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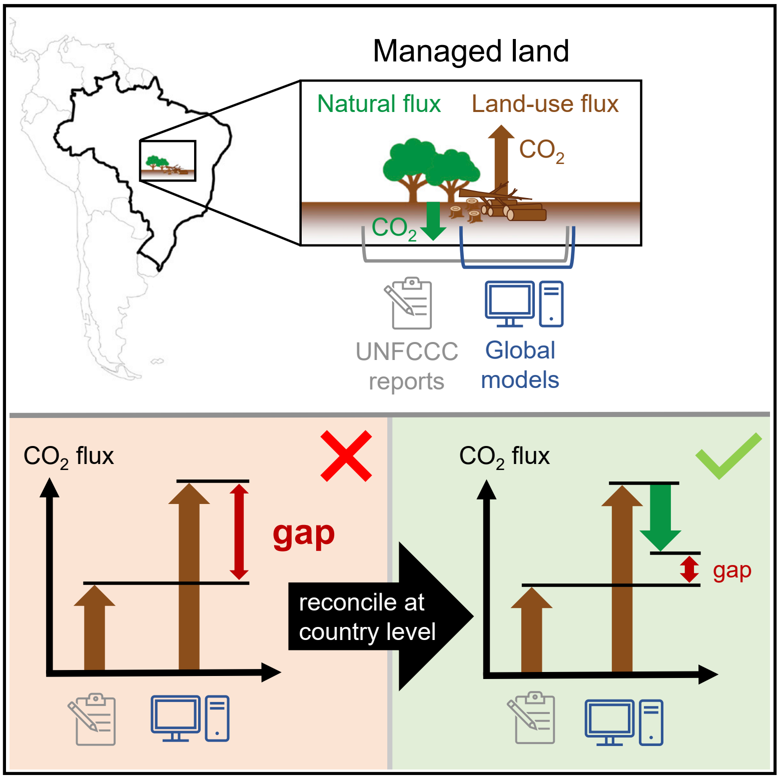
Article

Differences in land-based mitigation estimates reconciled by separating natural and land-use CO_2 fluxes at the country level

Graphical abstract



Highlights

- Land-use flux estimates from models and reports can be reconciled at country level
- Gaps between land-use flux estimates are reduced in the USA, Russia, China, and Brazil
- Remaining discrepancies due to country-specific differences in methods/definitions
- The reconciliation allows us to reassess countries' land-based mitigation ambitions

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In brief

Estimates of land-use-related CO_2 fluxes from global models and national reports to the UNFCCC can differ due to methodological and definitional discrepancies. Previous works established an adjustment to reconcile both estimates, achieving consistency at the global level. We apply this approach to eight countries in 2001–2015, evaluate the performance of the approach at the country level, and identify potential reasons for remaining differences. The result shows that more consistent estimates of land-use-related CO_2 fluxes at the country-level can improve the assessment of national land-based mitigation ambitions.

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Differences in land-based mitigation estimates reconciled by separating natural and land-use CO_2 fluxes at the country level

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SCIENCE FOR SOCIETY Accurate and consistent estimates of greenhouse gas emissions are essential for climate mitigation. Yet, recent work has shown that estimates of land-use-related CO_2 fluxes from global models and from country reports to the United Nation Framework Convention on Climate Change (UNFCCC) differ because of methodological and definitional discrepancies. This leads to partial double counting of the natural CO_2 uptake by soil and vegetation, causing an overestimation of the remaining carbon budget to limit global warming to 1.5°C or 2°C. An adjustment to reconcile model- and report-based estimates has been established recently, achieving consistent estimates at global level.

In our study, we apply and evaluate this approach at the country level. We show that the adjustment is generally successful at country level as well and identify potential reasons for remaining differences. Our analysis allows the reassessment of countries' land-based mitigation targets and supports a fair burden-sharing across countries.

SUMMARY

Anthropogenic and natural CO_2 fluxes on land constitute substantial CO_2 emissions and removals but are usually not well distinguished in national greenhouse gas reporting. Instead, countries frequently combine natural and indirect human-induced CO_2 fluxes on managed land in their reports, which diminishes their usefulness for designing policies consistent with climate mitigation targets. Here, we separate natural and land-use-related CO_2 fluxes from national reports in eight countries using global models to improve the assessment of attribution of terrestrial CO_2 fluxes to direct anthropogenic activities. In most investigated countries, the gap between model-based and report-based CO_2 flux estimates is reduced if natural and indirect human-induced CO_2 fluxes on managed land are considered. Further examinations show that remaining differences are linked to country-specific discrepancies between model-based and report-based estimates. Separating natural and land-use-related CO_2 fluxes at national scales supports a fair burden sharing of climate mitigation across countries and facilitates the assessment of land-based mitigation ambitions.

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INTRODUCTION

According to the Global Carbon Budget 2021 (GCB2021[1]), CO_2 fluxes from land use, land-use change, and forestry (LULUCF) accounted for 12% of total anthropogenic CO_2 emissions in the last 20 years while land simultaneously provided a natural sink for 29% of all anthropogenic CO_2 emissions. This dual role of being both an anthropogenic net source and a natural sink of CO_2 makes land a promising target for climate mitigation measures. Recent years have seen a growing scientific and political interest in land-based climate mitigation, driven by the prospect of storing large amounts of carbon through afforestation/reforestation and in wood products, bioenergy with carbon capture and storage (BECCS), and other natural climate solutions.[2] Providing reliable and consistent estimates of CO_2 fluxes from LULUCF and natural terrestrial CO_2 fluxes is thus a key element in support of countries' efforts to reach the goal of the Paris Agreement to hold global warming "well below 2°C."[3]

