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How to measure the efficiency of terrestrial carbon dioxide removal methods

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Abstract. The climate mitigation potential of terrestrial carbon dioxide removal (tCDR) methods depends critically on the timing and magnitude of their implementation. In our study, we introduce different measures of efficiency to evaluate the carbon removal potential of afforestation/reforestation (AR) and bioenergy with carbon capture and storage (BECCS) under the low-emission scenario SSP1-2.6 and in the same area. We define efficiency as the potential to sequester carbon in the biosphere in a specific area or store carbon in geological reservoirs or woody products within a certain time. In addition to carbon capture and storage (CCS), we consider the effects of fossil fuel substitution (FFS) through the usage of bioenergy for energy production, which increases the efficiency through avoided CO_2 emissions.

These efficiency measures reflect perspectives regarding climate mitigation, carbon sequestration, land availability, spatio-temporal dynamics, and the technological progress in FFS and CCS. We use the land component JSBACH3.2 of the Earth System Model MPI-ESM to calculate the carbon sequestration potential in the biosphere using an updated representation of second-generation bioenergy plants such as *Miscanthus*. Our spatially explicit modeling results reveal that, depending on FFS and CCS levels, BECCS sequesters 24 – 158 GtC until 2100, whereas AR sequesters around 53 GtC on a global scale with BECCS having an advantage in the long term. For our specific setup, we find that BECCS has a higher potential in the South American grasslands and Southeast Africa, whereas AR is more suitable in Southeast China. Hence, our results reveal that the efficiency of BECCS to sequester carbon compared to 'nature-based solutions' like AR will depend critically on the upscaling of CCS facilities, replacing fossil fuels with bioenergy in the future, the time frame, and the location of tCDR deployment.

1 Introduction

Meeting the Paris Agreement's climate targets to limit global warming to well below 2°C will likely require substantial carbon dioxide removal (CDR) (Azar et al., 2013; Roe et al., 2019; IPCC Working Group III, 2022c). CDR implies sequestering CO_2 from the atmosphere and storing it for decades to millennia in the biosphere, long-lived products, geological reservoirs,

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

or in the ocean (IPCC Working Group III, 2022c). Various CDR methods exist, from conventional methods applied at large scale for decades such as afforestation and reforestation (AR) to those only being explored in the laboratory such as artificial photosynthesis (May and Rehfeld, 2022). Nearly all CDR currently deployed depends on terrestrial ecosystems (tCDR), where carbon is stored in the biosphere (Smith et al., 2023). Within the Land use, land-use change, and forestry (LULUCF) sector, tCDR removes about 2 ($\pm$0.9) $GtCO_2yr^{-1}$ from the atmosphere, of which 0.2 – 0.4 $GtCO_2yr^{-1}$ are due to AR (Smith, 2016; Anderegg et al., 2020; Smith et al., 2023). An additional 2.3 $\cdot 10^{-3}$ $GtCO_2yr^{-1}$ comes from novel CDR (Smith et al., 2023) including 1.8 $\cdot 10^{-3}$ $GtCO_2yr^{-1}$ from bioenergy with carbon capture and storage (BECCS).

Scenario assessments suggest that tCDR measures will continue to play a major role in the future, while the projections of less explored options such as direct air carbon capture and storage (DACCS) are more uncertain (IPCC Working Group III, 2022c). Land-based measures, including tCDR and avoided emissions from the LULUCF sector equally, have the potential to mitigate approximately 10 – 15 $GtCO_2eq\ yr^{-1}$ by 2050, corresponding to about 20%–30% of the mitigation that would be needed to achieve the 1.5°C temperature target (Griscom et al., 2017; Roe et al., 2019). Among the various tCDR approaches, AR and BECCS are implemented on a large scale with the highest carbon removal. They remain most commonly applied also in future scenarios (Fuss et al., 2014; Meinshausen et al., 2020; IPCC Working Group III, 2022c). Across the scenarios that limit the warming to 2°C or below, agriculture, forestry, and other land use (AFOLU), mainly AR, remove about 0.23 – 6.38 (2.98) $GtCO_2eq\ yr^{-1}$ and BECCS removes about 0.52 – 9.45 (2.75) $GtCO_2eq\ yr^{-1}$ from the atmosphere in 2050 (IPCC Working Group III, 2022a). The large spread in the estimate of BECCS reflects the high uncertainty regarding CCS feasibility in the future. Various raw materials, such as energy crops, agricultural and forest residues, and waste fractions can be used for BECCS (e.g. Borchers et al. (2024)). They include woody and herbaceous crops on agriculturally managed plantations of tall and fast-growing grasses for biomass production. Especially, so-called second-generation bioenergy crops will gain relevance in the future (Clifton-Brown et al., 2017; Awty-Carroll et al., 2023). The distinguishing characteristics of second-generation biofuels are that they use a non-food feedstock (lignocellulose biomass, field crop residues, forest product residues, or fast-growing dedicated energy crops) compared to first-generation biofuels made from sugar-starch feedstocks (e.g., sugarcane and corn) and edible oil feedstocks (e.g., rapeseed and soybean oil). We will focus here on second-generation herbaceous biomass plantations (HBPs) such as *Miscanthus*. To compose an efficient and sustainable portfolio of tCDR methods, AR, BECCS, or any other CDR method needs to be carefully evaluated as they differ in risks and side effects.

Despite the large carbon removal potential of AR and BECCS, uncertainties in carbon sequestration rates are high, and side effects on land use, water use, biodiversity, and equity exist (Boysen et al., 2017; Fuss et al., 2018; Cheng et al., 2020). For example, pathways that are limiting warming to 1.5°C show an increase in forest cover of about 322 (-67 to 890) Mha and an increase in cropland area to supply biomass for BECCS of around 199 (56 to 482) Mha in 2050 (IPCC Working Group III, 2022a). The extended use of land and water for tCDR might provoke land use conflicts with other sectors and might cause deforestation, biodiversity loss, higher food prices and put a larger population at risk of hunger and malnutrition (Creutzig, 2016; Smith et al., 2016; Humpenöder et al., 2018; Roe et al., 2019; Doelman et al., 2020). Thus, not all methods are suitable everywhere on the globe and their carbon sequestration potential will evolve differently over time. Where risks and side effects are not precluding one method or the other, an important question is which method removes CO_2 more efficiently from the

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

atmosphere while optimizing the allocation of financial, land, and other resources. This question is surprisingly hard to answer. The carbon sequestration per square meter of forests and bioenergy crops is highly location-specific, since it depends on environmental, climate, and soil conditions and will thus change in the future (e.g. Sharma et al. (2023)). Thus, locations of tCDR deployment have to be chosen carefully. But even if the CO_2 sequestration per square meter might initially be the same for different tCDR methods, the temporal dynamics differ. BECCS could put similar amounts of carbon into CCS every year if the infrastructure for CCS is available, limited only by the inter-annual variability of biomass production. By contrast, forests show a distinct evolution of CO_2 sequestration with age, which may be altered by wood harvesting in managed forests. Moreover, plant growth, soil respiration, and natural disturbances are influenced by environmental changes (Canadell et al., 2021). The time BECCS needs to take up and store a similar amount of CO_2 as forests will further depend on how much of the CO_2 is transferred to geological storage or released to the atmosphere beforehand. In addition to CCS, bioenergy crops are typically used for energy production, which enables fossil fuel substitution (FFS). However, in practice, biomass production losses and energy conversion reduce the FFS potential of biomass (Chum et al., 2011; Babin et al., 2021). Such and other emissions along the process-chain including energy losses due to transport but also indirect land-use change through tCDR due to displacement of the prior land use to other regions can be captured by life cycle assessments (LCA). The processes considered in LCA, and thus the emissions avoided through substitution, depend on the choice of system boundaries. They have been found to vary across literature for BECCS (Terlouw et al., 2021) making a crucial difference in terms of carbon removal potential with its immanent purpose of energy production. Further, it must be considered to what extent bioenergy displaces fossil fuels in practice (Kalt et al., 2019; Cheng et al., 2022).

