitigation efforts because it represents a large, relatively inexpensive, additional CO_2 removal opportunity that works within agricultural landscapes and has low economic and social barriers to rapid global scaling. There is an urgent need for policy and incentive systems to encourage the adoption of these practices.

Keywords Tree cover, Agroforestry, Silvopasture, Natural climate solutions, NCS, Carbon dioxide removal, Global mitigation potential, Cropland, Grazing land

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Background

Integrating trees into agriculture is an ancient practice with climate-adaptive benefits as reviewed by van Noordwijk et al. [45], as well as a promising Natural Climate Solution [61]. Trees can reduce wind speeds over crops, reducing transpiration and drought stress [35, 39]. Trees in agriculture aid in regenerating and retaining soil carbon [40], improve biodiversity [18, 50], and provide other ecosystem services related to air, water, and carbon [33]. However, trees also compete with crops for space, light, water, and nutrients [47, 56], and are often cleared from agricultural areas, although tree management and arrangement can mitigate competition and trade-offs between trees and crop production.

Agroforestry research has been ongoing for decades across the globe to optimize tree spacing [51, 70] and management, including pruning to balance the trade-offs of competitive and facilitative effects of trees on crops [14], allowing crop production to remain stable or increase with trees. Maximum tree covers vary greatly depending on geography and the design of the agroforestry system, but they must allow for the required amount of sunlight, water, and nutrients to reach the crops. Water and nutrient balance are improved when trees and crops have different rooting depths [46] and trees contribute to soil fertility [8]. Trees can moderate the microclimate and potential negative effects of droughts on annual crops [42], Corraliza et al. 2018, Temani [64], and forage grasses [19, 48], which will be increasingly important in, and adaptive to, future climates [45]. Trees can increase production in grazing lands [32, 34] when the tree component provides fodder [24] and provide thermoregulation, improving animal health especially by protecting from extreme heat [3, 11, 12]. In their review of global alley-cropping system literature, [70] found that most research has been on utilizing niche complementarity to reduce the negative impacts of trees and crops; however, they suggest research on trees for crop facilitation, including through nitrogen fixation, on-farm mulch production, and the development of shade-tolerant crops, as an important research frontier.

The importance of maintaining food security for a growing global population is fundamental to Natural Climate Solutions, which aim to safeguard food security by allowing no changes in cropping areas [23]. Griscom et al. [23] described a “Trees in Croplands” NCS pathway with a maximum additional biophysical carbon dioxide (CO_2) removal potential of 1.04 $PgCO_2$ yr^{-1} from 608 M ha of cropland. Chapman et al. [9] generated global maps of aboveground woody biomass and tree cover in both croplands and grazing lands. They calculated the median value for standing carbon biomass on the agricultural land with >5 Mg C ha^{-1}, and used it to estimate the maximum additional carbon sequestration potential if lands with <5 Mg C ha^{-1} increased to that level, finding a maximum additional aboveground carbon sequestration potential of 49.4 Pg C in croplands and 44.5 Pg C in grazing lands [9]. Chapman’s work provided the basis for the estimations in Roe et al. [58] which split the potential over 30 years. A more recent study by Zomer et al. [71] estimated a lower global potential of increased tree cover on agricultural land based on an updated carbon density map [63] and two scenarios of incremental and systematic increases in tree cover. They estimated a total mitigation potential in the range of 4–19 Pg C, similar to IPCC 2022 [13] Tier 1 estimates of above and belowground biomass on agricultural land. The discrepancies in estimated mitigation potential between these studies, as well as their use of median standing biomass to determine tree cover increase scenarios, illustrates the need for further refinement of global CO_2 removal potential, based on estimates of tree cover increase tailored to specific biomes and agricultural systems.

Here we define Tree Cover in Agriculture (TCA) as a Natural Climate Solution (NCS) on agricultural lands achieved by increasing tree cover without reducing agricultural yields or exceeding the ecosystem’s native level of tree cover. We attempt to control for the risk of displacement of agriculture by emphasizing the maintenance of agricultural yields, recognizing that some changes in the configuration of the agricultural activities may occur to incorporate tree cover, but these changes should not cause displacement or ‘leakage’ of agricultural production if the yield of the area at the field scale is maintained. Per [44], in a general sense, leakage occurs when the actions to reduce GHG emissions for a particular project cause responses outside the project boundaries that also have GHG consequences. At the scale of the farm fields, we allowed for trade-offs between m^2 of agricultural land actually producing crops or non-tree forage within a field and yield per m^2 of the remaining m^2 not displaced within a field - as long as overall yield at the “field” scale was not reduced.

The ‘sharing vs. sparing’ debate [22] compares industrial farming in some areas to preserve other areas (sparing) vs. low intensity farming over all areas (sharing). ‘Sharing’ is considered less desirable than ‘sparing’ for conservation because biodiversity decreases in ‘sharing’ scenarios compared to protected (spared) areas [53]. TCA works in agricultural lands, without increasing their area, to attain the maximum extent of ‘sharing’ possible without displacement of agriculture, therefore it should not be a threat to ‘spared’ areas and will still rely on proximity to ‘spared’ areas for biodiversity enhancement [7]. The trees are integrated into the agricultural system and cropping area at a field and farm scale, while the land use continues to be agriculture.

While Tree Cover in Agriculture (TCA) is more specific than the broader categories of 'trees outside of forests; TOF' (reviewed by Schnell et al. [59] and 'trees in mosaic landscapes; TML' [5], it does not dictate the spatial arrangements of the trees. TCA can lead to the establishment of many types of agroforestry systems, including silvopastoral grazing systems with scattered trees, trees planted as windbreaks and along field boundaries, and alley cropping with rows of trees (but not high-density short-rotation trees for biomass- the trees must reach mature size in the system to be a part of this NCS). By this definition TCA includes shade-agroforestry systems, like traditional coffee production, but we have not been able to include them in this analysis because these systems cannot be reliably identified by existing globally available remote sensing techniques that this study depends on [30]. Hence, the findings of this paper are for tree incorporation into what are traditionally considered 'full sun' cropping systems. Other forms of tree crop cultivation, where the trees form the upper canopy and produce the crops (e.g. fruit trees or oil palm plantations), are not included as these fully tree-based systems are included within other NCS pathways (e.g. improved plantations as described in Griscom et al. [6, 23].

Trees growing in TCA systems will be subjected to different conditions than trees in a forest, plantation, or natural regeneration setting. They will generally be spaced wider apart, and thus are more exposed to sun and wind and have less competition with other trees. Since these trees share land with agricultural production, they may experience corresponding land management that could benefit or harm them, such as fertilization, soil compaction, irrigation, etc. Additionally, tree-crop relationships change over time and can only be considered stable when the tree has reached its final size. As such, we expect trees in agricultural lands to remove CO_2 at a different rate compared to trees in forests or areas of natural regeneration. However, there is no global dataset on the carbon accumulation rates of trees in agriculture, so we used Cook-Patton et al. [10]annual aboveground carbon accumulation of naturally regenerating forests as the best available and most relevant global dataset.

Ideal mature tree densities in agroforestry can vary greatly depending on climate and tree management [20]. Lasco et al. [38] showed that trees may not reduce food production while providing climate mitigation and adaptation, if the right combinations of trees and food systems are found. By limiting the integration of trees in agricultural landscapes to levels that avoid reductions in agricultural yields, we explore the global potential of a strategy for increasing tree cover that avoids a major cost barrier to restoration: the opportunity cost of delivering carbon removal at the expense of agriculture yields. For this research on the global carbon dioxide (CO_2) removal potential of Tree Cover in Agriculture (TCA), we aimed to define thresholds for maximum tree cover that would be relevant across multiple tree/crop/grazer combinations, using 'average' mature tree characteristics to set general guidelines, within which farmers, agronomists, and agroforesters can work to co-design tree-crop systems to maximize climate mitigation while ensuring continued food security. To do this, we consulted with experts on the integration of trees into agricultural systems, and compared their estimations of maximum tree covers to current values, to calculate the potential increases in tree cover and its corresponding CO_2 removal potential.

Methods

There were two main components to this research. First, we conducted two Delphi method expert elicitations to set biome- and continent-specific thresholds for maximum percent tree canopy cover (hereafter "tree cover") in 1: cropping and 2: grazing lands that would cause no decreases in agricultural yields. Then, we conducted a geospatial analysis of the additional CO_2 removal potential by comparing the estimations of maximum tree covers to current levels and applying spatially explicit carbon accumulation rates.

Literature review and expert identification

We started with a literature review to evaluate the state of knowledge and identify experts. Using Google Scholar, we sought articles that quantified 4 parameters: tree cover or density, size, age, and agricultural yields with and without trees for common cropping systems (search terms "tree density" and "{either wheat/soybean/maize} yield" and "agroforestry" which yielded 161/52/324 articles, respectively). After excluding articles with newly establishing trees (too small to impact crops) and high-density short-rotation plantings, 206 article abstracts and 75 full papers were reviewed. Only 22 of the papers included the four parameters we sought: it was rare for papers to quantify the tree size, and especially rare for them to include the comparison of crop yields with and without trees. The 22 studies did not seek a *maximum* tree density for maintaining yields, rather they tested one or a few tree densities for yield impacts, which only allowed us to extract *suggested upper limits* for tree cover for those systems (notably, Rivest et al. [2, 16, 17, 32, 57, 64, 65, 67]. There was even less applicable literature for grazing systems. Therefore, an expert elicitation approach was necessary, due to these limitations of the literature. We invited the authors of the relevant articles to participate in the expert elicitation, and contacted agroforestry organizations for expert referrals, seeking representation for almost all biomes on all continents. The "Tundra" biome was excluded to avoid potential albedo effects caused by relatively dark tree cover on a relatively light landscape, which may offset climate benefits of increased tree cover [26]. We excluded "Mangrove" and "Flooded Grassland and Savanna" biomes given the complexity of their hydrology, and spatial resolution constraints of these fringing ecosystems, and their relatively small total areas at the global scale, but they could be included in regional follow-up studies where relevant.

Delphi expert elicitations

We conducted separate Delphi expert elicitations for cropland and grazing land, each consisting of initial individual consultations followed by a finalization round. The flow of the initial questionnaire is shown in Fig. 1 and its content can be found in Additional Files 1 and 2.