Anthropogenic CO_2 fluxes from LULUCF are estimated independently by global carbon cycle models and by reports that countries are required to submit periodically to the United Nation Framework Convention on Climate Change (UNFCCC). Comparisons of both estimates revealed a substantial gap,[4] globally amounting to about 6 Pg CO_2 per year in 2000–2019.[1] This gap was mainly attributed to methodological discrepancies between models and country reports[5]: following the guidelines of the Intergovernmental Panel on Climate Change,[6] country reports to the UNFCCC in most cases consider all CO_2 fluxes on managed land as anthropogenic, regardless of whether they are directly human-made (e.g., from land-use change, harvest, and subsequent regrowth), caused by indirect anthropogenic effects (e.g., due to CO_2 fertilization), or entirely natural (e.g., due to wildfires or natural climate variability). In contrast, global models only consider direct emissions due to LULUCF as anthropogenic. Current approaches that combine data from models and country reports, e.g., to assess the progress toward global mitigation targets, thus risk double-counting parts of the natural CO_2 land sink, causing an erroneous overestimation of the amount of anthropogenic CO_2 being removed by land ecosystems and hence an overestimation of the remaining carbon budget. This enhances the risk of missing the goal to keep warming below 1.5°C or 2°C.[5]

The extent to which natural CO_2 fluxes and CO_2 fluxes due to indirect anthropogenic effects are included in LULUCF flux estimates may vary across countries. Here, we reconcile anthropogenic CO_2 fluxes from LULUCF at the country level by investigating eight countries/regions with high LULUCF fluxes, namely the USA, Russia, Canada, EU27 and the United Kingdom (EU27&UK), China, Brazil, Indonesia, and DR Congo, based on simulations from global carbon cycle models. We analyze the period 2001–2015, for which the UNFCCC country reports of the investigated countries deliver the most complete data. Our approach yields reduced gaps between model- and report-based CO_2 flux estimates in most of the investigated countries/regions. We further identify potential reasons for the remaining discrepancies, which can serve as guidance for future efforts to obtain more consistent LULUCF flux estimates from global carbon cycle models and from UNFCCC reports. Our analysis allows us to reassess countries' land-based mitigation targets and supports a fair burden-sharing across countries.

RESULTS

Separating natural and land-use-related CO_2 fluxes

In the context of GCB2021, anthropogenic CO_2 fluxes from LULUCF are estimated by bookkeeping models, which consider processes such as conversion of forests to agricultural areas, wood harvesting, and abandonment of farmland.[1] High LULUCF emissions are predominantly found in tropical countries (Figure 1A), due to deforestation and degradation of carbon-dense vegetation,[7,8] while regrowth after historical wood harvest and deforestation causes high CO_2 removals in the USA, Russia, and Europe.[9] Natural CO_2 fluxes on land are quantified by simulations with dynamic global vegetation models (DGVMs), which estimate the impacts of climate variability, climate change, and rising atmospheric CO_2 concentrations on vegetation dynamics, considering processes such as CO_2 fertilization, nitrogen deposition, and, in some cases, wildfires.[10] To eliminate impacts of LULUCF, estimates of natural terrestrial CO_2 fluxes are based on DGVM simulations that use pre-industrial land cover.[1] Natural CO_2 fluxes on land constitute a CO_2 sink in almost all regions of the world (Figure 1B), with forests contributing 81% globally (DGVM multi-model median; 73%–84% interquartile range of DGVM estimates). Due to this predominant importance of forests and consistent with UNFCCC reports, our analysis focuses on managed forests. Following Grassi et al.,[5] we approximate their extent using a map of non-intact forests, which globally agrees well with the total area of managed land in UNFCCC reports.[11] We further apply a gridded weighting field defined as a fraction of today's forest cover to pre-industrial forest cover to account for changes in forest cover since pre-industrial times (see experimental procedures). About 61% (5.1 Pg CO_2 per year) of the global natural terrestrial CO_2 sink during 2001–2015 was due to carbon uptake in managed (i.e., non-intact) forests. Related to the varying proportion of managed forest areas, the fraction of natural CO_2 sinks in managed forests differs across countries (Figure 1B), indicating that the size of the natural fluxes accounted for in the country reports does not necessarily reflect the country's relative importance for the global natural CO_2 sink. Noteworthy, all models agree that natural fluxes in managed forests constitute a CO_2 sink in all investigated countries. We add these natural sinks in managed forests to the LULUCF emissions estimated by bookkeeping models to make them comparable to the UNFCCC country report estimates.

Reconciling CO_2 fluxes at the country level

In the majority of the eight countries depicted here, including natural CO_2 fluxes in managed forests substantially reduces the gap in LULUCF fluxes (by up to 71%) between model estimates and country reports (Figure 2). This highlights that the methodology evaluated by Grassi et al.[5] on a global scale to make LULUCF estimates more consistent generally also holds at country level. Including natural CO_2 fluxes shifts the reported CO_2 fluxes downward toward lower emissions or larger sinks, considerably reducing the pronounced gaps in the USA (−52%), Russia (−71%), China (−28%), Indonesia (−37%), and DR Congo (−42%). In contrast, including natural CO_2 fluxes increases the gaps in the EU27&UK, in Canada, and particularly in Brazil. The varying degree to which the gaps are reduced in the investigated countries and the increasing gaps in some countries