These remarks reveal that various aspects need to be considered when assessing a certain tCDR target, either in absolute terms or in comparison to another CDR method. However, these aspects are typically not disentangled in studies that evaluate the future deployment of CDR, which limits our ability to understand the levers to deploy CDR methods efficiently. Several studies have assessed the carbon sequestration and climate mitigation potential of AR (Sonntag et al., 2016; Matthews et al., 2022), BECCS (Harper et al., 2018; Muri, 2018), or both (Krause et al., 2017; Melnikova et al., 2023; Cheng et al., 2024) using Earth System Models (ESM) and dynamic global vegetation models (DGVM). However, a direct comparison of the AR and HBPs carbon sequestration potential in the same areas is missing within a consistent setup. Many studies use abandoned agricultural areas for AR under different climate scenarios (Sonntag et al., 2016; Jayakrishnan and Bala, 2022). Others build on the output of Integrated Assessment models (IAMs) to determine the spatial distribution of AR and BECCS in different areas within the same or even different scenarios (Krause et al., 2017; Harper et al., 2018; Cheng et al., 2022, 2024). These different assumptions on the land area used for the CDR methods result in high differences in the estimated tCDR potential across studies (IPCC Working Group III, 2022a). Krause et al. (2017) find a larger spatial extent needed for avoided deforestation in combination with AR compared to BECCS to reach a similar carbon sequestration potential. However, there is no further exploration of the sensitivity of results concerning the time horizon, the amount of CCS, or substitution achieved.

In this study, we propose several measures that reflect biogeochemical mitigation efficiency, defined as the combined carbon sequestration, storage and substitution potential of a tCDR method (hereafter tCDR potential). These measures include the spatio-temporal dynamics, that is the change in the tCDR potential over time and space, the level of FFS and CCS required to

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

achieve a given tCDR potential, and the area required to achieve a given tCDR potential. These measures include the spatio-temporal dynamics, i.e. the change in tCDR potential in time and space, the level of FFS and CCS needed to reach a specific tCDR potential, and the area that is needed to reach a specific tCDR potential. We quantify results for BECCS using HBPs and AR in the same area under different assumptions on FFS and CCS over the 21st century. We use the state-of-the-art land surface model JSBACH3.2, which we have extended by a dedicated representation of HBPs and CCS. We use environmental conditions from the low-emission scenario SSP1-2.6, representing a scenario compatible with the 2°C target. Note that our analyses could be carried out under other scenarios and be extended to a comparison of sensitivities to background environmental changes. The SSP1-2.6 scenario projects a substantial gain in land for second-generation biofuels (up to 330 Mha), which mainly replaces pasture (Hurtt et al., 2020). We use this area for BECCS, and alternatively for AR, to assess the effectiveness of both methods within a consistent setup. Evaluating our different proposed measures of efficiency, we provide novel insights into the following research questions:

- Which of the two tCDR methods, BECCS and AR, has a higher carbon removal potential per area?
- At which level of FFS and CCS does BECCS become more efficient than AR in removing carbon from the atmosphere?
- How does the efficiency of the two tCDR methods evolve over time?
- How much additional land does BECCS need to reach the efficiency of AR?

In this study, we focus on the carbon sequestration and substitution potential of AR and BECCS and do not assess the side effects of tCDR. Socio-economic considerations, including side effects, are, at least partly, implicitly accounted for in the land use scenarios. A comprehensive assessment covering ecological side effects as well as issues of governance and societal acceptance would be needed to evaluate the overall suitability of tCDR methods under certain normative targets.

2 Methods and data

2.1 Terrestrial carbon dioxide removal (tCDR) methods in JSBACH3.2

We use the land component JSBACH3.2 (Raddatz et al., 2007; Reick et al., 2021) of the Max Planck Institute Earth System Model (MPI-ESM) (Mauritsen et al., 2019). JSBACH3.2 participated in large international intercomparison studies (e.g. LU-MIP (Lawrence et al., 2016) within the CMIP6 framework (Eyring et al., 2016)), is evaluated against observational data for various ecosystem indicators (e.g. TRENDY (Friedlingstein et al., 2023)), and is a state-of-the-art concerning land management implementation. We extend JSBACH3.2 by a new plant functional type (PFT) that was originally implemented by Mayer (2017). This new PFT represents the specific physiology and phenology of highly productive herbaceous biomass plantations (HBPs) such as *Miscanthus*. We revised several photosynthetic parameters of Mayer (2017) because more recent and accurate data are available now (Li et al., 2018a). The tested parameter values based on observations for the HBP PFT in JSBACH3.2 can be found in Nützel (2024). We connected HBPs with the nitrogen cycle and the latest soil model Yasso in JSBACH3.2

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

(Goll et al., 2015). These perennial C4 crops grow under most climates and are even frost-tolerant (Naidu and Long, 2004). Their stems grow to 3–4 m in height, allowing them to produce more biomass per area than first-generation bioenergy crops. They produce leaves up to a maximum LAI of 9 m^2/m^2 (LeBauer et al., 2018). The dried stems and leaves provide feedstock for coal power plants or pyrolysis for the production of biofuels. Outside the tropics, plants typically remain on the fields throughout the winter to dry, because they are better suited for burning if the moisture content is low and the later harvest enables nutrient translocation back to the rhizome (Clifton-Brown et al., 2010). They are harvested before the new growing season when a specific heat sum is exceeded (Frühwirth et al., 2006) which allows nutrients such as nitrogen to leach back into the soil reducing the need for fertilization (Clifton-Brown et al., 2017). In particular, under a temperate climate, this reduces soil erosion and soil carbon and nutrient loss compared to conventional cultivation of annual crops that are usually harvested in autumn. Within the tropics, they are harvested at the beginning of the new year within the model. HBPs in general require less management and fertilizer input than annual crops (Christian et al., 2008). By affecting water or nutrient supplies, management can influence how much plants must invest in roots. Especially the water availability influences rooting depth and the extent of root networks (Ercoli et al., 1999). These root-to-shoot ratios range from 0.4 to 0.8 (Meyer et al., 2010) corresponding to a shoot fraction between 0.55 and 0.71 of the total biomass meaning that 55% to 71% of the total biomass production (above- and below-ground) is harvested (Mayer, 2017). We take the mean of these values and assume a harvested fraction of 63% in this study. The previous implementation of HBPs in JSBACH has been evaluated against observational data for yields and water use efficiency with satisfactory results (Mayer, 2017). A comparison against observational data of the updated HBP version used in this study is provided in section 2.4 and shown in Fig. 2.

In the absence of better information, we assume that the type of forest chosen for AR reflects the current preferences of existing forests. Thus, to represent AR in JSBACH3.2, we increase the fraction of the existing forest PFTs (tropical broadleaf evergreen trees, tropical broadleaf deciduous trees, extra-tropical evergreen trees, and extra-tropical deciduous trees) proportionally to their current fraction in each grid cell. To eliminate confounding effects of carbon sequestration through temporary forest regrowth in shifting cultivation, we use net instead of gross land-use transitions in our simulations (Wilkenskjeld et al., 2014). In the underlying land use scenario (see Section 2.2), the area used for AR and HBPs increases monotonously over time and shifting cultivation plays a minor role. We assume that the forests grow in the same areas as HBPs. While the climate, soil, and ecological conditions might not be favorable for forests in these regions, this setup is adequate for the aim of our study of a comparison of CDR methods at the same location. The low CDR potential of the forest due to unsuitable conditions would be captured by our model and thereby could find its way into subsequent decision-making processes.

2.2 Land use and climate forcing

The land surface is prescribed by spatial maps of land use and land cover classes derived from the land use harmonization project version 2 (LUH2) (Hurtt et al., 2020). LUH2 includes a harmonized set of land-use scenarios that smoothly connects historical reconstructions of land use from HYDE 3.2 and estimates of historical global wood harvest for 850–2015 (Klein Goldewijk et al., 2017) with multiple future scenarios provided by IAMs as spatio-temporal global maps. The future spatial extent of second-generation biofuels of LUH2 is given as a fraction of cropland for every grid cell and year. In the SSP1-2.6

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

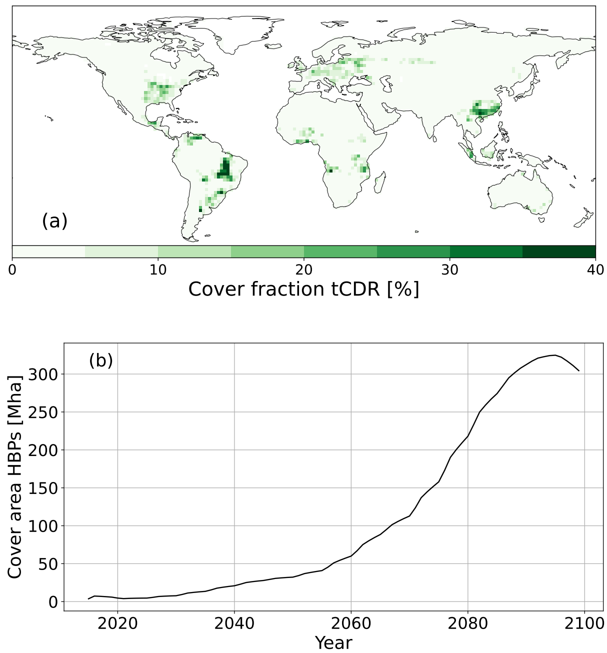

Figure 1. (a) Fraction of grid cell that is covered by a tCDR method (HBPs or AR) respectively in 2100 and (b) change in global land area [Mha] covered by HBPs or AR as compared to 2015 according to the implementation of the LUH2 SSP1-2.6 land use scenario in JSBACH3.2.