The questionnaire was available in English, Spanish, French, and Portuguese. Experts first confirmed the system of their expertise (biome, continent, and crop/grazing system). They were then asked to give specifications on the "tree of reference" for which they would be providing estimations, including the tree species and its mature height and mature crown width. We also asked them to characterize the cropping or grazing system in their region for which they were making their recommendations, with regards to the average field size and frequency of mechanization.

We collected expert estimations of percent tree canopy cover that would maximize tree density without significantly reducing long-term agricultural yields within that cropping or grazing system. Estimations were made in one of 3 ways- trees/ha, row spacing, or percent tree cover, depending on the preference of the expert. The unit of analysis was the field level, and we requested specifications for field boundaries separately from trees in the fields themselves, with and without mechanization, specific to their crop/grazer of expertise. Finally, we asked them for their estimation for the maximum overall percent tree cover in fields / grazing lands and their boundaries that could be applied "across all" of the crop/grazing land in their region without reducing long-term agricultural yields. For details on the Delphi data processing please see Additional File 3.

To finalize the expert elicitation, we sent each expert a summary of their own responses, comparing them to the average response of all the experts for the same system in the same continent, and the average response for that system, across all continents. We asked the experts to either revise or confirm their responses after reviewing average results from the other experts, to complete the Delphi expert elicitation process.

Geospatial data processing

We attached the mean expert elicited maximum tree cover values to their corresponding biomes [15]. We used the spatial extent, i.e., presence/absence, of cropland from Potapov et al. [54] and grazing land from Chapman et al. [9], at 30m^2 and 1km^2 pixel size, respectively. To avoid double counting, in cases where a pixel was marked both as crop and grazing land, we labeled those pixels as cropland because the cropland dataset is more recent in time and higher spatial resolution than the grazing land layer. While definitions of forests using tree cover differ (depending on the use and ecosystem, definitions range from 10 to 30%) and agriculture does occur in areas with >25% tree cover, we used 25% tree cover as a cutoff in order to avoid any double counting of natural climate solution potential with forestry-based solutions (please see the following paragraph for further discussion of tree cover). This cutoff also avoids the need for distinguishing high-shade agroforestry from natural forests using remote sensing, which is not yet available globally [30].

Within agricultural land we used forest cover ca. 2015 [66] for croplands and forest cover ca. 2000 [25] for grazing lands as baseline tree cover. While the Potapov

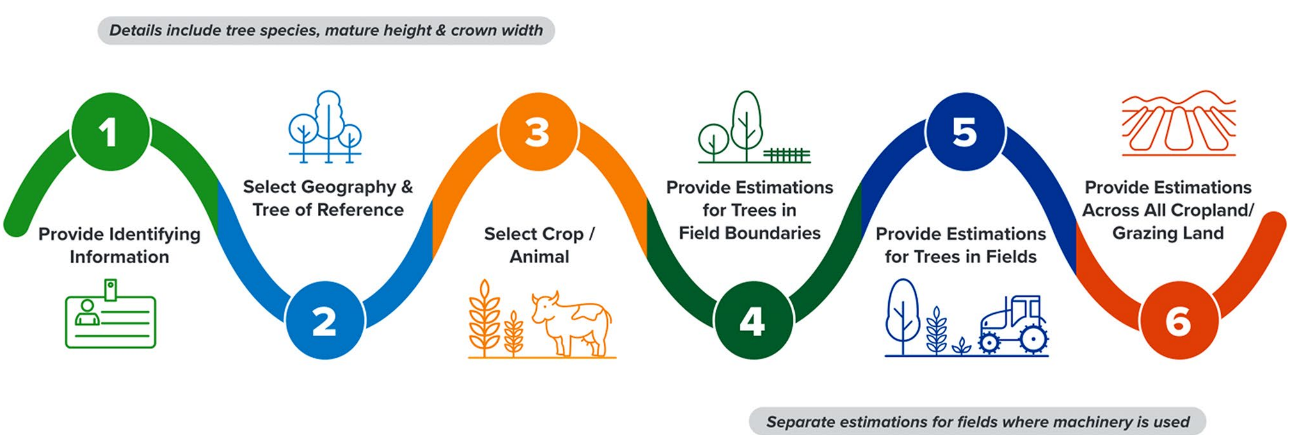

Fig. 1 Overview of expert questionnaire components. Experts were asked to provide identifying information, select their geography and tree(s) of reference, select their crop or animal for integration with trees, provide estimations of tree spacing or tree covers for trees in field boundaries, trees in fields with and without mechanization, and estimations across all cropland or grazing land

cropland layer is from 2019, we used global tree cover from 2015 because there were no global tree cover products with a global extent available closer in time to 2019. We then calculated the per-pixel difference between the mean expert estimated maximum tree cover per biome and baseline tree cover. We only included pixels with positive values, i.e., where the mean expert estimated maximum tree cover exceeded baseline tree cover, where there was an opportunity for increasing tree cover.

We used a modified, gap-filled version of the 1-km resolution Cook-Patton et al. annual aboveground carbon accumulation rate dataset for naturally regenerating forests [10]. The filled gaps are areas of transition from forest to grassland, which were excluded in the original dataset, but because some of these areas naturally support tree cover, we included them in our study. Gaps in the original data were filled following the methods of Cook-Patton et al. [10]but use fewer model runs and predict outside the extent of the training data. To quantify the potential aboveground carbon gains from the increase in tree cover per pixel, we multiplied the Cook-Patton et al. [10]carbon accumulation rate by the margin for increase in tree cover as described above. We then estimated belowground carbon accumulation per biome using biome-specific root to shoot ratios [43]. We converted results from "carbon" to "carbon dioxide (CO_2)" by multiplying by 44/12, which is the molecular weight ratio of CO_2 to carbon. We resampled the data to 30 m using the nearest neighbor algorithm to produce summarized baseline tree cover, mean tree cover increase, and potential CO_2 removal (per hectare per year and per 30 years) by crop/grazing land, biome, and country. We calculated the uncertainty of the estimated potential biophysical CO_2 removal as the 95% confidence intervals propagated from three of the four data sources: baseline tree cover, expert elicited maximum tree cover values, and carbon accumulation rates. We did not calculate uncertainty related to the spatial extent of cropland and grazing land, so we are only able to report the 95% confidence intervals for estimated annual CO_2 removal per hectare per year. For analysis, we used Google Earth Engine [21]d Studio [55] [55], packages terra [27] and sf [52]. Figures were created using the ggplot2 package [68] or ArcGIS Pro Version 3.2.1 [1].

Results

Expert estimations for maximum percent tree cover

After inviting 148 experts for cropland and 224 experts for grazing land to participate, the Delphi Expert Elicitation included 53 contributions from 35 experts (21 for croplands and 14 for grazing lands), representing 6 continents and 10 biomes. Experts include agronomic, environmental, rangeland and rural development scientists and practitioners from 11 universities and 14 institutes for agriculture and/or forestry including CIFOR-ICRAF, CATIE, CNR/IRET in France, FAO, and IUCN. A list of the experts who agreed to be cited, along with their affiliations and regions of expertise can be found in Additional File 4. The final Delphi expert estimations for maximum tree cover in agricultural lands in each biome, across all crops/grazers, are summarized in Fig. 2.

Both Temperate and Tropical/Subtropical biomes were well represented in the expert pool, and overall, we had at least 3 experts for more than 90% of the included cropland and grazing land areas. We had no experts respond for coniferous forests, and none for croplands in Deserts & Xeric Shrublands, Montane Grasslands & Shrublands, or for grazing lands in Temperate Grasslands, Savannahs & Shrublands. Estimated values for these biomes, representing < 5% of total tropical/subtropical cropland, 1% of total temperate cropland, < 10% of temperate grazing land, and approximately 1% of total tropical/subtropical grazing land, were extrapolated from the expert-derived averages for comparable biomes.

A large variety of reference trees were used by the experts, with 87 total species, the most common of which are included in Table 1. Of the 49 reference tree species from 34 genera in croplands, the most common were *Populus deltoides x nigra* (hybrid poplar, 8 times), *Faidherbia albida* (6 times), *Quercus robur* (5 times), *Acacia tortillis* (4 times) and *Grevillea robusta* (4 times). Commonly referenced genera in croplands included *Quercus* (8 different species), *Populus* (3 species), and 2 different species from *Acacia*, *Alnus*, *Cordia*, *Malus, and Pinus*. In grazing lands there were 50 reference tree species from 31 genera, with the most common being *Glircidia sepium* (4 times), *Balanites aegyptiaca* (3 times) and *Leuceaena leucocephala* (3 times). Other species used as reference trees more than once in grazing lands included *Acacia albida*, *Acacia nilotica*, *Brosimum alicastrum*, *Faidherbia albida*, *Morus alba*, *Prosopis cineraria*, and *Quercus petraea*. The most common reference tree genera recommended in grazing lands were *Quercus* (6 different species), *Acacia* (5 species) and *Pinus* (5 species). Two different reference species were suggested from *Balanites*, *Cordia*, *Cratylia*, *Morus*, *Prosopis*, and *Pterocarpus* genera in grazing lands.