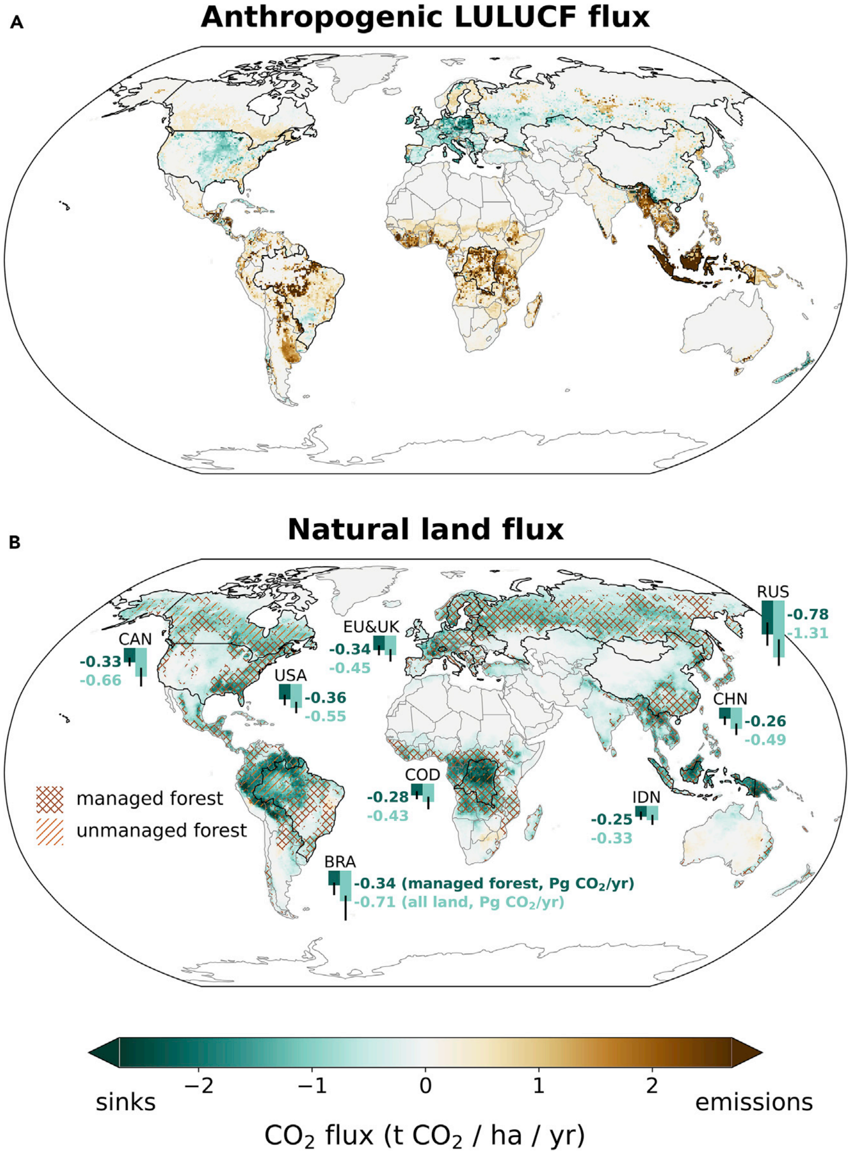

Figure 1. Anthropogenic CO_2 fluxes from LULUCF and natural CO_2 fluxes on land averaged over 2001–2015

(A) Anthropogenic CO_2 fluxes from LULUCF calculated as average of three bookkeeping models. Data from the models OSCAR and H&N2021, available only at country/regional level, were spatially distributed to the BLUE grid based on the spatial pattern of the gross flux density in BLUE (see experimental procedures for more details).

(B) Natural CO_2 fluxes calculated as multi-model median of 17 DGVMs and areas with managed and unmanaged forests (hatching). Managed and unmanaged forest areas are only shown for grid cells with at least 20% forest cover. Globally, natural CO_2 fluxes amount to a sink of 8.4 Pg CO_2/year, with 5.1 Pg CO_2 per year occurring in managed forests (note that our estimate of the global natural sink differs from the GCB2021 estimate, see experimental procedures). Bars for single countries indicate countrywide fluxes (in Pg CO_2 per year) from all land (light green) and from managed forests only (dark green), the latter being frequently included in UNFCCC country reports. Black lines in bars denote the uncertainty calculated as interquartile range of the 17 DGVM estimates. Black borders in the maps highlight the eight countries and regions investigated.

suggest that the remaining differences in model-based and report-based LULUCF estimates are due to further discrepancies, which we examine in detail below.

In the USA, Russia, the EU27&UK, and DR Congo, the uncertainties of the CO_2 flux estimates are relatively large compared to the size of the remaining gaps, which suggests that the remaining differences might be connected to the uncertain flux estimates. The uncertainty of model-based anthropogenic LULUCF fluxes is highest in the USA, Russia, and the EU27&UK (around 0.4–0.5 Pg CO_2 yr^{-1} in each country), where individual models even show opposing flux signs. Uncertainties in model-based natural land fluxes are highest in Russia (0.5 Pg CO_2 yr^{-1}), followed by the USA (0.2 Pg CO_2 yr^{-1}) and the EU27&UK (0.2 Pg CO_2 yr^{-1}). LULUCF fluxes from country reports are most uncertain in Russia (0.5 Pg CO_2 yr^{-1}), DR Congo (0.4 Pg CO_2 yr^{-1}), and the USA (0.3 Pg CO_2 yr^{-1}). In contrast, the remaining gaps in Canada, China, Brazil, and Indonesia are substantially larger than the uncertainties, highlighting that in these countries, additional definitional and methodological discrepancies contribute to the differences in model-based and report-based LULUCF estimates. Uncertainties of the estimated fluxes are generally low in Indonesia and Canada (around 0.1–0.2 Pg CO_2 yr^{-1} in each country). In Brazil and China, uncertainties are particularly high for model-based (0.4 Pg CO_2 yr^{-1} in each country) and report-based LULUCF fluxes (0.6 Pg CO_2 yr^{-1} in Brazil, 0.4 Pg CO_2 yr^{-1} in China), but the large remaining gaps point to further relevant discrepancies between model-based and report-based LULUCF flux estimates in these countries.