land use scenario from IMAGE3.0 (Stehfest et al., 2014; van Vuuren et al., 2017), the plantation of second-generation biofuels onset in 2015. They expand mainly on former pasture land to a global area of 330 Mha until 2095, which decreases slightly afterward until 2100 (Fig. 1 (b)). While second-generation biofuels in IMAGE3.0 include dedicated herbaceous and woody energy crops (van Vuuren et al., 2017), LUH2 does not differentiate between herbaceous and woody bioenergy. Thus, we consider only HBPs in JSBACH3.2. To assure a consistent comparison, the same areas occupied by HBPs are used for the establishment of new forests in our counterfactual AR simulation.

We use bias-corrected down-scaled climate forcing of MPI-ESM1.2-HR (Gutjahr et al., 2019) for SSP1-2.6 from the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013) (https://www.isimip.org/). MPI-ESM1.2-HR represents a climate model with low climate sensitivity (Lange, 2020; Meehl et al., 2020). The ISIMIP climate forcing is provided daily at 0.5° spatial resolution. The climate data is remapped conservatively to T63 resolution using the climate data operators (CDOs, Schulzweida (2023)). The daily climate data are transformed into sub-daily information needed in JSBACH3.2 through an internal weather generator.

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

2.3 Simulation setup

We simulate the carbon sequestration potential of AR and HBPs using JSBACH3.2 in its low-resolution configuration with a T63 global grid (corresponding to 1.875°x1.875° at the equator). We perform a spin-up of 5000 years to equilibrate the carbon and nitrogen pools followed by a historical run from 1700 to 1850 with cyclic climate forcing (1850-1870) and historical land-use change from LUH2 (see Section 2.2) (Hurtt et al., 2020). The historical period continues from 1850 to 2015 with transient climate and CO_2 forcing and land-use change. Future projections start in 2015 and run until 2100 using SSP1-2.6 LUH2 land use and SSP1-2.6 climate forcing. The simulations include disturbances of forests by wildfires and wind throw (Thonicke et al., 2010; Lasslop et al., 2014) and wood harvest from 1700 onward. We use the default product pool fractions from wood harvest in JSBACH3.2, which are PFT-specific and constant over time. In the HBPs simulation (C1HBP), the future spatial extent of HBPs is derived from the LUH2 layer that indicates the fraction of cropland used for second-generation biofuels in every grid cell and year. We compare the carbon sequestration potential of the newly implemented HBPs and AR by replacing the area occupied by HBPs in C1HBP with forests in the AR simulation (C1AR). Fig. 1(a) shows the spatial extent of second-generation biofuels in 2100 based on the SSP1-2.6 scenario of LUH2 as implemented in JSBACH3.2 (Hurtt et al., 2020).

2.3.1 Additional wood harvest in the afforestation and reforestation scenario

The wood harvest used in JSBACH3.2 is calculated by IAMs based on regional demands for wood products and harmonized by LUH2 (Hurtt et al., 2020). However, LUH2 does not provide a demand-based estimate of additional future carbon removal due to wood harvest in the C1AR. Hence, we keep the absolute amount of wood harvest equal in all simulations following LUH2 SSP1-2.6.

We give a rough supply-driven estimate of carbon that might be stored in woody products or used for energy generation due to wood harvest. There are no datasets available that project how far new forest is managed or left to natural regrowth. Thus, we assume that the new forest is managed similarly to the existing forest in the same grid cell. We implement this by increasing the absolute amount of wood harvest following LUH2 SSP1-2.6 by a ratio that reflects the additional vegetation carbon that AR areas provide. We assume that all additional bioenergy from the wood harvest is produced without CCS and FFS. We acknowledge this is just a first-order estimate, ignoring that the carbon balance of wood harvest is time-dependent and impacted by many factors including the forest age, its use for energy or products, and regional climate and environmental conditions. Future studies could apply our framework to investigate different assumptions of wood harvest in AR areas.

$$wh_{AR}(y) = wh_{LUH2}(y) \cdot \frac{Ctree_{C1AR}(y) - Ctree_{C1HBP}(y)}{Ctree_{C1HBP}(y)} \tag{1}$$

where:

wh_{AR} = Global additional wood harvest of AR [kg]

wh_{LUH2} = Global demand-based wood harvest of LUH2 [kg]

y = year

$Ctree$ = Global tree vegetation carbon in the C1AR or C1HBP scenario [GtC]

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

2.4 Model evaluation with observational yield data

We evaluate the HBP yields of our revised model version against a recent comprehensive global dataset of bioenergy crop yields compiled from scientific literature (Li et al., 2018a). It includes 990 observations of *Miscanthus* yields with and without irrigation and fertilizer amendment. Note that the observational sites concentrate on the Eastern USA and Europe, and no observations in the tropics exist. For the comparison, we use all available *Miscanthus* yields, regardless of whether fertilizer or irrigation was applied because the yields do not differ significantly from untreated yields (Li et al., 2018a; Littleton et al., 2020). We run simulations from 1980 to 2010 forced by WATCH-ERA-interim climate data (Weedon et al., 2014) mapped to T63 spatial resolution using conservative remapping. In our setup, 10% of the vegetated area in each grid cell is covered with HBPs to account for a more realistic scenario than fully covering the whole grid cell with HBPs. We apply a carbon-to-dry-matter ratio of 0.5 such that 1 t of dry biomass could substitute 0.5 t of carbon (Cannell, 2003). We compare the modeled HBP yields in the grid cell of the specific site to observed *Miscanthus* yields compiled in Li et al. (2018a) for the respective year, or years if multiple (compare Figs. 2 and 3).

We find an observed mean HBP yield of 12.7 t (dry matter) DM ha^{-1} yr^{-1} and median of 11.5 t DM ha^{-1} yr^{-1} for all sites and a modeled yield mean of 12.1 t DM ha^{-1} yr^{-1} and median of 12.7 t DM ha^{-1} yr^{-1} across all respective grid cells and respective years. The maximal observed yield is 52.2 t DM ha^{-1} yr^{-1} and the maximal modeled yield is 22.3 t DM ha^{-1} yr^{-1} (Table 1). Low yields of less than 4 t DM ha^{-1} yr^{-1} are much more common in the observations (Fig. 3) (Li et al., 2018a). Lower maximal and higher minimal modeled yields as compared to observations might be caused by the averaging effect within the large extent of the modeled grid cells, which might include other areas with sparse plant growth compared to the observation sites. Higher diversity in observed yields emerges due to different local conditions (soil, micro-climate), different management techniques (irrigation, fertilization) (Mayer, 2017) or different cultivars of *Miscanthus* (Littleton et al., 2020; Awty-Carroll et al., 2023). Therefore, we also show the spatio-temporal median values of the observations for every grid cell (Fig. 3(b)). The very low and high values are thereby ruled out and the frequency distribution agrees better with the one of modeled yields.

Compared to other modeling studies (Li et al., 2018b; Littleton et al., 2020), HBP productivity in JSBACH3.2 is similar in the middle and high latitudes, but lower in the tropics, where no observations exist. Hence, our estimate of HBP efficiency is rather conservative in the tropics. We find smaller maximal yields compared to other modeling studies (Table 1) that could be due to their higher spatial resolution (0.5°x0.5°) and generally higher yields in the tropics (Littleton et al. (2020), Li et al. (2018b)). While the global mean of the modeled yields agrees well with the observations, there are large differences for the single sites (Fig. 3) similar to Littleton et al. (2020) and Li et al. (2018b) due to the low spatial resolution of models.