Expert estimations for maximum tree cover (hereafter 'estimated maximum') were generally lower in drier biomes with the lowest values in Deserts & Xeric Shrublands (6%), and then in Mediterranean Forests, Woodlands & Scrub (9.75% for croplands, 23% for grazing lands). The mean estimated maximum for grasslands, savannas, and shrublands are around 27% tree cover for temperate and tropical climates, and generally lower than the estimated maximum for the forest biomes within that same climate type, but there was a large amount of variation within each biome and cropping system, as

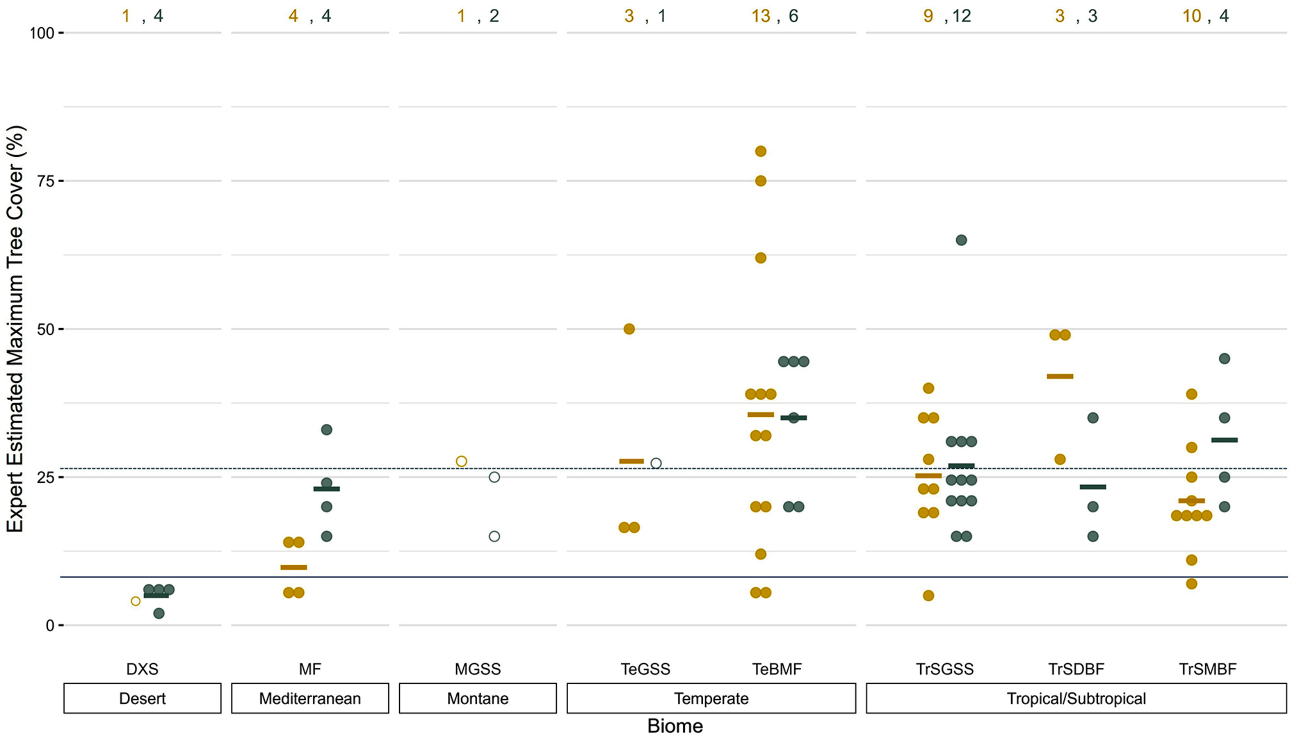

Fig. 2 Expert estimations for maximum tree cover in croplands and grazing lands. Each dot represents an expert estimate, color coded by cropland (gold) and grazing land (grey). Horizontal bars represent the mean expert estimate for that category. Hollow dots represent extrapolated estimates due to low sample size. Numbers at top of figure are sample sizes for that biome, color coded by crop (gold) or grazing land (grey). The dotted blue line represents the overall mean expert estimate (27%) while the solid blue line represents the overall mean baseline tree cover (7%). X-axis biome codes are as follows. DXS: Deserts and Xeric Shrublands. MF: Mediterranean Forests, Woodlands, and Scrub. MGSS: Montane Grasslands & Shrublands. TeBMF: Temperate Broadleaf and Mixed Forests. TeGSS: Temperate Grasslands, Savannas, and Shrublands. TrSDBF: Tropical and Subtropical Dry Broadleaf Forests. TrSGSS: Tropical and Subtropical Grasslands, Savannas, and Shrublands. TrSMBF: Tropical and Subtropical Moist Broadleaf Forests

Table 1 Commonly used reference tree species. This table lists the reference tree species that were most used by the experts during the expert elicitation process in descending order. It includes all reference trees used three or more times and includes the tree species name, common name, average mature height, continent of origin, and frequency of use as a reference in croplands and grazing lands, as well as the total frequency of use. Information on the species comes from Agroforestree database [49] and Wikipedia

Reference tree species	Common name	Continent of origin	Average mature height (m)	Frequency in cropland	Frequency in grazing land	Total frequency
Populus deltoides	Eastern cottonwood	North America	20–30, up to 50	2	8	10
Faidherbia albida	White acacia, apple ring	Africa & Middle East	30	6	2	8
Quercus robur	English oak	Australia, Europe, North America	25, up to 40	5	1	6
Gliricidia sepium	Gliricidia	North & Central America	2–15	1	4	5
Leucaena leucocephala	Leucena	North & Central America	3–15, up to 20	2	3	5
Acacia nilotica	Arabic Gum Tree	Africa	2.5–25	2	2	4
Acacia tortilis	Umbrella thorn	Africa & Middle East	21	4		4
Grevillea robusta	Silky oak	Australia	12–25, up to 40	4	0	4
Robinia pseudoacacia	Acacia locust	North America	25	3	1	4
Alnus acuminata	Alder	South & Central America	30	3	0	3
Balanites aegyptiaca	Jericho balsam	Africa	Up to 10		3	3
Calophyllum brasiliense	Brazilian beauty-leaf	South & Central America	20, up to 45	3	0	3
Castanea mollissima	Chinese chestnut	Asia	Up to 20	3	0	3
Catalpa longissima	Spanish Oak	North America	Up to 25	3	0	3
Markhamia lutea	Markhamia	Africa	10–15	3	0	3
Olea europa	Wild olive	Africa, Asia, Europe	18	3	0	3
Populus tomentosa	Chinese white poplar	Asia	Up to 30	3	0	3

illustrated in Fig. 2. The mean estimated maximum in croplands in Temperate and Tropical/Subtropical Forest biomes range from 21% in Moist Broadleaf Forests up to 42% for cropland in Dry Broadleaf Forests. Two experts estimated 100% maximum tree cover in the that biome, specifically suggesting a reverse-deciduous tree native to Africa, *Faidherbia albida.* We concluded it may not be appropriate to apply this estimation to other continents where the tree is not present. Hence, we excluded these values- which would have increased the mean estimation to 65%, while noting that there is a possibility for higher levels of tree integration within the native range of *Faidherbia albida*.

Potential increases in tree cover

The global differences between baseline and mean estimated maximum tree cover are illustrated in Fig. 3. It is available as a global data layer in Google Earth Engine at 30 m resolution (please see Data Availability section for access).

The mean expert estimated tree cover increases (hereafter 'mean increase') generally ranged from 16 to 18% across the biomes, with two exceptions on the low side: Deserts & Xeric Shrublands had a very low baseline value and a 3% mean increase, and Tropical & Subtropical Dry Broadleaf Forest which contrarily had a high estimated maximum and a high baseline, resulting in a mean increase of only 12%. The greatest mean increase was 25%

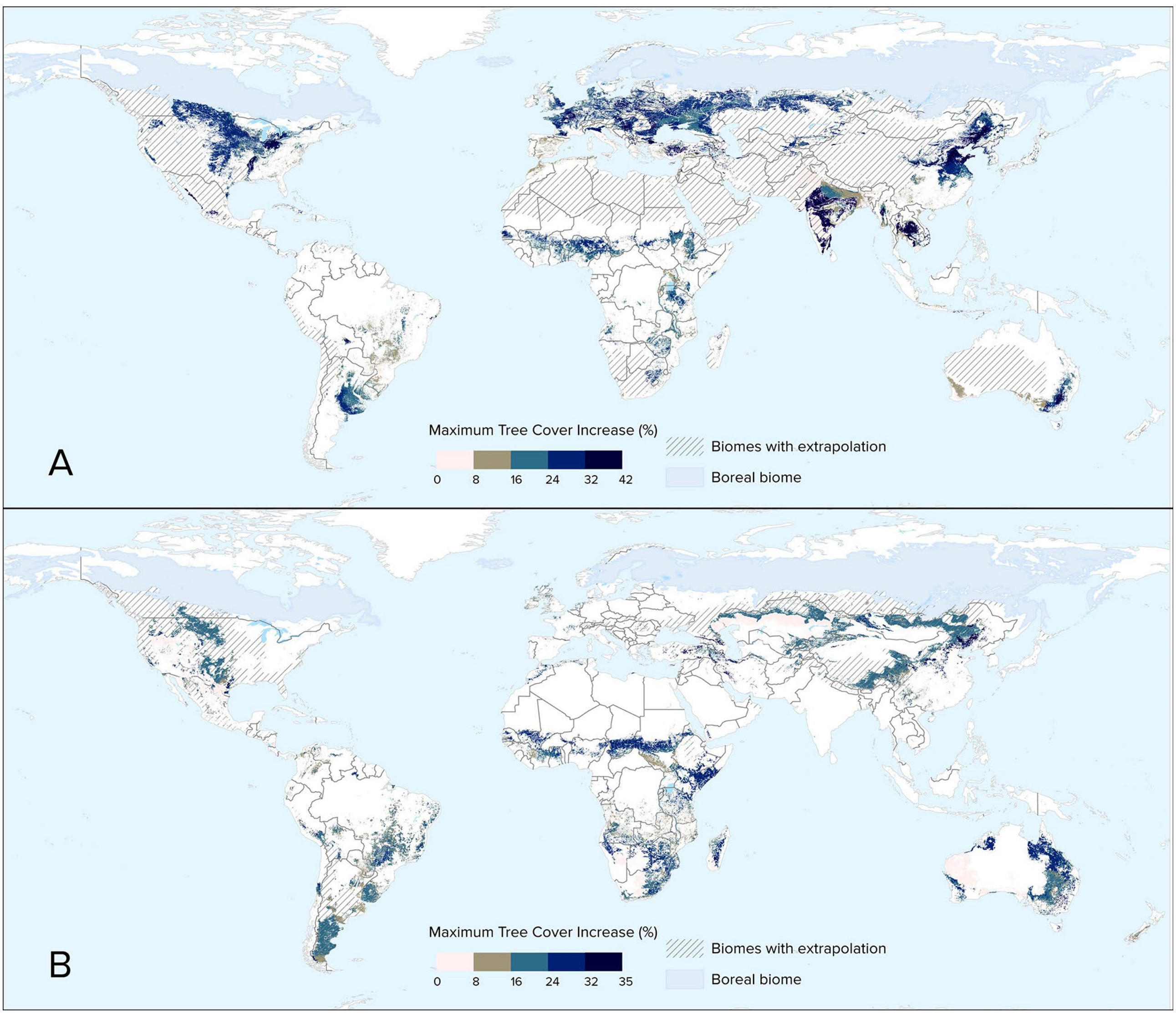

Fig. 3 Opportunities for tree cover increases in Earth's agricultural systems. The mean difference between baseline and expert-estimated maximum percent tree cover in (**A**) croplands c. 2015 and (**B**) grazing lands c. 2000. Biomes with hatching are biomes that had low sample size of expert estimates ($n < 3$). Boreal areas are included in mapping but were excluded from total global potential estimated to avoid changing albedo in a way that may offset the climate benefits of increased tree cover