After showing that differences between model-based and country-reported LULUCF estimates are substantially lowered in most of the investigated countries when considering terminological differences, we can now explore the reasons for the remaining discrepancies, which provide indications where future improvements in modeling and reporting would be most urgent. The comprehensiveness of country reports varies considerably, as UNFCCC requires detailed and extensive reports from Annex 1 countries (which include Canada, EU27&UK, Russia, and the USA), while reporting guidelines are more flexible for Non-Annex 1 countries (which include Brazil, China, DR Congo, and Indonesia). In the USA, the small remaining gap between model-based and report-based CO_2 flux estimates is partly due to CO_2 removals from trees in settlements included in the US report to UNFCCC but not considered in the bookkeeping model estimates. For Russia, the lower report-based sink estimate may reflect the usage of inventory data that were recorded more than 25 years ago, as first results from a newly conducted

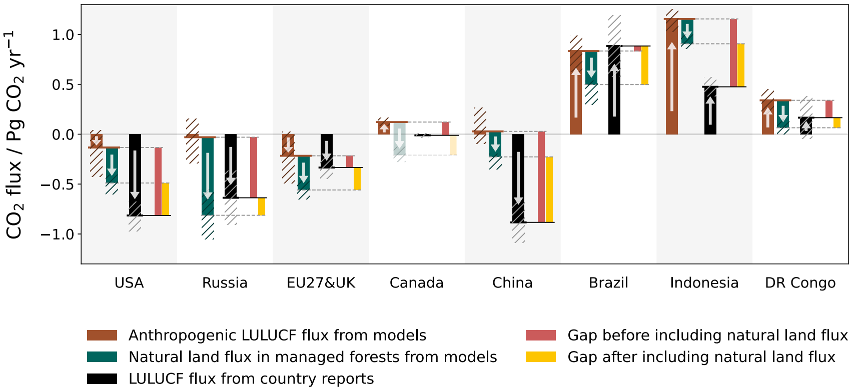

Figure 2. Waterfall chart of anthropogenic CO_2 fluxes from LULUCF and natural CO_2 fluxes on land in models and UNFCCC country reports for the eight countries investigated, averaged over 2001–2015

Natural CO_2 fluxes on land from global carbon cycle models are added on top of anthropogenic LULUCF fluxes from bookkeeping models and compared to the LULUCF fluxes from country reports. Hatching denotes uncertainty, indicated as minimum-to-maximum for bookkeeping model estimates of anthropogenic LULUCF fluxes, interquartile range of the 17 DGVMs for natural land fluxes, and using uncertainties derived from the UNFCCC country reports. For DR Congo, the displayed LULUCF flux from country reports indicates the average of the UNFCCC report estimate and the REDD+ estimate, with the uncertainty spanning the range between both estimates. Transparent bars for Canada indicate that natural land fluxes are largely not included in the LULUCF flux estimate from the Canadian country report.

inventory indicate a shift toward larger sinks.[12] In the EU27&UK, the slightly lower report-based sink estimate is likely due to a few EU countries excluding natural CO_2 fluxes from their reports and not all countries reporting non-biomass forest pools.[5] In Canada, report-based fluxes more closely resemble bookkeeping model estimates as natural CO_2 fluxes in managed forests are only partly included in the reported LULUCF fluxes owing to the usage of empirical yield curves.[5,13] Additionally, Canada reports CO_2 fluxes on areas subject to wildfires and severe insect disturbances in a separate category, motivated by the increasingly frequent occurrence of substantial natural CO_2 emissions from such events.[14] In China, the remaining gap is likely explained by substantial (but uncertain) CO_2 removals attributed to large-scale afforestation,[15–17] which are included in the national report but hardly captured by bookkeeping model estimates (Figure 3). The Brazilian UNFCCC report mostly includes natural CO_2 fluxes,[5] yet adding them to the model-based LULUCF estimates considerably increases the gap. This discrepancy may be caused by the temporal asymmetry of short-term emissions from deforestation and long-term removals from afforestation, as gross deforestation and afforestation areas are much larger in the Brazilian country report than in model estimates despite net deforestation areas being similar.[18] Moreover, the model-based natural CO_2 sink in Brazil might be overestimated because most DGVMs assume forested areas to consist of intact mature forest, while many areas actually suffer from severe degradation.[8,19] LULUCF flux estimates in Brazil further show a strong dependence on the underlying land-use-change dataset,[1,20] with LULUCF emission estimates of the GCB2021 (which are used here) being relatively low compared to estimates based on other land-use-change data, likely causing underestimated LULUCF emissions in Brazil. In the Indonesian UNFCCC report, CO_2 emissions from degradation are likely underestimated.[21] Additionally, bookkeeping models estimate higher emissions from deforestation than Indonesia's UNFCCC report (not shown). Data for DR Congo are highly uncertain, reflected by the largely differing LULUCF emission estimates in DR Congo's UNFCCC and REDD+ reports. Additionally, large uncertainties exist in DR Congo regarding the distinction of managed and unmanaged forests, firewood emissions, detection of small-scale logging, and the selection of IPCC factors for calculating biomass change.[18] Presently, the gap in DR Congo can thus not be quantified accurately enough for a proper discussion.