2.5 Measures of efficiency

We define the efficiency of a tCDR method for a certain year as the sum of the annual mean carbon sequestered in the biosphere, the emitted carbon avoided by FFS, and stored in products and geological reservoirs (CCS) since the start year y_0 (Mayer, 2017). The carbon sequestered in the biosphere is the change in carbon density in the vegetation, soil, and litter times the spatial

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

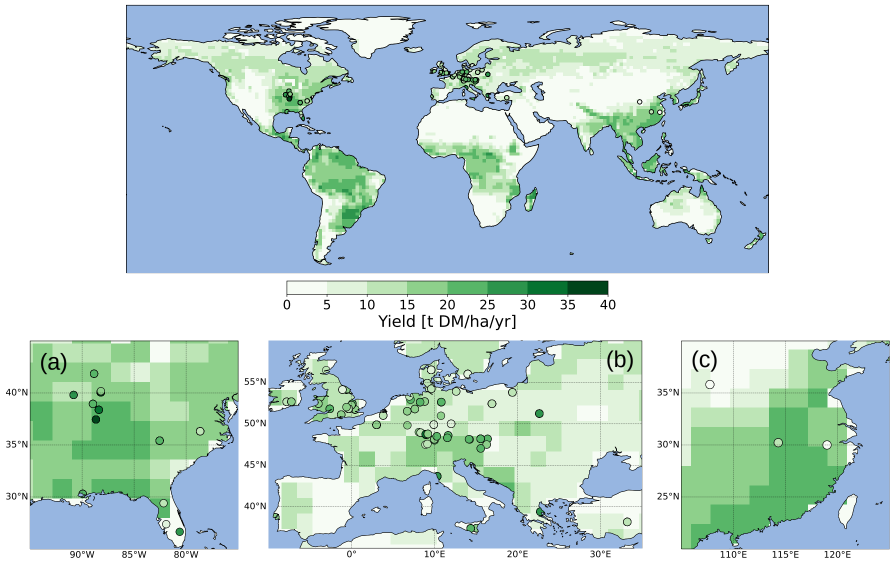

Figure 2. Modeled HBP yields in JSBACH3.2 and observed yield between between 1984 and 2006 Li et al. (2018a) (circles). We use the respective year of observed yields, or years if multiple, for evaluation. The lower panels show the zoom-in maps of (a) North America, (b) Europe and (c) East Asia.

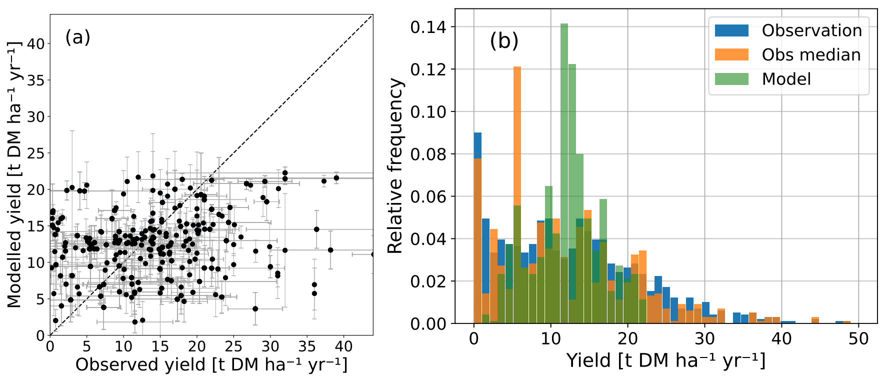

Figure 3. Modeled yields with harvest fraction 63% compared to observed yields of *Miscanthus* from Li et al. (2018a). In (a), the observed range (horizontal error bars) accounts for variation between sites and fertilizer or irrigation treatment if different sites exist within a grid cell; the modeled range (vertical error bars) reflects interannual variability if several observed yields in different years correspond to the same grid cell. The dashed line represents the 1:1 line. In (b), the relative frequency of observed values, observed median values for every grid cell, and modeled values are shown. This figure is similar to Fig. 3e–f in Li et al. (2018b) and Fig. 5 in Littleton et al. (2020).

extent of the tCDR method. Carbon removal from the atmosphere is achieved by increasing the carbon density, extending the area of AR and HBPs, or increasing the share of FFS, CCS, or carbon storage in long-lived products of harvested biomass.

https://doi.org/10.5194/egusphere-2024-1451
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Table 1. Spatio-temporal mean, median, minimum and maximum yields [DM ha^{-1} yr^{-1}] at the observed sites.

	Mean	Median	Max
	[DM ha^{-1} yr^{-1}]		
Li et al. (2018a) (obs)	12.7	11.5	52.3
Li et al. (2018a) (sim)	10.8	-	33
Littleton et al. (2020)	14.3	-	37
This study	12.1	12.7	22.3

Since we compare AR and HBPs in the same areas, differences in the CDR potential are due to the environmental, climate and CO_2 impact on carbon densities and the level of FFS (f_{FFS}) and CCS (f_{CCS}) in this study. For the main analysis of our study, we use a default value of 50% for f_{FFS}, which is the mean provided by Gallagher (2008). f_{CCS} is based on a decadal time series of primary energy production from biomass with and without CCS from the CMIP6 AR6 database (Peters et al., 2023) for the SSP1-2.6 scenario calculated with IMAGE3.0 (Fig. 4, van Vuuren et al. (2017); later on referred to as SSP1-2.6 CCS rates). In this scenario, they assume that 20% of primary energy from biomass is produced with CCS in 2050 and around 58% in 2100. We assume that the share of primary energy production for biomass with and without CCS is equivalent to the share of HBPs with and without CCS and interpolate the time series linearly over time.

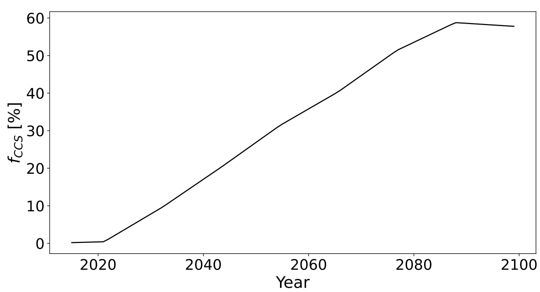

Figure 4. Fraction of primary energy from biomass with CCS on primary energy from biomass provided by the CMIP6 AR6 database (https://data.ece.iiasa.ac.at/ar6/) for the SSP1-2.6 scenario calculated with IMAGE3.0 for every decade and interpolated in between.

The spatial carbon removal potential of AR and HBPs is calculated by the following equations:

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

$$C_{AR}(y) = C_{L,AR}(y) \tag{2}$$

$$= \overline{\Delta\rho_{AR}(y)} \cdot A_{AR}(y) \tag{3}$$

$$C_{HBPs}(y) = C_{L,HBPs}(y) + \sum_{t=y_0}^{y-1} H_{HBPs}(t) \cdot (f_{FFS} + f_{CCS}) \tag{4}$$

$$= \overline{\Delta\rho_{HBPs}(y)} \cdot A_{HBPs}(y) + \sum_{t=y_0}^{y-1} H_{HBPs}(t) \cdot (f_{FFS} + f_{CCS}) \tag{5}$$

where:

C	= Total carbon captured by AR/HBPs [kg]
C_L	= Land carbon (vegetation, soil, and litter) of AR/HBPs [kg]
$\overline{\Delta\rho}$	= Annual mean change in carbon density of AR/HBPs compared to the start year [kg/m^2 (vegetation)]
A	= Area of AR/HBPs [m^2 (vegetation per grid cell)]
H_{HBPs}	= Harvested carbon of HBPs [kg]
f_{FFS}	= Efficiency of fossil fuel substitution (FFS) [%]
f_{CCS}	= Efficiency of carbon capture and storage (CCS) [%]
y	= Year
y_0	= Start year

Since the levels of FFS and CCS are additive, we can use them simultaneously to analyze their effect on the area-wise CDR potential for AR and HBPs. Overall, we identify the following 3 measures for CDR efficiency:

1. The level of FFS or CCS needed for HBPs to exceed the efficiency of AR in 2100.

$$L_{FFS/CCS}(y) = (C_{AR}(y) - C_{L,HBPs}(y)) / \sum_{t=1}^{y-1} H_{HBPs}(t) \tag{6}$$

2. The year in which the 5-years running mean of carbon sequestrated by HBPs exceeds the one of AR for the first time.

$$\tilde{y} = min\{y| \sum_{t=y-5}^{y} (C_{HBPs}(t) > C_{AR}(t) \cdot (1 + 1e - 4)\} \tag{7}$$

3. The additional area that would be needed per grid cell for HBPs to reach the efficiency of AR.

$$a_{HBPs}(y) = C_{AR}(y) \cdot A_{HBPs} / (C_{HBPs}(y)) - A_{HBPs} \tag{8}$$

where:

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

$L_{FFS/CCS}$	= Combined level of fossil fuel substitution and carbon capture and storage
a_{HBPs}	= Area of HBPs needed to reach a similar efficiency as AR [m^2]

All grid cells for which the HBPs fraction is smaller than 0.1% are masked out to avoid numerical artifacts.