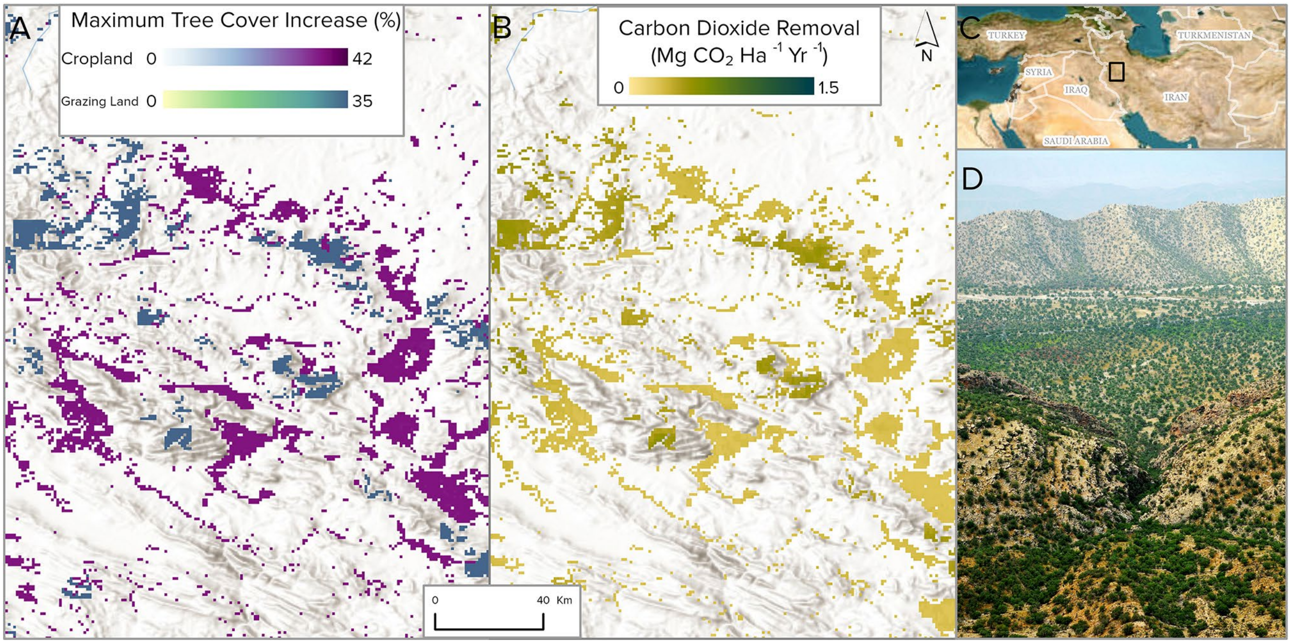

Fig. 4 Detail of dry temperate zone with high potential for tree cover increase and low additional carbon density. An arid Temperate Broadleaf Mixed Forest in the Northern Zagros Mountains shows (**A**) High additional tree cover potential in croplands (purple) and grazing lands (blue). (**B**) Potential increase in carbon density from additional tree cover. (**C**) Inset map of region in Middle East. (**D**) Photo from the Fars Province illustrating natural tree cover outside of agriculture and grazing areas (Credit: Alireza Javaheri, CC BY 3.0 license)

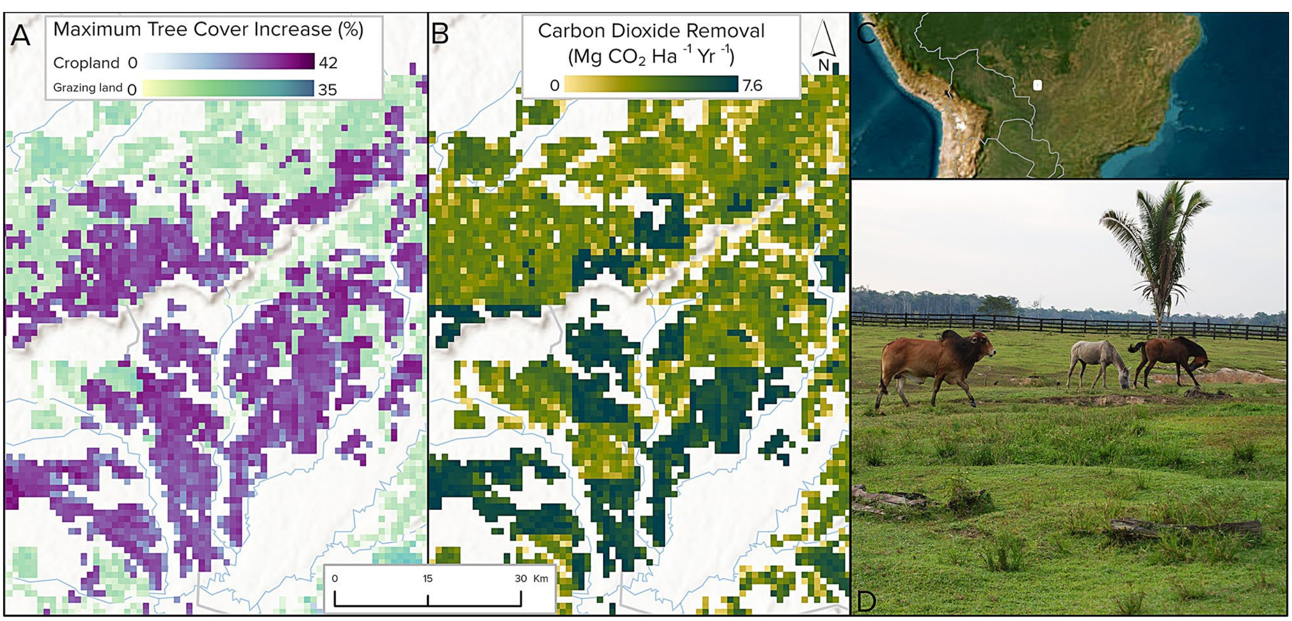

Fig. 5 Detail of high potential tree cover increase and high additional carbon density in tropics.(**A**) High additional tree cover potential in croplands (purple) and grazing lands (blue-green). (**B**) Potential increase in CO_2 removal from additional tree cover. (**C**) Inset map of region in Central South America. (**D**) Photo illustrating a cattle ranch in the Amazon (Credit: Ben Sutherland, *CC BY 2.0 license)*

in Temperate Broadleaf & Mixed Forests. Figure 4 illustrates an area with high potential increase in both cropland and grazing land resulting from a large difference between baseline and expert estimated maximum tree cover for the Temperate Broadleaf Mixed Forest biome. This area is on the driest end of that biome's extent, which is evident in the low potential CO_2 removal associated with these changes in percent tree cover (Fig. 4b). In contrast, in a more humid area like the Brazilian Amazon, the mean increase and CO_2 removal potential are both high (Fig. 5).

Table 2 Summary of the estimated carbon dioxide removal potential of tree cover in croplands by biome. Includes total crop area in hectares that had tree cover increase opportunity based on the expert estimate in the biome, the mean baseline tree cover in croplands in the biome, the mean maximum tree cover increase, and the equivalent potential CO_2 removal over 30 years. The table is ordered from largest to smallest cropland potential. *The Boreal Forests/Taiga potential is excluded from the total global potential

Biome	Total cropland area (ha)	Cropland area with tree cover increase opportunity (ha)	Mean baseline % tree cover	Mean increase % tree cover	Estimated annual CO_2removal potential Pg CO_2 Yr^{-1}	Estimated 30-year CO_2removal potential Pg CO_2 30 Yr^{-1}
Temperate Broadleaf & Mixed Forests	287,073,304	269,841,429	7.7	27.8	0.48	3.96
Tropical & Subtropical Grasslands, Savannas & Shrublands	190,255,033	156,210,738	5.8	19.4	0.46	3.80
Tropical & Subtropical Dry Broadleaf Forests	79,099,917	74,050,141	6.0	36.0	0.34	2.8
Temperate Grasslands, Savannas & Shrublands	289,876,393	255,281,258	3.9	23.8	0.30	2.42
Tropical & Subtropical Moist Broadleaf Forests	132,683,746	123,031,420	10.0	11.1	0.19	1.59
Montane Grasslands & Shrublands	23,117,456	20,411,537	4.6	23.1	0.05	0.43
Mediterranean Forests, Woodlands & Scrub	70,992,016	49,631,509	3.3	6.7	0.02	0.12
Temperate Conifer Forests	8,453,397	7,816,659	6.6	13.2	0.01	0.05
Deserts & Xeric Shrublands	102,914,900	81,865,410	4.3	1.1	0.01	0.05
*Boreal Forests/Taiga**	*11,949,741*	*11,467,286*	*6.0*	*2.9*	*0.00*	*0.01*
Tropical & Subtropical Coniferous Forests	1,315,942	1,249,706	9.2	10.5	0.00	0.01
Total	***1,185,782,103***	***1,039,389,807***	***6.1***	***17.3***	***1.86***	***15.22***

Table 3 Summary of the estimated carbon dioxide removal potential of tree cover in grazing lands by biome. Includes total grazing area in hectares that had tree cover increase value based on the expert estimation in the biome, the mean baseline tree cover in grazing lands in the biome, the mean maximum tree cover increase, and the equivalent potential CO_2 removal over 30 years. The table is ordered from largest grazing land potential to smallest grazing land potential. *The Boreal Forests/Taiga potential is excluded from the total global potential

Biome	Total grazing area (ha)	Grazing area with tree cover increase opportunity (ha)	Mean baseline % tree cover	Mean increase % tree cover	Estimated annual CO_2removal potential Pg CO_2 Yr^{-1}	Estimated 30-year CO_2removal potential Pg CO_2 30 Yr^{-1}
Tropical & Subtropical Grasslands, Savannas & Shrublands	719,865,647	542,968,290	8.8	18.1	0.81	6.63
Tropical & Subtropical Moist Broadleaf Forests	147,459,225	91,620,636	13.6	17.7	0.24	1.99
Temperate Grasslands, Savannas & Shrublands	389,541,265	346,075,603	3.3	16.7	0.17	1.38
Montane Grasslands & Shrublands	159,605,026	128,989,142	4.0	16.1	0.10	0.82
Temperate Broadleaf & Mixed Forests	95,479,664	56,201,739	10.5	24.5	0.07	0.54
Tropical & Subtropical Dry Broadleaf Forests	41,557,919	32,367,139	11.6	11.8	0.04	0.36
Deserts & Xeric Shrublands	680,700,563	302,317,889	2.3	3.2	0.03	0.21
Temperate Conifer Forests	48,928,428	35,201,103	6.5	18.7	0.02	0.20
Mediterranean Forests, Woodlands & Scrub	68,237,835	46,352,613	5.7	17.3	0.02	0.18
Tropical & Subtropical Coniferous Forests	9,392,467	6,690,699	12.2	16.0	0	0.03
*Boreal Forests and Taiga**	5,055,482	3,273,913	6.5	1.2	0	0
Total	***2,360,768,040***	***1,588,884,854***	***7.85***	***16.0***	***1.50***	***12.29***

The mean increase by country can be found in the country data table in Additional File 5 and the mean increase by biome are summarized in Tables 2 and 3.