DISCUSSION

The reconciliation of anthropogenic LULUCF fluxes presented here is based on simulations by DGVMs and bookkeeping models, and thus dependent on the ability of these models to replicate natural and anthropogenic processes. DGVMs vary substantially concerning their complexity and process details,[1,25,26] which may impact their CO_2 flux estimates. In particular, differences in the sensitivity of land carbon uptake to the increase in atmospheric CO_2 concentrations contribute to the divergence of DGVM results,[27] and large uncertainties also remain in the trends of regional carbon fluxes.[10] The uncertainties indicated in Figure 2 at least partly reflect the degree to which these differences across models influence the natural land sink estimates in the investigated countries. The bookkeeping estimates included in our analysis are based on different land-use-change datasets (see experimental procedures), which is of importance as the choice of land-use-change forcing and the considered land management practices can considerably influence anthropogenic LULUCF flux estimates,[20,28,29] as can model choices concerning carbon densities or allocation of cleared and harvested material.[30,31] Consequently, the uncertainties of anthropogenic LULUCF flux estimates are rather high in several of the investigated countries. In this context, Earth observations may be a powerful tool to better quantify terrestrial CO_2 fluxes globally and at country level, e.g., Baccini et al.[7] and Harris et al.[32] but the distinction between anthropogenic and natural fluxes remains difficult without ancillary information on the underlying drivers.[32,33] The reliability of LULUCF flux estimates from UNFCCC country reports also varies across countries due to methodological differences and the degree to which different processes are considered.[4,5] UNFCCC provides guidance and feedback on the preparation of country reports, which are thus improving over time.[34] Particularly for Non-Annex 1 countries, important changes are expected in the coming years due the implementation of Biennial Transparency Reports in 2024 with standardized data formats.

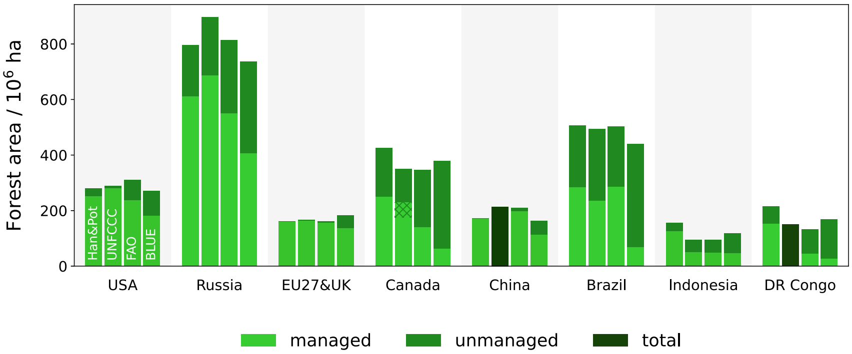

Figure 3. Comparison of managed, unmanaged, and total forest areas in different datasets

The terms "unmanaged" and "managed" forests are used in a broad sense here, with unmanaged forests referring to primary forests hardly affected by humans, while managed forests include all forests that are used by humans, such as secondary forests, non-intact forests, afforested areas, and plantations, with the exact definition depending on the respective dataset. Data include, from the left to the right bar for each country, (1) non-intact and intact forest areas from the forest map used by Grassi et al.,[5] which combines forest cover data from Hansen et al.[22] and data on non-intact forests from Potapov et al.[23] for 2013; (2) managed and unmanaged forest areas from the UNFCCC country reports (estimated between 2014 and 2018 for all countries except Brazil, for which data stem from 2010); (3) secondary and primary forest areas from the FAO Global Forest Resources Assessment using data from 2015[24]; and (4) secondary and primary forest areas from the bookkeeping model BLUE (average of the years 2011–2015) using data from the BLUE simulation for GCB2021. The sum of managed and unmanaged forest areas corresponds to the total forest area of a country. UNFCCC reports of China and DR Congo only provide total forest area. Hatching in Canada's UNFCCC managed forest area indicates the forest area with natural disturbance impacts.

In most countries, the area of non-intact forests that we use as proxy for managed forests agrees well with other estimates of managed forests by UNFCCC reports and by the Food and Agriculture Organization (FAO) of the United Nations (Figure 3), except for Indonesia and DR Congo, where the area of non-intact forest is larger than UNFCCC and FAO estimates. For DR Congo, this reflects the challenge of distinguishing between managed and unmanaged forests,[18] while in Indonesia the difference mainly stems from a larger total forest area estimated by the Global Forest Change dataset[22] compared to UNFCCC and FAO data. The overall good agreement between the different forest area estimates suggests that non-intact forests are a good proxy for the identification of managed forests, although spatially explicit information about the location of managed land in UNFCCC reports could substantially facilitate future analyses.[35]

To further improve the compatibility between report-based and model-based LULUCF flux estimates, UNFCCC reports of all countries should strive toward comprehensively and separately quantifying the anthropogenic and natural components of reported fluxes, include all relevant carbon pools, and provide full details on the used methodologies. Improving bookkeeping model estimates requires better representation of carbon sinks from afforestation projects, better representation of spatially heterogeneous carbon stocks, and more accurate land-use data to reliably identify managed and unmanaged forests (Figure 3). Further, improved representation of wildfires and insect disturbances in DGVMs is crucial, as with progressing climate change, they may increasingly impact the carbon cycle.[36]

The combination of anthropogenic and natural CO_2 fluxes on managed land in many UNFCCC reports is politically highly relevant, as increasing terrestrial CO_2 sinks is an important component in the mitigation plans of several countries. For instance, Canada, China, Russia, and the USA are implementing carbon trading systems based on CO_2 sinks in forests to offset fossil emissions,[37–39] and China recently issued the first carbon-neutral bond based on forest carbon sinks.[40] These activities effectively support sustainable mitigation if creating CO_2 removals in addition to natural fluxes. However, mitigation efforts fail if natural sinks are merely relabeled as anthropogenic. In Russia, where about 40% of fossil emissions (data from GCB2021[1]) are currently offset by LULUCF (2001–2015 average of Russia's report-based LULUCF estimate), a debate is ongoing whether to declare all forests as managed, which would then use an existing non-additional terrestrial CO_2 sink that could potentially offset most domestic fossil CO_2 emissions with no mitigation benefit.[1,41] As many countries lack concrete information on the role of LULUCF in their nationally determined contributions,[42] it currently remains uncertain how LULUCF fluxes might affect their future reporting under UNFCCC.