3 Results

In this section, we at first assess the efficiency of carbon removal from the atmosphere by the two tCDR methods in a SSP1-2.6 land use and climate scenario, which includes carbon sequestration in vegetation, litter, soil and the proportion of harvested HBP yield used for FFS and CCS. We further evaluate the different measures of efficiency described in Section 2.5, i.e. the level of FFS, the temporal dynamics, and the area of cultivation comparing AR and HBPs. Thereby, we differentiate between HBPs with CCS (equivalent to BECCS) and without CCS.

3.1 Efficiency of AR and HBPs

The amount of CDR realized by HBPs and AR in the same areas in 2100 differs substantially. The most important factors determining the difference between both are assumptions on levels of CCS and FFS for BECCS (Fig. 5(a)). For 50% FFS and SSP1-2.6 CCS rates (Fig. 4), the carbon potential of HBPs outpaces the one of AR after 2071 and is about twice as high towards the end of the century. HBPs become even more efficient in storing carbon than AR in the 100% FFS and 100% CCS case (a factor of three). In contrast, if theoretically no FFS and no CCS are assumed for HBPs, i.e. all bioenergy is used in addition to fossil fuel-based energy, AR is more efficient towards the end of the 21st century, storing about twice as much carbon as the HBP fields do. Depending on FFS and CCS levels, HBPs sequester 24–158 GtC until 2100, whereas AR sequesters around 53 GtC. The accumulated harvested HBP yield until 2100 is 67 GtC, reaching levels of about 2.5 GtC harvested per year towards the end of the century (Fig. 5(b)). The amount of CCS accumulates to 34 GtC until 2100 assuming SSP1-2.6 CCS rates. The difference in tCDR potential only becomes substantial after around 2070, when the land conversion to tCDR increases rapidly in the SSP 1-2.6 land use scenario (Fig. 1). The cumulative global wood harvest as estimated by the LUH2 data ($wh_{LUH2}(2100)$) between 2015 and 2100 is 91.6 GtC. Our estimate based on Section 2.3.1 reveals an additional wood harvest wh_{AR} of 1.29 GtC. We argue that wood harvest will have a relative small effect on the carbon cycle compared to carbon sequestration by AR (Fig. 5) and thus we will not further consider it in our global estimates.

The spatial difference in CDR potential in 2100 between C1HBP with 50% FFS and SSP1-2.6 CCS rates and C1AR is shown in Fig. 6(a). The CDR potential of HBPs is almost everywhere higher than that of AR, especially in South American grasslands, and Southeast Africa. The only exception is Southeast China, where even for 50% FFS and with CCS, AR stores slightly more carbon. When no FFS and no CCS are assumed for the HBPs (Fig. 6(b)), the potential of AR is higher everywhere, especially in Southeast China and the Eastern USA. The difference in carbon stored stems mainly from the vegetation pool with its high

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

carbon storage in trees in the AR scenario (Fig. A1 (a)). By contrast, the soil and litter carbon pools show substantially fewer changes between the two CDR methods (Fig. A1 (b, c)).

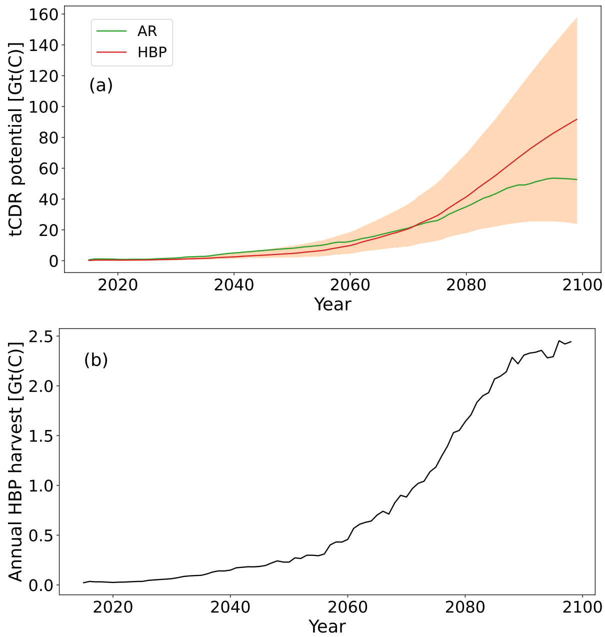

Figure 5. (a) tCDR potential of AR and HBPs assuming 50% FFS and SSP1-2.6 CCS rates from 2015 to 2100 (Fig. 4). The shaded areas indicate the range of tCDR potential without FFS and CCS to 100% FFS and 100% CCS. (b) Annual harvest of HBPs [GtC].

3.2 Level of Fossil fuel substitution (FFS)

Given that for 0% FFS, HBPs are less efficient in sequestering carbon until 2100 as compared to AR while for 100% FFS, HBPs exceed the CDR potential of AR in most regions, there must be a FFS level where the efficiency of HBPs and AR are similar. The lower the level of FFS that is needed for HBPs to reach a similar efficiency as AR, the more potential the cultivation of HBPs to remove carbon in a region has. We find that, as previously noted, even for 100% FFS but without CCS, HBPs do not reach the CDR levels of AR in Southeast China until 2100, which is one of the hotspots of tCDR deployment in SSP1.2-6 (Fig. 1. In some areas of Eurasia, the East Coast of the USA, and South America, the level of FFS without CCS needed for HBPs to exceed the efficiency of AR in 2100 is very high ($>$ 80%) (Fig. 7(a)). The FFS level needed for HBPs to exceed the efficiency in AR is at a medium level, between 50% and 80%, in Europe, the Kongo basin, South American grasslands, and the Eastern USA. For Subsaharan Africa, the Australian coast, and Argentina the FFS level needed is the lowest ($<$ 50%). With SSP1-2.6 CCS rates, HBPs become more efficient in 2100 than AR even without additional FFS (Fig. 7(b)). Even in regions

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Preprint. Discussion started: 22 May 2024

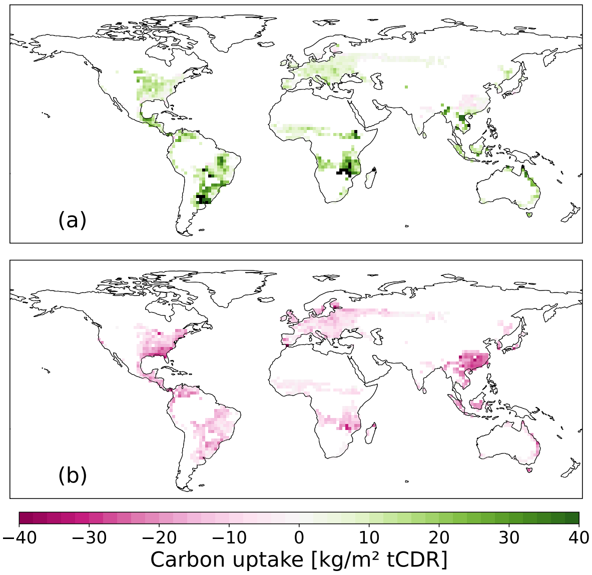

Figure 6. Difference in tCDR potential per area [kg/m^2 tCDR] in 2100 between HBPs and AR (a) for 50% FFS and SSP1-2.6 CCS rates and (b) without FFS and CCS. Positive values indicate that HBPs store more carbon than AR.

where AR is more efficient such as Eurasia, the East Coast USA, and Southeast China, HBPs become more efficient with CCS and around 50% FFS.

3.3 Temporal dynamics in the SSP1-2.6 scenario

In our simulations, bioenergy plants store more carbon in the soil than AR in the vegetation in Eurasia and the Eastern USA, whereas forests can sequester more carbon in the vegetation and litter over long periods (Fig. A1). If the harvested carbon from HBPs is used for FFS or stored (CCS), HBPs might become more efficient in removing carbon from the atmosphere over time because they regrow quickly and are harvested every year. Additionally, forests tend to absorb less carbon with increasing age (Pugh et al., 2019), compensating/fostering effects of rising/falling CO_2 levels, which enhance/reduce net ecosystem productivity even in old-growth forests (Luyssaert et al., 2008, 2021). However, forest age is not represented explicitly in JSBACH3.2. Instead, the impact of forest age on plant productivity is only implicitly represented through structural limits. Assuming 50% FFS and SSP1-2.6 CCS rates, HBPs become on average more efficient around 2070 (Fig. 5).