Carbon dioxide removal potential of tree cover in agriculture

Taking into account the mean expert estimated maximum tree cover increases ('mean increase'), the resulting estimated maximum technical CO_2 removal potential (hereafter 'potential') varied greatly from biome to biome along an annual rainfall gradient, as shown in Fig. 6. The estimated per-hectare values were highest for cropland in Tropical/Subtropical Dry Broadleaf Forest, and then Tropical/Subtropical Grasslands, Savannahs, and Shrublands. However, there is a large uncertainty associated with these values, a result of the accumulated uncertainty from the expert elicitation steps and the multiple spatial layers used in the calculation, as shown with error bars for the 95% confidence intervals in Fig. 6.

When we extrapolate these per hectare values across the total global area of opportunity, the biome with the greatest total estimated potential in croplands is

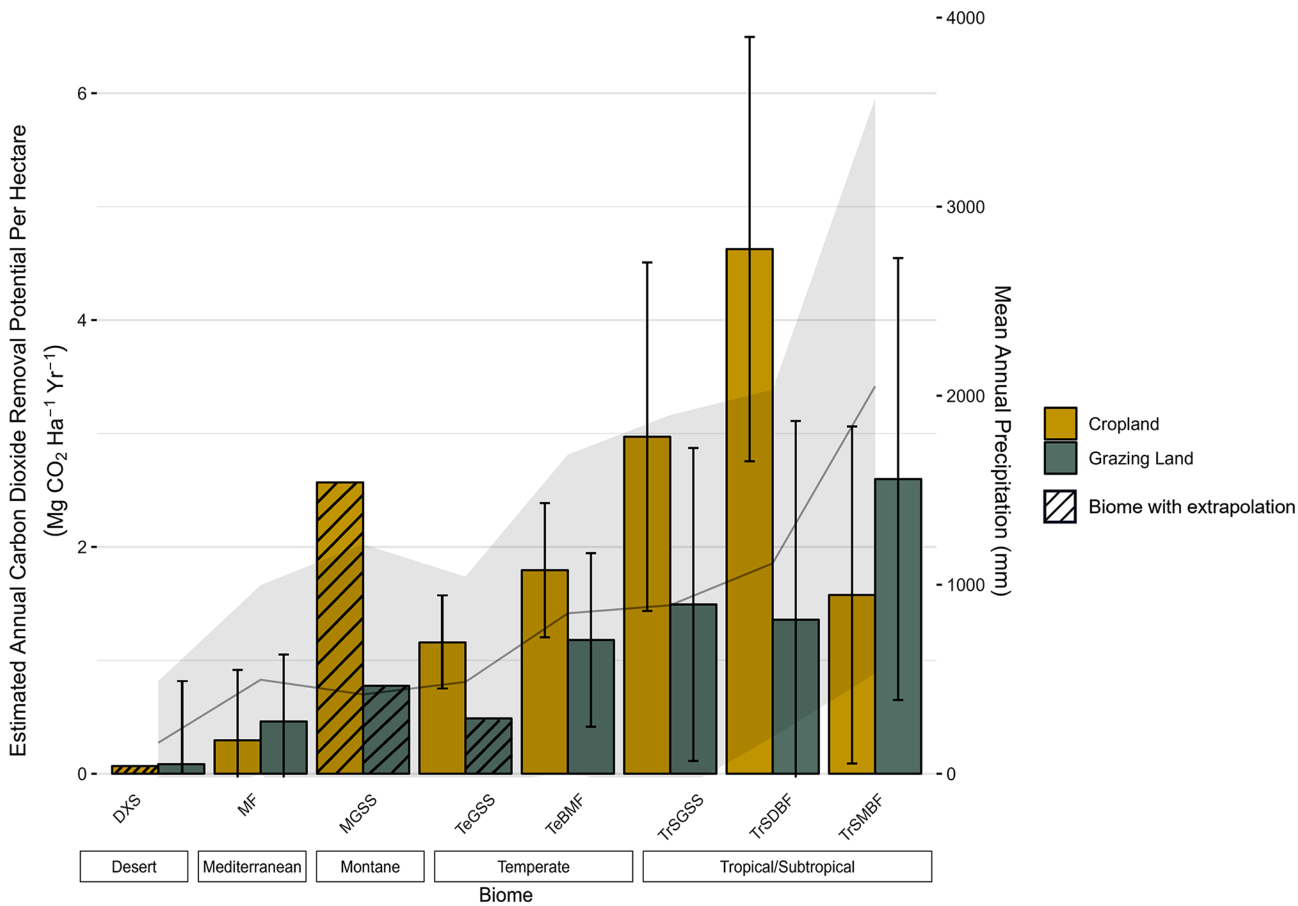

Fig. 6 Estimated annual carbon dioxide removal potential per hectare ($MgCO_2Ha^{-1}Yr^{-1}$) from increasing to maximum tree covers in croplands and grazing lands by biome and climate zone, considering annual rainfall. Error bars represent 95% confidence intervals. Error bars were not included in biomes with extrapolation due to low sample size of expert estimates. The secondary y-axis and line represent mean annual rainfall (from 1950–2000) for each biome [28]. The shading on either side of the line is the 95% confidence interval. X-axis biome codes are as follows. DXS: Deserts & Xeric Shrublands. MF: Mediterranean Forests, Woodlands, & Scrub. MGSS: Montane Grasslands & Shrublands. TeBMF: Temperate Broadleaf Mixed Forests. TeGSS: Temperate Grasslands, Savannas, & Shrublands. TrSDBF: Tropical/Subtropical Dry Broadleaf Forests. TrSGSS: Tropical/Subtropical Grasslands,Savannas, & Shrublands. TrSMBF: Tropical/Subtropical Moist Broadleaf Forests

Temperate Broadleaf Mixed Forests, with a potential of 0.48 Pg CO_2 yr^{-1} from a mean increase of 28% tree cover, followed by Tropical & Subtropical Grasslands, Savannas & Shrublands and Dry Broadleaf Forest biomes, with potentials of 0.46 Pg CO_2 yr^{-1} and 0.34 Pg CO_2 yr^1, respectively (Table 2). However, with large 95% confidence intervals for each biome, the differences between biomesmay be smaller than what is suggested based on this analysis of mean values.

It was estimated that the Tropical & Subtropical Dry Broadleaf Forest biome had the highest mean increase (36%) over a smaller extent (74 Mha) than the two more extensive biomes (269 Mha & 156 Mha) with the highest total potential. Temperate Grasslands, Savannas & Shrublands came in fourth overall in potential, with 0.30 Pg CO_2 yr^{-1} over a large extent of 255 Mha. The last biome with potential > 0.1 Pg CO_2 yr^{-1} is Tropical & Subtropical Moist Broadleaf Forests, with 0.19 Pg CO_2 yr^{-1}. We note that this tropical rainforest biome has the highest baseline tree cover (10%) and the lowest mean increase of the top 5 biomes (11%), which limits its total potential.

In grazing lands, the total potential is dominated by Grasslands, Savannas & Shrublands (GSS), with tropical/subtropical GSS comprising more than half of the global potential at 0.81 Pg CO_2 yr^{-1} over the largest number of hectares (543 M), with a mean tree cover increase of 18% (Table 3). The estimated potential in this biome, for grazing lands alone, is greater than the total potential of croplands and grazing lands in any other biome. However, increasing tree cover to maximum levels as a Natural Climate Solution would rely on the use of trees that do not require additional water, and without the tree density exceeding the natural amount for the system (expected to be higher in savannahs compared to grasslands, within the biome, for example), so this potential may be difficult to realize. Tropical/Subtropical Moist Broadleaf Forests followed with an estimated potential of 0.24 Pg CO_2 yr^{-1}

over 91 Mha of grazing lands, followed by Temperate GSS with 0.17 Pg CO_2 yr^{-1} over 346 Mha, and Montane Grasslands & Shrublands with 0.10 Pg CO_2 yr^{-1} over 128 Mha.

The distribution of the potential follows the distribution of the mean increases, but concentrates in tropical regions where carbon accumulation tends to be faster and of greater magnitude. However, there are some notable areas of high estimated potential in temperate croplands, especially in northern Europe (Fig. 7).

According to our estimations, tropical/subtropical biomes are likely to contain slightly over half (54%) of the global potential for TCA in croplands at 1.0 Pg CO_2 yr^{-1}; with more than double the per hectare carbon accumulation rate at 2.8 Mg CO_2 ha^{-1} yr^{-1} (SD=0.45) in tropics vs. 1.2 Mg CO_2 ha^{-1} yr^{-1} (SD=0.22) in temperate. Tropical/subtropical biomes also contain an estimated 73% of the potential from TCA in grazing lands at 1.1 Pg CO_2 yr^{-1} with 3.5 times the per hectare carbon accumulation rate at 1.6 Mg CO_2 ha^{-1} yr^{-1} (SD=0.47) in tropics vs. 0.4 Mg CO_2 ha^{-1} yr^{-1} (SD=0.19) in temperate. Figure 8 illustrates the global potential of TCA in grazing lands.