With the increasing importance of nature-based solutions, thorough monitoring and evaluation of terrestrial CO_2 fluxes is needed to guarantee that mitigation activities to enhance terrestrial CO_2 sinks are truly additional and sustainable. Using model data to reconcile estimates of LULUCF emissions in individual countries provides an important step toward a transparent assessment of LULUCF fluxes from UNFCCC reports. With further improvements in reporting and modeling (including complementary approaches, such as atmospheric inversions[43]), this approach can be a valuable support for an operational and consistent comparison of collective country efforts with modeled global emission pathways, as intended for instance in the global stocktake in 2023, and facilitate a fair allocation of mitigation targets across countries.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for data should be directed to and will be fulfilled by the lead contact, Clemens Schwingshackl (c.schwingshackl@lmu.de).

Materials availability

This study did not generate new unique materials.

Data and code availability

Data supporting this study, including gridded data and country-level estimates of LULUCF fluxes from bookkeeping models, gridded data and country-level estimates of the natural land sink, country-level estimates of LULUCF fluxes from UNFCCC reports, and estimates of forest area, are publicly available on Open Data LMU under https://doi.org/10.5282/ubm/data.346. The programming code used for the analyses and for creating the figures is available under https://github.com/schwings-clemens/OneEarth2022_LULUCF-fluxes_country-level. The model version OSCAR v3.1.2 is available at https://github.com/tgasser/OSCAR. The full TRENDY-v10 model output is not available publicly, and interested users are advised to contact Stephen Sitch (s.a.sitch@exeter.ac.uk) on data availability. UNFCCC data are available at the following websites: National Inventory Submissions 2021 and data in the common reporting format at https://unfccc.int/ghg-inventories-annex-i-parties/2021, Biennial Update Report submissions from Non-Annex I Parties at https://unfccc.int/BURs, and National Communication submissions from Non-Annex I Parties at https://unfccc.int/non-annex-I-NCs. Forest cover data are available at https://www.globalforestwatch.org and maps of intact forests at https://intactforests.org. FAO forest areas can be retrieved from https://fra-data.fao.org. FAOSTAT data are available from http://faostat.fao.org/.

Anthropogenic LULUCF fluxes from models

The three bookkeeping models BLUE,[44] H&N2021[45] (updated in 2021), and OSCAR[31] are used to calculate anthropogenic CO_2 fluxes from LULUCF for 2001–2015. Bookkeeping model estimates are based on carbon densities related to specific land-cover/land-use types and on response functions of carbon emissions and removals specific for each land-cover and land-use transition.[44,46] We employ data from the bookkeeping model runs performed for the GCB2021[1]. Land-use change data for the BLUE simulations stem from the harmonized land-use change dataset LUH2-GCB2021, which is an updated version of the LUH2 v2h dataset.[47,48] H&N2021 estimates use statistics on forest-area change and management from the Forest Resource Assessment (FRA) of FAO,[24] which are based on country reporting to FAO (see data and code availability for information on how to access this data). The best-guess OSCAR estimate is a combination of results from LUH2-GCB2021 and FAO/FRA land-use data and a large number of perturbed parameter simulations weighted against an observational constraint.[1] CO_2 emissions from peat fire (based on the Global Fire Emission Database, GFED4s[49]) and peat drainage (based on FAO data[50]) are added to the anthropogenic CO_2 fluxes estimated by the bookkeeping models. Further details about the models, their input data, and their setup can be found in Friedlingstein et al.[1]

H&N2021 provides data for 187 countries and OSCAR for 96 regions/countries. BLUE provides gridded data on 0.25 × 0.25° resolution, which we aggregate at the country level. Several countries including Russia, DR Congo, and several EU27 countries are not modeled individually in OSCAR but are part of larger regions. To obtain an OSCAR estimate for these countries, we separately partition the yearly gross CO_2 fluxes (i.e., LULUCF CO_2 emissions and LULUCF CO_2 removals) of the respective OSCAR regions to individual countries, based on each country's average share of regional emissions/removals in BLUE and H&N2021.

As BLUE is the only spatially explicit bookkeeping model, we derive the map of anthropogenic CO_2 fluxes (Figure 1A) based on the spatial pattern of the BLUE CO_2 flux estimates. We include data from OSCAR and H&N2021 by spatially distributing the yearly national/regional OSCAR and H&N2021 gross fluxes to the BLUE grid. For each country/region, we use the spatial pattern of the gross flux density (i.e., flux per grid cell area) in BLUE and scale the pattern such that the country-wide/region-wide gross flux estimate matches the OSCAR and H&N2021 gross flux estimates in the respective country/region. For Figure 1A, we average the net LULUCF fluxes from the gridded BLUE, OSCAR, and H&N2021 data.