We evaluate the time between the onset of tCDR and the year in which the carbon harvested and stored through HBPs will exceed that of forests spatially if 50% FFS of HBPs is assumed. The year of tCDR onset is defined as the year when the respective tCDR method covers more than 0.1% of the grid cell. We find that especially in Southeast China, and some areas of the Eastern USA and Eurasia, HBPs do not reach the potential of AR without CCS until 2100 (Fig. 8(a)). Note that in these areas the tCDR onset happens late in the century, between 2060 and 2070 (Fig. 8(c)). Especially in Eastern Europe, HBPs

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

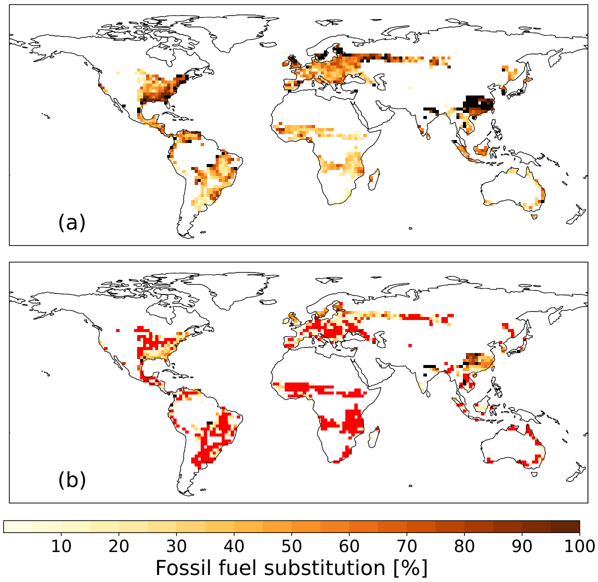

Figure 7. Level of fossil fuel substitution (FFS) [%] needed for HBPs to exceed the efficiency of AR in 2100 (a) without carbon capture and storage (CCS) and (b) for SSP1-2.6 CCS rates. Black color indicates that HBPs do not exceed the effectiveness of AR even with 100% FFS, while red color indicates grid cells where HBPs exceed the efficiency of AR without FFS.

become already more efficient than AR shortly after their plantation, whereas in the South American grasslands HBPs need between 20 and 50 years to become more efficient although in both regions, the plantation starts in the first half of the 21st century. With CCS (Fig. 8(b)), the time period for HBPs to become more efficient is shortened. Even in those regions where the efficiency would not be reached until 2100 without CCS (Eastern USA, Eurasia, Southeast China) and where the tCDR onset is late, HBPs become more efficient with CCS within this century.

We conclude that in this specific SSP1-2.6 land use and climate scenario, the time until HBPs become more efficient than AR depends very much on the region. The additional implementation of CCS will shorten this time or even enable HBPs to become more efficient within the century. The potential of AR to store additional carbon in above-ground biomass decreases over time, whereas the cumulative harvest of HBPs increases steadily. Thus, HBPs have an advantage over long periods in most regions, especially when CCS is realized in addition to FFS.

In Fig. A2, we show the relative tCDR potential from HBPs compared to AR globally as a function of different levels of FFS and for different years. We find that, without CCS, HBPs become only more efficient than AR for a level of FFS above 50 % and never before 2060. With CCS, HBPs become more efficient for any level of FFS by 2100 but also for that case, never before 2060. That confirms our finding that HBPs only exceed the efficiency of AR over long periods, independent of the level of FFS and assuming plausible CCS.

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

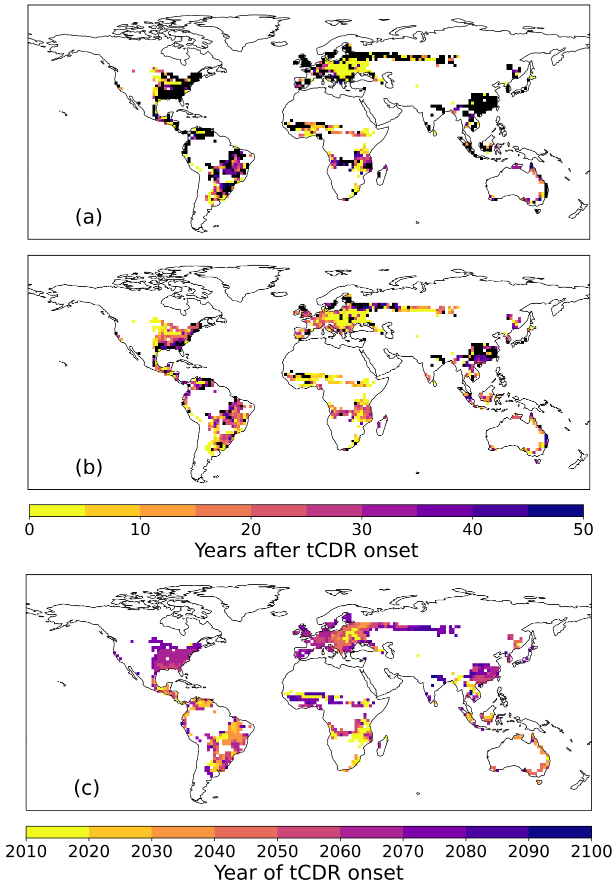

Figure 8. Years after the onset of the CDR method when HBPs become more efficient than AR per grid cell assuming 50% FFS (a) without CCS and (b) with CCS. (c) shows the year of tCDR onset (> 0.1% of grid cell). Black color indicates grid cells, where HBPs are less effective until 2100.

3.4 HBPs area needed to reach efficiency of forests

We find that more than 4.000 km^2 per grid cell of bioenergy plantations are necessary in Southeast China when no CCS is assumed (Fig. 9 (a)), as compared to AR in our SSP1-2.6 scenario. This area corresponds to roughly 12% of the land given the size of a grid cell is up to 43.000 km^2 in the tropics and about 20.000 km^2 in the higher latitudes (62.5° N). The area is slightly positive in Russia, the East Coast USA, and Southeast China meaning that more area is needed for HBPs compared to AR to reach the same efficiency. It is slightly negative in Europe, Subsaharan Africa, the Australian coast and the Eastern USA, meaning that less area is needed for HBPs compared to AR. In the South American grasslands and Southeast Africa, much less area of HBPs is needed to be as efficient as AR. With CCS (Fig. 9(b)), HBPs need less area to be as efficient as AR

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

340 in almost all regions, except for Southeast China. In the South American grasslands, even more than 4000 km^2 of extra area would be needed for AR to reach the efficiency of HBPs.

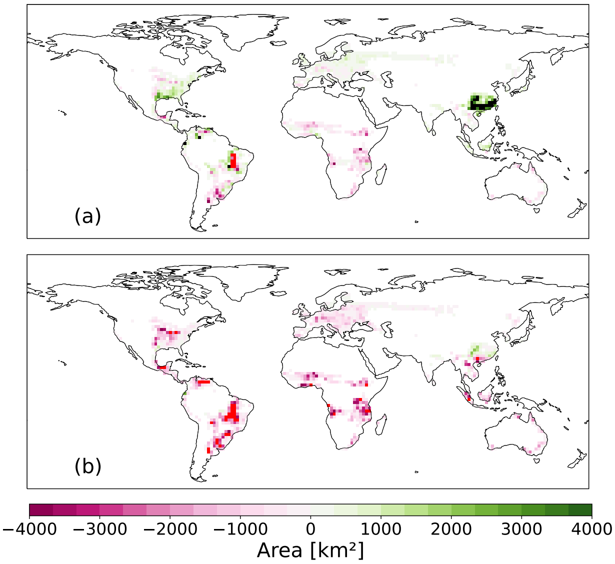

Figure 9. Additional HBPs area [km^2] that is needed per grid cell to reach the efficiency of AR in 2100 assuming 50% FFS (a) without CCS and (b) with CCS. Red color indicates grid cells where implementation of HBPs could spare more than 4000 km^2 of land area to reach similar efficiency as AR.