Within countries, we have estimated the total potential and the per hectare potential, illustrated in Fig. 9. The countries with the highest estimated total potential across croplands and grazing lands have large areas with industrialized agriculture, such as India, China, the U.S.A., Brazil, Australia, and Russia. Countries with high potentials included Brazil with 0.30 Pg CO_2 yr^{-1} / 2.4 Mg CO_2 ha^{-1} yr^{-1} (SD=0.21) in grazing land and India with 0.24 Pg CO_2 yr^{-1} / 1.85 Mg CO_2 ha^{-1} yr^{-1} (SD=0.1) in croplands. The top three countries for cropland potential, India, China, and the U.S.A., contain 31% of the global potential in croplands. Similarly, the top three countries for grazing land potential, Brazil, China, and Australia, comprise 37% of the global potential in grazing lands. Full results by country are included in Additional File 5.

Central and West Africa appear to contain hotspots of CO_2 removal potential in croplands, with the top four countries globally in terms of potential per hectare of cropland being Gabon, Benin, Republic of Congo, and Togo. The countries with the highest potential per hectare of grazing lands are also concentrated in Central and West Africa, with only one country in South America, listed here in descending order: Gabon, The Republic of Congo, Guyana, Ghana, and Burundi. Gabon, Ghana, and The Republic of Congo also appear in top 10 rankings for total cropland potential per hectare. Figure 9 illustrates that according to our estimations, the countries with the highest total potential generally have lower CO_2 removal rates per hectare, and vice versa, except for Brazil for grazing lands and Nigeria and Thailand for croplands, which contain both large potential per hectare and large total potential.

Discussion

The mean expert estimations for maximum tree cover (hereafter 'mean estimation') varied by biome, following a climate driven expected density of trees across the landscape; the mean estimations for forested biomes were the highest overall, and deserts the lowest, with Grasslands, Savannas & Shrublands falling in the middle. Nevertheless, the mean estimations for forested biomes appear to be strongly limited by the need to maintain agricultural production, which is to say, they did not follow the increasing trend and approach typical forest tree cover. The mean estimation across forested biomes was around 35%, a level that is sometimes considered shade-agroforestry, so these estimations must be applied with caution and close monitoring of agricultural yield impacts on shade-intolerant crops. The mean estimation across all biomes and agricultural systems was 27% with a relatively large standard deviation of 16%. We note that the only significant ($p<0.001$ by Wilcoxon rank sum test) difference in means was between Temperate/Tropical/Subtropical biomes (29%) and the drier biomes (14%).

Our expert selection methods may have resulted in an over-estimation bias since the selected experts may have a disciplinary interest in the integration of trees and crops. Moreover, the questionnaire left "without significantly reducing long-term agricultural yields" to the interpretation of the experts, which should be more precisely defined in future consultations to ensure protection of agricultural yields, production, or outputs. The variance observed in the expert estimations also indicates that there is a large range of maximum values, depending on specific tree-crop systems. The authors acknowledge that some specific crops and forages are more shade-tolerant than others and that different species have different canopy and rooting architectures that impact the way that they interact with crops, and coming up with mean, generalized values was the most important design challenge that this study faced. Generalizations across croplands and grazing lands were necessary for this initial global study, but more specific parameterization will be necessary for specific agricultural systems and locations, as well as careful monitoring of agricultural yield and production impacts.

Within the forest biomes, there were higher estimations for tree covers in croplands in dry forest compared to moist forest. This could be due to a maximization of the water-balance related advantages of agroforestry, such as reduced temperature and evapotranspiration [38], in climates with seasonal droughts including the Mediterranean biome [2, 64]. The climate adaptation benefits of agroforestry are also clear in seasonally dry Tropical/Subtropical Dry Forest [62], and Tropical/Subtropical Grasslands, Savannas & Shrublands, especially in Africa [36, 41]. The CO_2 removal potential in Africa

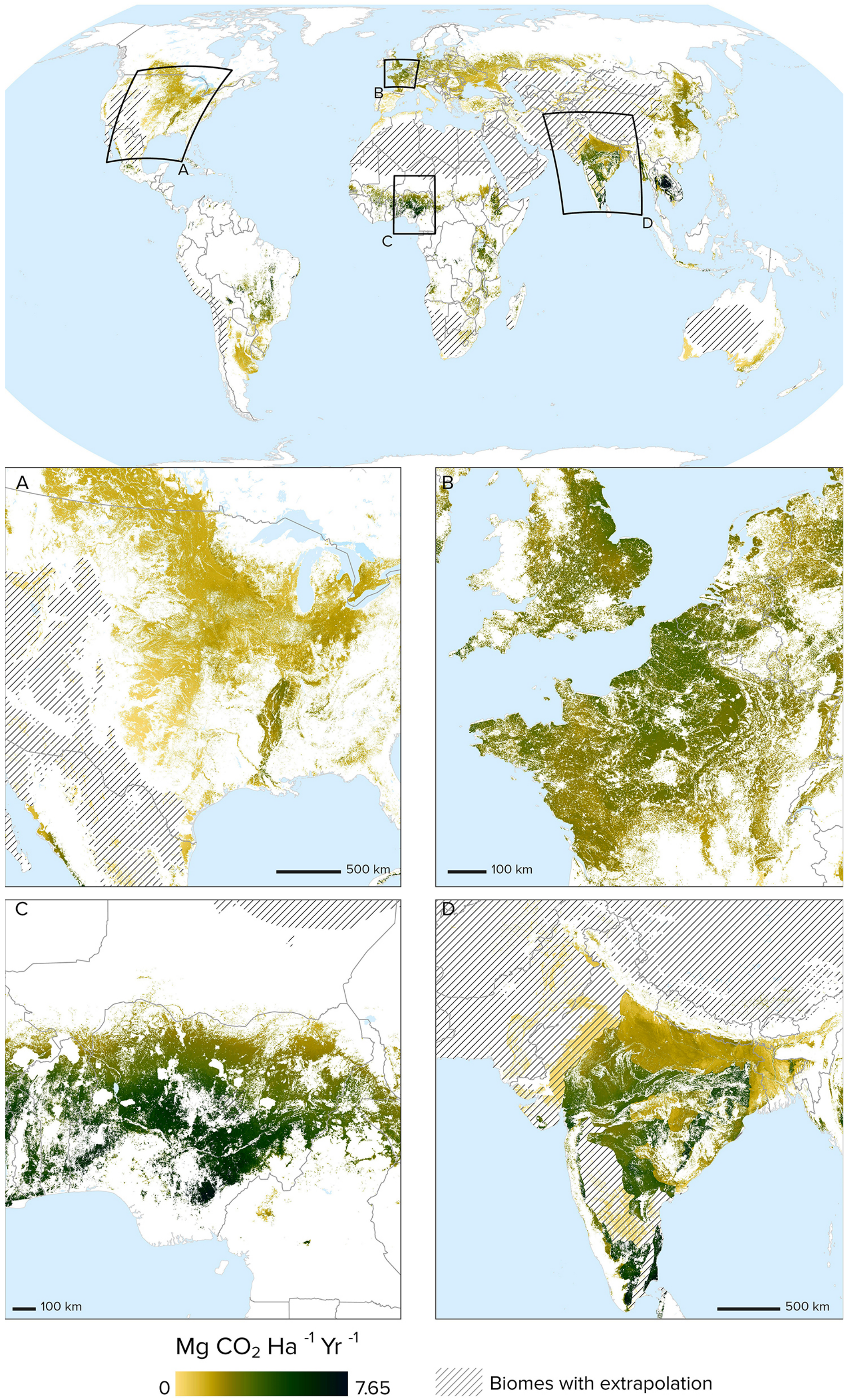

Fig. 7 Potential increases in carbon density in Earth's agricultural systems from tree cover in croplands. Total potential includes average aboveground and belowground carbon density in one year within the first 30 years of growth. Inset maps show example areas in (**A**) Eastern U.S.A. (**B**) Northern Europe (**C**) Nigeria and (**D**) India. Native resolution is 30 m but for the purposes of visualization, these figures were resampled to 1000 m. Biomes with hatching are biomes that had low sample size of expert estimates