Natural CO_2 fluxes on land from models

Natural CO_2 fluxes on land are derived from the variable net biome productivity (NBP) from 17 DGVMs, employing the Trendy-v10 model ensemble used in GCB2021.[1] Like in GCB2021, we use yearly data from the Trendy S2 simulations (see, e.g., Obermeier et al.[51]), which are based on historical environmental conditions (climate, CO_2 concentrations, nitrogen deposition) and fixed pre-industrial land cover (from around 1700). These simulations thus include both natural effects (e.g., climate variability, droughts) as well as indirect anthropogenic effects (e.g., CO_2 fertilization, nitrogen deposition) but exclude effects from LULUCF. The yearly NBP values of the S2 simulations represent the net natural CO_2 fluxes on land.

To extract natural CO_2 fluxes in managed forests, we follow the approach of Grassi et al.[5] and use the Global Forest Change dataset[22] to identify forests and estimate gridded forest fraction in 2013 and a map of intact forests in 2013.[23] Forests not considered as intact are assumed to be non-intact, which constitutes a proxy for managed forests.[5] We use data for forest fraction and non-intact forests at a resolution of 0.5 × 0.5°. We interpolate these data to the grid of each DGVM by conservative remapping using Climate Data Operators to quantify each grid cell's fraction of intact and non-intact forest. Since natural CO_2 fluxes in grid cells with low forest fraction might be primarily occurring in non-forest vegetation types, we define forests as all grid cells having at least 20% forest fraction in 2013 based on the Global Forest Change dataset.[22] With this threshold, our global estimate of natural land fluxes in managed forests (5.1 Pg CO_2 yr^{-1}) matches the global estimate of 5.1 Pg CO_2 yr^{-1} by Grassi et al.[11] To test how variations of the threshold affect our estimates of natural CO_2 fluxes, we perform a sensitivity analysis (see below). The results of the sensitivity test shows that variations of the forest cover threshold between 10% and 30% yield sink estimates that are within the uncertainty range of the natural land sink estimated as spread across DGVMs (Figure 2), highlighting that the approach to calculate the natural land sink in managed forests generally yields robust results.

The forest area in S2 simulations, which is based on pre-industrial land cover, differs from today's forest fraction and thus causes comparatively higher (lower) natural sink estimates where forest cover has decreased (increased). To account for changes in forest area since pre-industrial times, we calculate a gridded weighting field for each DGVM defined as the ratio of today's forest fraction (from Trendy S3 simulations) to pre-industrial forest fraction (from Trendy S2 simulations) and multiply it with the natural CO_2 flux estimates from the S2 simulations (see below for more details on the methodology). The weighted natural CO_2 flux estimates are multiplied with the (gridded) fraction of non-intact forests, and the resulting natural CO_2 flux in managed forests is then aggregated at country level and added to the bookkeeping model estimates of anthropogenic LULUCF fluxes. The natural CO_2 fluxes on all land (as shown in the map and the light-green bars in Figure 1B and used for calculating the percentage of the natural land sink occurring in forests) are calculated using a weighting factor of 1 in all grid cells that are not forested. Note that this approach for calculating the natural CO_2 fluxes of all land yields different values than the natural land sink estimated by GCB2021 (e.g., Friedlingstein et al.[1]), where the S2 simulations are directly used without any weighting despite being under pre-industrial land cover.

Applying the weighting field to calculate the natural CO_2 fluxes of all land implicitly corrects for overestimations of the natural land sink in S2 simulations, which is due to the larger forest areas under pre-industrial compared to present-day conditions that accumulate more carbon due to indirect anthropogenic effects (CO_2 fertilization, nitrogen deposition; Obermeier et al.[51]). The reduction of the natural land sink of about 1.8 Pg CO_2 yr^{-1} (2001–2015 average) if using the weighted estimates is in line with the increased LULUCF fluxes under present-day compared to pre-industrial environmental conditions, as quantified by the environmental equilibrium difference (EED) of about 1.8 Pg CO_2 yr^{-1} (2009–2018 average[51]).

LULUCF fluxes from UNFCCC country reports

All parties of the UNFCCC are required to submit reports about their domestic greenhouse gas emissions, including CO_2 fluxes from LULUCF. We retrieve CO_2 emissions from LULUCF for the eight investigated countries from all UNFCCC country reports that contain data for the years 2001–2015. In case multiple reports exist, we use the most recent version. For the UNFCCC Annex 1 parties Canada, EU27&UK, Russia, and USA we use data from their National Inventory Submissions in 2021, which are available in form of common reporting format (CRF) tables, while for the four other countries, we use information from biennial update reports (BURs) or national communications (NCs). China provides inventory data only for the years 2005 (3rd NC[52]), 2010 (3rd NC[52]), 2012 (1st BUR[53]), and 2014 (2nd BUR[54]), which we linearly interpolate to the years in between (i.e., data for 2006–2009 are obtained by linearly interpolating the 2005 and 2010 LULUCF estimates, data for 2011 are calculated as the average of the 2010 and 2012 LULUCF estimates, and data for 2013 as the average of the 2012 and 2014 LULUCF estimates), while we replicate the 2005 LULUCF estimates in the years 2001–2004 and the 2014 LULUCF estimates in 2015. LULUCF data for Brazil are obtained from Brazil's 4th NC,[55] and data for Indonesia are retrieved from Indonesia's 3rd BUR.[56] For DR Congo, data are only available for 2001–2010, and thus we replicate the 2010 values in the years 2011–2015. Due to uncertainties about the LULUCF emissions stated in the UNFCCC report of DR Congo,[18] we additionally employ LULUCF emission data from DR Congo's submission to REDD+[57] and combine them with the removal data of the 3rd NC[58] to calculate net emissions.