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

4 Discussion

Due to the annual HBP harvest and the saturation of carbon sequestration in forests, HBPs have an advantage over forests in the long term. Without FFS and CCS, HBPs sequester less carbon than AR globally until 2100. In the case of 50% FFS and assuming SSP1-2.6 CCS rates (Fig. 4), the efficiency of HBPs is higher in most regions compared to AR by the end of the century. There are substantial regional differences in CDR potential in the SSP1-2.6 scenario. In Southeast China, the East Coast USA, and parts of Eurasia, AR is more efficient than the cultivation of HBPs. In these regions, HBPs reach the efficiency of AR later, at a higher FFS level, or if more area is available. However, it must be considered that the onset of tCDR in these regions happens mostly after 2050 in the SSP1-2.6 scenario and thus, they have less time to establish. In contrast, in the South American grasslands and Southeast Africa, where the onset of tCDR happens before 2050, HBPs have an advantage over AR, the efficiency is reached earlier and at lower levels of FFS, or less area is needed. In other regions, such as the Eastern USA, Europe, Subsaharan Africa, and Central America, it depends mainly on the level of CCS and FFS which tCDR measure is more efficient.

4.1 Comparison with previous studies

Table 2 shows the results of earlier DGVM/ESM studies on future tCDR potential. The tCDR potential per area in our study agrees well with these studies for a similar climate scenario for BECCS. The studies with a higher emission climate scenario (Mayer, 2017; Melnikova et al., 2022) project a higher tCDR potential per area. The high uncertainty in BECCS potentials stems from a large variety of CCS and FFS within the studies. Most studies do not consider FFS whereas Cheng et al. (2024) show a very high spread in FFS due to different technological and economic scenario assumptions. Several studies assume a fixed level of CCS higher than 50% whereas others do not consider CCS. However, our results are at the lower end for AR. BECCS exceeds the climate mitigation potential of AR globally in a fully coupled SSP5-3.4-OS overshoot scenario (Melnikova et al., 2023). In their study, the efficiency varies regionally and temporally and depends critically on the CCS conversion efficiency of bioenergy crops. Although they use a different future scenario and a different model, they also found that BECCS is more efficient on longer time scales similar to Zhao et al. (2024). Most ESMs in CMIP6 do not distinguish second-generation bioenergy crops and other crops yet (Krause et al., 2017; Harper et al., 2018; Melnikova et al., 2021). This may be a key reason why Harper et al. (2018) find a potential of only 20 to 35 GtC until 2100 to meet the 1.5°C temperature target compared to 67 GtC in our study using the SSP1-2.6 scenario, although the area used for bioenergy crops is higher (up to 550 Mha) than in our study (up to 330 Mha). Mayer (2017) use a previous version of JSBACH and find a HBP harvest of 293 GtC (mean of 55% and 71% HBP harvest) on 560 Mha for RCP4.5. The lower productivity in our model version can be explained by the larger area, later cultivation of HBPs in the SSP1-2.6 land use scenario, a different climate forcing, the inclusion of nitrogen limitation, and the use of prescribed maps instead of land use transitions. Harper et al. (2018) identify the land cover transition of bioenergy plants as a critical factor. If bioenergy plants replace high-carbon content ecosystems, e.g. forests, forest-based mitigation could be more efficient for atmospheric CO_2 removal than BECCS (Searchinger et al., 2018;

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

Seo et al., 2024). In the SSP1-2.6 land use scenario that we use in our study, HBPs mainly replace pasture, whereas the net forest area increases in the future limiting the danger of deforestation due to HBPs in our scenarios.

4.2 Fossil fuel substitution

The future substitution of fossil fuel by bioenergy depends on several factors: (1) the energy conversion between bioenergy and fossil fuels (i.e. how much of each is needed to produce the same amount of energy) and the type of biofuel and displaced fuels, (2) the carbon content of the bioenergy and the fossil fuel, and (3) to what extent bioenergy is displacing fossil fuels. Cheng et al. (2022) prescribe a conversion factor up to 234% assuming that bioenergy is fully displacing fossil fuels and assuming maximal inefficient fossil-fuel-to-energy conversion. As these assumptions are unlikely, we used a more plausible level of FFS between 0% and 100% with a default of 50% as in Gallagher (2008) (FFS 30%-70%) similar to the assumptions by Kalt et al. (2019)). They consider different scenarios, including one with a FFS factor between 0% and 90% depending on the energy conversion and type of displaced fuel and one with a dynamic FFS assuming a declining FFS factor over time from 55%-70% in 2020 to 25%-40% in 2100 due to the upscaling of renewable energy sources. In our simulations, we chose a constant level of FFS because we assume that both bioenergy and other renewables replace fossil fuels in a similar manner (van Vuuren et al., 2017). In addition, we investigate the impact of different levels of FFS in Fig. A2. The IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation provides FFS factors between -9% for diesel and 78% for coal from several local studies (Chum et al., 2011). Because the FFS factor can vary in space and time, we support our study with a sensitivity analysis, where we determine the tCDR potential of HBPs relative to AR over time in a SSP1-2.6 scenario and as a function of the level of FFS (Fig. A2) inspired by Kalt et al. (2019). We find that an increasing level of FFS reduces the time until HBPs become more efficient than AR but that happens in no case before 2060.

4.3 Carbon capture and storage

The latest IPCC Assessment report estimates about 8.7–211 (median 90.3) GtC (1.5°C temperature target) and 47–177 (median 78.6) GtC (2°C temperature target) captured from BECCS (IPCC Working Group III (2022b), Table 3.5). The large spread reflects the high uncertainty of BECCS deployment in the future among the IAM scenarios. The amount of captured carbon through BECCS in our study (34 GtC) is below average compared with the amount projected in the IPCC. Compared to other studies, our assumptions on CCS are rather conservative. While we assume a consecutive rise of CCS up to 58% following the CMIP6 scenario database for SSP1-2.6 (van Vuuren et al., 2017), Rose et al. (2014) assume between 50% and 97% in 2050 and between 86% and 100% in 2100 for different IAMs. However, only a tiny fraction of current CDR results from novel CDR methods, including BECCS (Smith et al., 2023) and future projections of CCS are very uncertain (IPCC Working Group III (2022b), Table 3.5). Therefore, our assumptions on CCS deployment are rather conservative. Barriers to the upscaling of CCS facilities include the current lack of infrastructure for large-scale power generation from biomass with subsequent CCS, the currently high costs (Budinis et al., 2018), the need for governance and monitoring of CCS facilities, legal constraints and public perception of geologic storage of CO_2 (Vaughan and Gough, 2015; Smith et al., 2023). While the CDR potential is very

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

sensitive to CCS and FFS, the assumptions on either of them are highly uncertain in the literature. Thus, the underlying values have to be made transparent, and a sensitivity analysis should be provided in future studies.

4.4 Side effects of tCDR

Several trade-offs and side effects occur in connection with tCDR and might limit their efficiency. Previous studies found that the land, water, and fertilizer, especially for first-generation bioenergy plants, required by BECCS could cause deforestation, exacerbate water stress, and pose a risk to food security (Creutzig, 2016; Smith et al., 2016; Boysen et al., 2017; Humpenöder et al., 2018; Roe et al., 2019; Cheng et al., 2022). These negative side effects can be alleviated by e.g. using crop residues for bioenergy production. Furthermore, the extensive cultivation of bioenergy plants, wood plantations, and forest monocultures may harm biodiversity (Veldman et al., 2015; Hanssen et al., 2022; Searchinger et al., 2022).

4.5 Limitations

Our results come with several caveats. We did not perform coupled simulations with a global circulation model. Thus, we can not evaluate the climate feedback of tCDR methods. Those include biogeochemical effects through altering the atmospheric CO_2 due to land use change and biogeophysical effects due to changes in surface properties such as albedo and roughness length (Winckler et al., 2019; Pongratz et al., 2021). These non-CO_2 effects could counteract up to one-third of the climate effect of carbon emissions due to deforestation (Weber et al., 2024). While CCS can store carbon permanently, the durability of the carbon sequestration of AR is uncertain. Either carbon is stored in woody products or released back into the atmosphere after trees die or short-lived products decay. In addition, the risk of disturbances from fires, wind throw, droughts, and parasites increases with climate change and might limit the permanent storage of CO_2 in trees (Seidl et al., 2017; Anderegg et al., 2020, 2022). These effects are not yet represented well in state-of-the-art land surface models used in CMIP6 projections (Fisher et al., 2018; Anderegg et al., 2022) meaning that the durability of forests is potentially overestimated in our study. We do not assess the sensitivity of our results towards different types of management, such as irrigation or fertilization. Instead, the harvested nitrogen is applied as a fertilizer to the soil which is the standard procedure for crops in JSBACH3.2. However, in general, HBPs need little irrigation and fertilizer (LeBauer et al., 2018; Li et al., 2018a; Cheng et al., 2020). IAMs include agricultural and forest residues and waste fraction for BECCS in addition to HBPs, which we did not consider in our study. Including these additional biomass sources for energy production would likely increase the potential of BECCS. The study does not account for additional wood harvest in the AR scenario. Even when assuming AR is being used for wood harvest in the same intensity as the other, typically older, forest in the grid cell, additional global wood harvest from our AR scenario yields a relatively small amount of cumulative sequestered carbon of 1.3 GtC between 2015 and 2100, which does not substantially alter our results (Section 2.3.1). Further, the benefits of storing carbon in wood long-lived products or using wood for bioenergy might be outweighed by decreased carbon sequestration in the forest and increased CO_2 emissions to the atmosphere if used for bioenergy (Obermeier et al., 2021; Soimakallio et al., 2021).