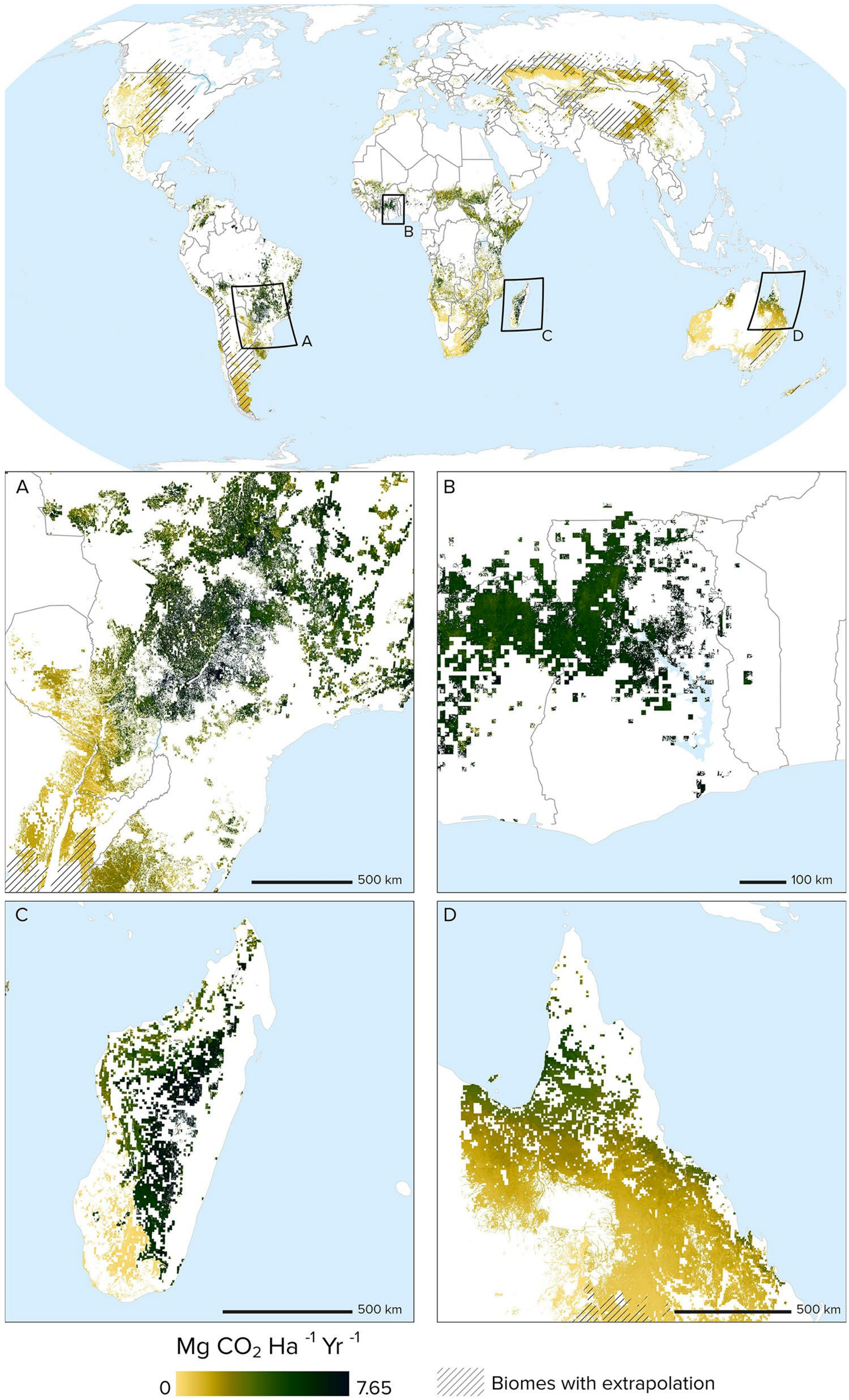

Fig. 8 Potential increases in carbon density in Earth's agricultural systems from tree cover in grazing lands. Total potential includes average aboveground and belowground carbon density in one year within the first 30 years of growth. Inset maps show example areas in (**A**) Southern Brazil/ Northern Argentina & Paraguay (**B**) Cote d'Ivoire and Ghana in Western Africa (**C**) Madagascar and (**D**) Northeast Australia. Native resolution is 30 m but for the purposes of visualization, these figures were resampled to 1000 m. Biomes with hatching are biomes that had low sample size of expert estimates

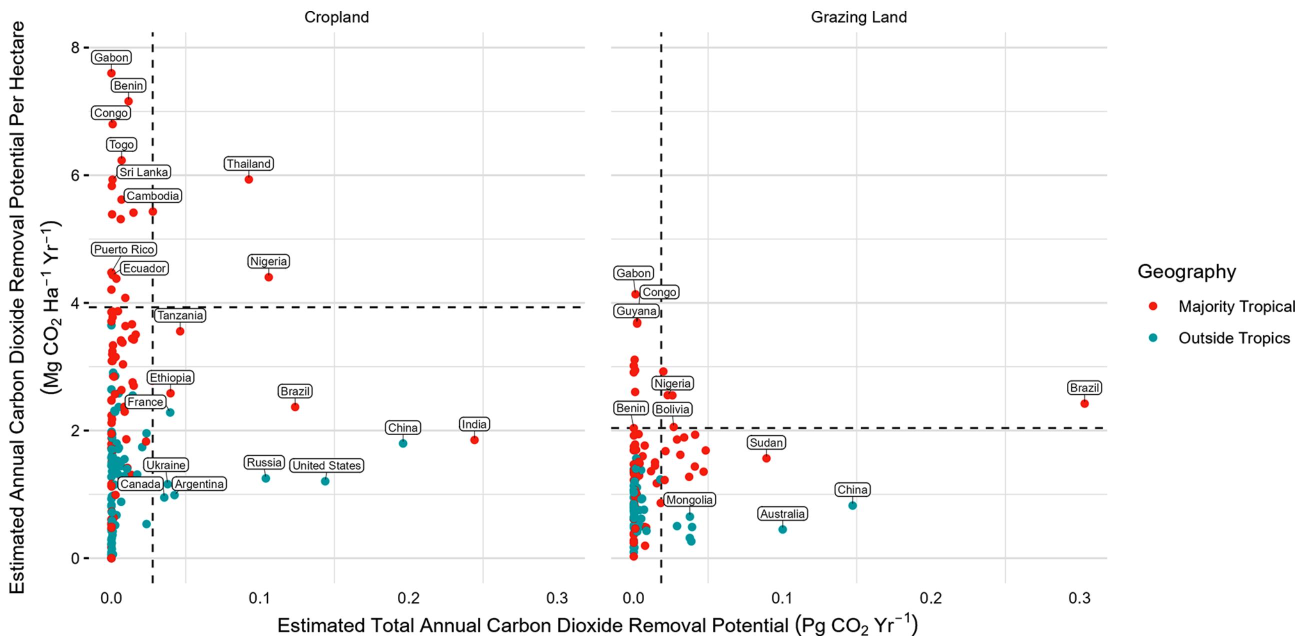

Fig. 9 Tree Cover in Agriculture's estimated total annual carbon dioxide removal potential per country compared to its estimated annual carbon dioxide removal potential per hectare. For cropland (left) and grazing land (right). Each point represents a country, with different colors indicating whether the majority of the country falls within the tropics (red) or outside of the tropics (blue). Dotted lines indicate the 90th percentiles

may be higher than our estimations if *Faidherbia albida*, a reverse-deciduous tree that only has leaves in the dry season, is used across its native range.

The Desert biome contains large areas of agriculture and grazing totaling more than 810 M ha, with low baseline percent tree cover, but its total estimated CO_2 removal potential is comparably low. In desert croplands, the (extrapolated) estimation for tree cover increase is extremely low (1%) and its total potential (0.02 Pg CO_2 30 yr^{-1}) was the second lowest. The Desert biome had the second largest number of hectares in grazing lands, and so even with the smallest mean increase of all of the biomes for grazing lands (3%), it had a higher total potential (0.75 Pg CO_2 30 yr^{-1}) and annual CO_2 removal rate (0.03 Pg CO_2 yr^{-1}) than Mediterranean Forests/Woodlands/Scrub, Boreal, and Conifer Forests. Our global total potential estimate excludes the values from Boreal climate domains, 0.0002 Pg CO_2 yr^{-1} from grazing lands and 0.001 Pg CO_2 yr^{-1} from croplands, where local biophysical effects (i.e. albedo) may offset climate benefits of increased tree cover [26], although it may be possible to mitigate this effect by using deciduous versus evergreen tree species [29].

The largest estimated tree cover increases (hereafter 'increases') are generally found in the global North and other areas where industrialized agriculture is prevalent and agroforestry practices are limited, with increases from 20 to 25%, very close to the mean estimated maximum, indicating that the baseline tree covers are very low. Agroforestry system designs have been made for mechanized agriculture, for example modifying the spacing of lines of trees to meet the turning radii and/or width of the equipment and restoring and reinforcing windbreaks (for example see the extension work recommendations of Rivest et al. [57]in Canada), which would allow for integration of some tree cover with minimal disruption to the farming systems. In any case, significant education and extension will likely be required to foster the adoption and scaling of this NCS in areas where agroforestry is practically nonexistent.

On the other hand, tropical/subtropical regions and countries where agroforestry is more common have significant climate mitigation potential even with their generally smaller margins for increasing tree cover, and they may have the potential to achieve scale for this NCS more rapidly due to more prevalent traditional knowledge and practice of the systems. They could be very important areas for rapid climate mitigation actions that could also serve to counteract the loss of intergenerational traditional knowledge about agroforestry systems. Furthermore, because we excluded areas with baseline tree cover > 25% to avoid overlap with forestry-related NCS pathways, this means that there could be 'hidden' potential; for example, in dry forest biomes where areas with a baseline tree cover > 25% could increase up to the estimated maximum value of 36%, but this is not included in our estimates of potential because of the exclusion of areas with baselines > 25%. Further research could develop more complex rules for definitions of opportunity areas to include pixels with >25% tree cover while avoiding double counting and overlap with other NCS. The 1.86 Pg CO_2 yr^{-1} estimated maximum technical CO_2 removal potential in croplands is more evenly distributed than the potential in grazing lands; 54% of cropland potential occurs in the tropics (which contain 34% of global cropland area), whereas 73% of grazing land potential occurs in the tropics (which contain 66% of global grazing land area). Biomes with high potential for TCA are found in both temperate and tropical climates. The uncertainty associated with the annual CO_2 removal rates per hectare per biome indicate the overall level of uncertainty across biomes and limit our ability to make speculations on the differences between biomes and even between cropping and grazing systems. The goal of this study was to build on the previously vague concept of a "Trees in Agriculture" NCS and get an improved, expert-informed global estimate of the potential of this NCS. This analysis has improved our understanding of the sources and types of uncertainty, and we see this work as a first step towards setting up further research and deeper investigations of the climate mitigation potential of Tree Cover in Agriculture (TCA) in different countries and regions.

It is notable that out of the 87 tree species chosen by the experts as reference trees, only 13 were used for both cropland and grazing land. The three most commonly used reference trees, *Populus deltoides* (Eastern cottonwood), *Faidherbia albida* (White acacia), and *Quercus robur* (English oak) are representative of three different regions: North America, Africa, and Europe, respectively. Two Central American species, *Gliricida sepium* and *Leucaena leucocephala*, round out the top 5 reference trees used in both cropland and grazing land, reflecting a good general global distribution with the exception of Asia, which also had the lowest expert representation. The spatial arrangement of the trees can have very important effects on agricultural production within a fixed canopy cover threshold. For example, the orientation of tree rows (i.e. N/S or E/W) can mitigate competition for solar radiation at high latitudes and has huge implications for crop production in agroforestry systems at high latitudes [17]. Tree cover may also be concentrated in less productive areas of fields such as field edges or boundary areas, which may be enough to attain the optimum threshold in landscapes with lower targets. Further research is needed on the optimal spatial arrangements in different tree-crop-climate combinations, at regional and more localized scales.