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

5 Conclusions

This study highlights the different measures of efficiency affecting the biogeochemical climate mitigation potential of bioenergy with carbon capture and storage (BECCS) and afforestation and reforestation (AR): the location and spatial extent of the plantations, the level of fossil fuel substitution (FFS) through bioenergy plants, the share of bioenergy that is captured and stored in long-lived products or geological reservoirs (CCS), and the temporal dynamics. Depending on the research question or the climate mitigation target set, different measures for the efficiency of tCDR are meaningful: for reaching our near-term climate goals, the time horizon is key, while for biodiversity and spatial planning, the additional area measure is meaningful and the level of FFS and CCS is a question of technical feasibility.

In our study, the benefit of BECCS to remove carbon only becomes substantial after around 2070, when the areas converted to either AR or HBPs increase rapidly in the SSP1-2.6 land use scenario. Thus, BECCS has a higher carbon removal potential over a longer time period compared to AR, especially in the South American grasslands and Southeast Africa, but will not contribute substantially to reaching short-term climate mitigation targets. However, the temporal dynamics of tCDR methods are scenario-specific. An idealized setup where all tCDR is applied simultaneously and everywhere would help to compare the CDR efficiency across time and space more precisely. Further, the efficiency of BECCS as compared to 'nature-based solutions' like AR will depend critically on the upscaling of CCS facilities, replacing fossil fuels with bioenergy in the future, and the planting of bioenergy crops in suitable locations that do not harm biodiversity, water retention, or risk food security. We show, for the first time, how these different measures can be considered simultaneously within a consistent setup as a base for a sensible balancing of interests.

Appendix A: Vegetation, soil, and litter carbon

Author contributions. JP initialized the project and provided the research idea. SE designed, performed and analysed the simulations and wrote the manuscript. DM implemented HBPs in JSBACH in a previous model version. SF, TN and SE ported and adapted the code to

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

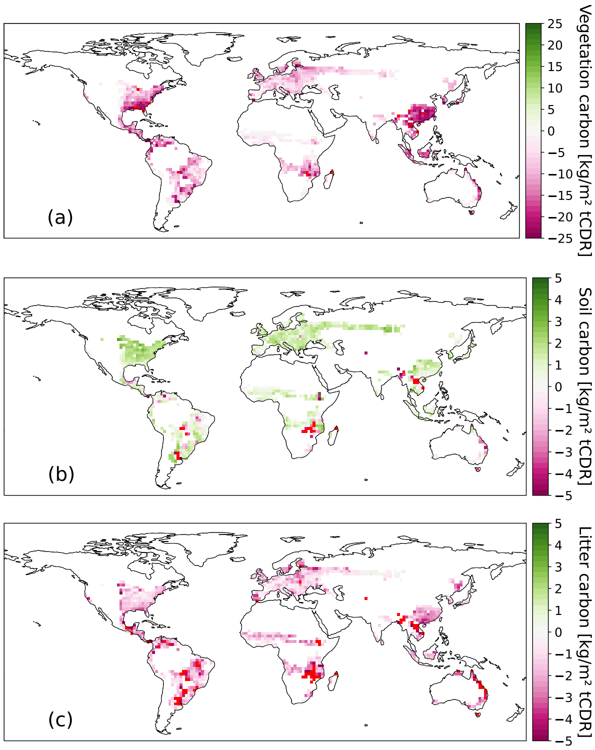

Figure A1. Difference in vegetation (a), soil (b), and litter (c) carbon [kg/m^2 tCDR] between HBPs and AR in 2100. Note that the scales differ. Red color indicates grid cells with values lower than the minimum value of the scale. Positive values indicate that HBPs store more carbon than AR. Note that this excludes carbon removal through CCS and FFS.

JSBACH3.2 and connected the HBP implementation with the N cycle. TN revised the HBP parameter values. SE and TN evaluated the revised HBP version against observational data. All co-authors proofread and provided input to the model design and the manuscript.

Competing interests. The authors have no competing interests to declare.

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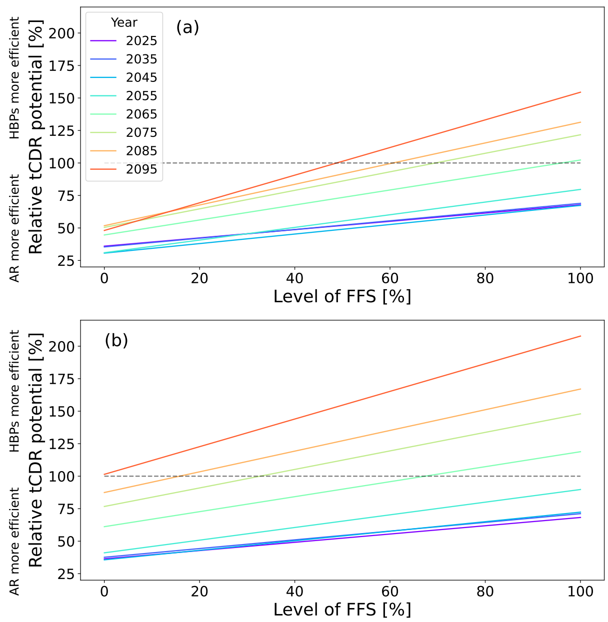

Figure A2. Relative tCDR potential of HBPs in contrast to AR (i.e. value for HBPs divided by that for AR) depending on different levels of FFS and years (a) without and (b) with CCS in the SSP1-2.6 scenario.

https://doi.org/10.5194/egusphere-2024-1451
Preprint. Discussion started: 22 May 2024

Table 2. Comparison of tCDR efficiency with previous global model studies.

Study	Area [Mha]	tCDR [GtC]	tCDR/Area [tC/ha]	Climate scenario	Land use scenario	Assumptions	FFS [%]	CCS [%]
Bioenergy with Carbon Capture and Storage (BECCS								
Cheng et al. (2024)	1760	78 - 621	44 - 353	SSP2-2.6	SSP2-2.6 (IAM—GCAM)	large uncertainty of FFS	31 - 234	16 - 57
Harper et al. (2018)	550	29 - 122	53 - 222	SSP2-1.9	SSP2-1.9 (IMAGE3.0)	first-generation BE	-	60
	325	35 - 127	108 - 391	SSP2-2.6	SSP2-2.6 (IMAGE3.0)	first-generation BE	-	60
Krause et al. (2017)	363/493	99/125	201/344	RCP2.6	IMAGE3.0/MAgPIE	bioenergy crop as corn	-	100
Melnikova et al. (2023)	$\sim$ 500	335 - 430	670 - 860	SSP5-3.4-OS	SSP5-3.4-OS	generic crop type with higher soil carbon turnover, higher harvest fraction	-	50 - 90
Mayer (2017)	560	390 - 469	696 - 838	RCP4.5	abandoned agriculture areas		30 - 70	-
This study	330	24 - 158	73 - 479	SSP1-2.6	SSP1.2-6		50	0 - 58
Afforestation/Reforestation (AR)								
Cheng et al. (2024)	1070	242 - 483	226 - 451	SSP1-2.6	SSP1-2.6 (IAM—GCAM)	include wood products		
Krause et al. (2017)	628/772 (natural vegatation)	106/113	169/146	RCP2.6	IMAGE3.0/MAgPIE	do not include wood harvest		
Mayer (2017)	840	212	252	RCP4.5	abandoned agricultural areas	include wood harvest		
Melnikova et al. (2023)	$\sim$ 600	172	287	SSP5-3.4-OS	SSP5-3.4-OS	do not include wood harvest		
Sonntag et al. (2016)	840	215	256	RCP8.5	RCP4.5	include wood harvest		
This study	330	53	161	SSP1.2-6	SSP1.2-6	do not include additional wood harvest for AR		

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