We found that the lowest potentials were in drier areas including deserts, coniferous biomes, and Mediterranean regions, partially due to their biophysical limits of tree cover and partially because carbon accumulation rates are slower in drier areas. This is important to note, because the biggest differences between our estimates and Chapman et al. [9] occur in grasslands and deserts, areas with low precipitation and that tend to use irrigation. In total, our estimates are less than a third of the prior maximum scenario estimation of the carbon mitigation potential of trees in agriculture by Chapman et al. [9], which found a maximum global (aboveground) potential of 181.13 Pg CO_2 (49.4 Pg C) in croplands and 163.17 Pg CO_2 (44.5 Pg C) in grazing lands, however, our results are within the range of their lower levels of integration scenarios. We estimate the annual maximum technical CO_2 removal potential at 1.86 Pg CO_2 yr^{-1} in croplands and 1.5 Pg CO_2 yr^{-1} in grazing lands, including aboveground and belowground biomass. Our results are influenced by patterns of annual carbon accumulation rates and the relationship between tree cover and carbon accumulation, compared to previous estimates. Whereas Chapman et al. [9] and Zomer et al. [71] used projections up to an upper quartile of observed biomass, we used predicted, climatically adjusted rates of carbon accumulation [10]. The differences in our findings suggest that drier areas may take much longer than 30 years to achieve their maximum unbounded CO_2 removal potential. Additionally, the grazing land area in the Desert biome used by Chapman et al. [9] is slightly more than twice the amount of area in the same biome in this study. Chapman et al.'s methods are based on field- and lidar-derived aboveground biomass. Therefore, our results would bias towards fast growing areas while Chapman et al.'s results would bias towards overall high biomass accumulation areas. Finally, there could be discrepancies in results due to some of our underlying data layers being at 1 km resolution, compared to Chapman et al.'s 30 m resolution.

Our use of the Cook-Patton et al. [10] natural regeneration growth rates may result in an under-estimation of the carbon accumulation of trees in agricultural fields which will be less crowded, receive more light, and more nutrients and weed control, compared to naturally regenerating trees. This should result in fewer, larger individuals holding more carbon, more like the CO_2 removal rates of trees in plantation forestry. At the same time, the Cook-Patton et al. [10] rates use linear averages, whereas the real growth function is more of a sigmoidal (s) curve of slow, fast, then slow growth rates. This could result in an over-estimation of the very early growth/establishment phase. The estimated maximum potentials therefore represent the average rate across a 20–30 year timeframe. Agroforestry-specific tree allometries and carbon accumulation spatial layers are an important research frontier to refine these estimates.

Establishing trees in grazing systems requires grazing exclusion during the tree establishment phase. This may benefit localized CO_2 removal and biodiversity [69], but it can be challenging in extensive rangelands that are typically lightly managed, so cost-effective methods will be important [60]. One strategy would be farmer-managed natural regeneration, a practice that takes advantage of trees with existing root systems, such as those that are coppiced, to prune and cultivate them into larger trees in agricultural or grazing systems [37].

We constrained the potential extent of TCA to existing farmland and grazing lands, with the latest global mapping available at the time of the study (2015 data available in 2023). The large time lag in availability of agricultural land use maps is a major constraint of this study, as areas under cultivation are likely to change, and total areas under cultivation have been increasing over time. Additionally, our baseline tree cover estimates could be subject to error due to the known difficulties of estimating low-density tree cover using large-scale remote sensing datasets; however, the literature is inconclusive whether these datasets consistently over-estimate or under-estimate tree cover in open-canopy, heterogeneous landscapes [4]. We recognize the potential inaccuracies of using low canopy cover values from global remote sensing products and that these inaccuracies could result in under or over estimation of our maximum tree cover increase values and resulting carbon dioxide mitigation estimates.

Conclusion

The estimated maximum technical CO_2 removal potential of Tree Cover in Agriculture (TCA) over the next 30 years, 100.8 Pg CO_2, would exceed global annual emissions from cars. Compared to the previous works on this topic based on observations of standing biomass on agricultural lands, this estimate is based on new input from agricultural experts, and the best available knowledge on actual CO_2 removal rates (Cook-Patton 2020).

There are regions of high potential in both tropical and temperate zones, with the Tropical/Subtropical Grasslands, Savannas & Shrublands (GSS) biome showing the highest estimated potential of 1.3 Pg CO_2 yr^{-1}. We caution that GSS biomes cover a very wide range of natural tree cover, and further research should seek separate maximum tree cover estimations for the 3 sub-types within the biome (grasslands, savannas, shrublands) to ensure that afforestation (which is not an NCS), is avoided, particularly in grasslands. Further research at regional or national scales could use more accurate local crop extent databases and include a larger variety of crops and grazing systems. Moreover, technology is rapidly advancing and the application of more accurate carbon accumulation curves specific to agroforestry systems and more up-to-date data on tree cover (e.g., Brandt and Stolle [5] could further refine future analyses.

The large variation in estimated maximum tree covers within each biome reflects the diversity of agricultural systems and the complexity of interactions taking place within them, but it limits the potential application of these results in two important ways. Firstly, we used the mean of the expert recommendations after seeking consensus among the experts in an effort to capture what we could expect to be an average level of maximum tree cover over the entire landscape. Recognizing that these mean values approached the “do not exceed” thresholds we were able to extract from the literature, we treated the mean expert recommendations as the *maximum* values throughout the analysis.

Secondly, the large variation in expert estimations also reduces our ability to draw conclusions on broad spatial patterns and drivers in the resulting CO_2 removal potentials, which have a high level of uncertainty due to the propagation of multiple types of error from different data sources over extremely large areas. We will, however, note that the estimated potentials seem to be driven by two main characteristics: (1) the *opportunity for increase* in tree cover which in turn varies depending on cultural factors, including dietary and aesthetic landscape preferences, the inherent traits of the cultivars, and technical agricultural practices especially including the level of mechanization, and (2) *bioclimatic factors* affecting the natural biophysical limits to non-irrigated tree cover, CO_2 removal rates, and their influence on underlying tree-crop-forage interactions. We note an interaction in climates with seasonal droughts which may have higher maximum levels of tree cover that may counterbalance their lower CO_2 removal rates. It is a very important finding, overall, that the potential is spread across biomes in both temperate and tropical/subtropical climates, for different reasons such as high industrialization, deforestation, or potential for climate adaptation benefits, to name a few. A deeper analysis of regional spatial patterns and drivers would require modeling.

Tree species selection can be critical to supporting biodiversity within natural climate solutions. The principles of TCA suggest the selection of locally native species and incorporating a diverse mixture of tree species to the maximum extent feasible to protect against homogenization of agroforestry system design. We want to highlight the diversity captured by the expert’s use of 87 different reference tree species and underscore that the common reference tree species should in no way be taken as a proscriptive list. There are publicly available tools for agroforestry tree selection such as the Agroforestree Database from the Center for International Forestry Research and World Agroforestry (CIFOR-ICRAF) that should be used for localized system designs [49].

It is generally challenging to find land for restoration when agricultural production is excluded. Tree Cover in Agriculture (TCA) opens new territories for restorative climate mitigation with trees as a Natural Climate

Solution by 'sharing' space within the boundaries of the world's extensive agricultural systems, as long as agricultural production continues to be protected by design, properly managed, and carefully monitored in concurrence with external factors such as extreme weather, pests and disease. The 2.9 B ha of agricultural land we estimate to have a margin for sustainable increase in tree cover, making up more than half of global agricultural land, provides an enormous opportunity for achieving international restoration policy targets while contributing to global climate mitigation targets. It far exceeds the Bonn Challenge target of 350 Mha and could be instrumental in achieving the 100 Mha target of the Great Green Wall in Africa's Sahel region while improving drought resiliency of agricultural systems [64]. The potential additional associated benefits to faunal and floral biodiversity, ecosystem services, and influences on regional climatic patterns, remain to be analyzed.

The key to the large total estimated potential of this NCS is the vast hectarages of agricultural land. It represents a relatively small change per hectare, the addition of 2–6 trees per hectare on average, scaled over large areas. Even so, the potential displacement of crops by the tree basal areas, and whether or not this is fully compensated for in yield improvements around the trees, and whether any leakage occurs as a result of TCA, must be investigated further in ways that can take into account the different scales of landscape-level impacts of the trees on local climates and production. Trees may be placed in less productive agricultural areas such as field boundaries and riparian areas, and may be concentrated on steep slopes especially in grazing lands as suggested by Iñamagua-Uyaguari et al. [31]. Across all landscapes, a strategy maximizing the use of unproductive spaces in fields such as fence lines or field edges, should be the first step towards increasing tree cover in agriculture because it will be the least likely to interfere with cropping and grazing systems.

There is a higher trees per hectare potential increase in tropical/subtropical regions, considering average mature reference tree sizes and mean increases, of 5.2 trees ha^{-1} in croplands and 4.6 trees ha^{-1} in grazing lands, vs. 3.8 and 2.3 trees ha^{-1}, respectively, in non-tropical areas. Distributed among the hectares with a margin for increase, this equates to 184 M trees in cropland and 396 M trees in grazing lands in non-tropical areas, and 68 M trees in croplands and 145 M trees in grazing lands in tropical areas, totaling 793 M trees. This is, however, < 0.1% of the Trillion Tree pledge, suggesting that planting trees at much higher densities would be required to meet that goal. Scaling and acceleration of Tree Cover in Agriculture (TCA), including carbon methodology development that properly accounts for leakage, exploration of its potential to contribute to Scope 3 insetting, policy work including but not limited to increasing incorporation into NDCs, and direct technical assistance to farming and grazing land managers, should be prioritized. This may be especially beneficial in both countries with large total estimated maximum technical CO_2 removal potentials, and in the hotspots of TCA potential identified in this paper.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13021-024-00268-y.

Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

Supplementary Material 4

Supplementary Material 5

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Author contributions

The authors confirm contribution to the paper as follows: study conception and design: SSH, BG, EM, MC; data collection: SSH, EM, MC, VG; analysis and interpretation of results: SSH, VG, BG; draft manuscript preparation: SSH, VG. All authors reviewed the results and approved the final version of the manuscript.

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Data availability

Additional datasets supporting the conclusions of this article are included in the article's additional files as AdditionalFile5_countrytable.csv. Raw data and scripts to reproduce these analyses can be found at the github repository, https://github.com/Catalytic-Science-for-NCS/Trees_in_Agriculture.

Declarations

Competing interests

The authors declare no competing interests.

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