Derivation of weighting field

The forest area in S2 simulations, which is based on pre-industrial land cover, differs from today's forest fraction causing comparatively higher (lower) natural sink estimates where forest cover has decreased (increased). To account for changes in forest area since pre-industrial times, we calculate a gridded weighting field for each DGVM defined as the ratio of today's forest fraction to pre-industrial forest fraction and multiply it with the natural CO_2 flux estimates from the S2 simulations (see experimental procedures for more details). Forest fraction is calculated as sum over the land cover fractions of all DGVM plant functional types (PFTs) that are considered forest (e.g., broadleaf and needleleaf forest). We use PFT maps from S2 simulations for pre-industrial forest cover and from S3 simulations for today's forest cover, employing data from Trendy-v9[59] and calculating forest fraction as average of the last 20 simulation years. For the model CABLE-POP, no Trendy-v9 data are available, and we thus employ data from Trendy-v8.[60] For the model ISBA-CTRIP, we use tree cover fraction, as land cover fractions are not provided. For the models DLEM and IBIS, which do not provide land cover fractions for PFTs, the weighting fields are calculated as average of the weighting fields of all other DGVMs. To avoid numerical instabilities due to very large weighting factors in single grid cells (caused by forest fraction changes in grid cells with very small pre-industrial forest fractions), we require grid cells to have at least 0.1% pre-industrial forest cover and 0.1% present-day forest cover to classify them as forest (i.e., the weighting factor is set to unity if pre-industrial forest cover or present-day forest cover in a grid cell is smaller than 0.1%). Note that this adjustment is exclusively relevant for Europe, which is the only region with forest cover increase since pre-industrial times. Finally, we multiply the weighted natural CO_2 flux estimates with each grid cell's fraction of non-intact forests. The resulting natural CO_2 flux in managed forests is then aggregated at country level and added to the bookkeeping model estimates of anthropogenic LULUCF fluxes.

Uncertainty analysis

The uncertainty for the bookkeeping estimates of anthropogenic CO_2 fluxes from LULUCF is defined as minimum-to-maximum range over the three bookkeeping estimates. For DGVM estimates of natural terrestrial CO_2 fluxes, we quantify uncertainty as interquartile range across the 17 DGVM estimates. UNFCCC country reports contain uncertainty estimates for LULUCF fluxes, though with varying degrees of detail (see below). We assume that estimates in the UNFCCC reports are indicated as 95% confidence intervals (as specified in the respective IPCC guidelines, see below), although only some countries (e.g., Brazil, Canada, the USA) explicitly mention the 95% confidence interval in their reports. The IPCC best practice guideline states that " ... uncertainty analysis should be seen, first and foremost, as a means to help prioritize efforts to improve the accuracy of inventories in the future and guide decisions on methodological choice" (IPCC[6]; chapter 3). Thus, the uncertainties of the LULUCF fluxes from country reports shown in Figure 2 should be interpreted as general indications of how uncertain LULUCF fluxes potentially are, rather than as exact uncertainty estimates.

Uncertainty assessment of LULUCF estimates from UNFCCC

The IPCC established guidelines for calculating uncertainties for LULUCF estimates in the "Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories,"[61] the "Good Practice Guidance for Land Use, Land-Use Change and Forestry,"[62] and the "2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volumes 1 and 4."[6,63] All countries investigated in this study that report uncertainties refer to these guidelines, which specify that uncertainties should be indicated as 95% confidence intervals. Thus, we assume that all countries indicate their uncertainties as 95% confidence intervals, although only some (e.g., Brazil and the USA) explicitly state this in their reports.

The UNFCCC reports from Annex 1 countries include annual LULUCF estimates, and for most years, also their uncertainties (the latter usually indicated as percentage). To calculate the uncertainty of the average net LULUCF flux in 2001–2015 (as displayed in Figure 2), we convert yearly percentage uncertainties (U_{perc}) to yearly absolute uncertainties (U_{abs}) by multiplying U_{perc} with the LULUCF estimate of the respective year. By summing up all yearly U_{abs} values between 2001 and 2015, we obtain the total absolute LULUCF flux uncertainty ($U_{abs,tot}$), which we convert to percentage uncertainty ($U_{perc,tot}$) by dividing with the sum of all LULUCF estimates in 2001–2015.

The uncertainty estimates indicated in each annual Annex 1 country report refer to the LULUCF values that are reported in the same document. However, LULUCF estimates frequently get updated in subsequent years, and the analysis presented in this study is thus based on the LULUCF time series that is reported in the most recent reports submitted in 2021 (containing inventory data through 2019). To provide uncertainty estimates for the updated LULUCF data, we apply the methodology described above using yearly U_{perc} from the original reports and LULUCF data from the most recent reports.

Canada

Canada provides percentage uncertainties for each LULUCF subcategory individually. As, additionally, the respective greenhouse gas (GHG) emitted is indicated as well, it is possible to split yearly net LULUCF fluxes and their uncertainties into CO_2 and other GHGs. Consistent with our general methodology, we only consider LULUCF subcategories that cause CO_2 fluxes. For each LULUCF subcategory, we multiply U_{perc} with the respective LULUCF estimate to obtain U_{abs} and sum them up to obtain the total yearly LULUCF uncertainty. Subsequently, the methodology described above is applied to derive the uncertainty of the 2001–2015 net LULUCF flux. LULUCF uncertainty estimates for Canada are only available from 2008 onwards. We approximated yearly uncertainties in 2001–2007 by the average uncertainty in 2008–2012.

European Union (EU)

The EU provides U_{perc} for each yearly net LULUCF estimate, which we combine to obtain the uncertainty of the 2001–2015 net LULUCF flux following the methodology described above. LULUCF uncertainty estimates for the EU are only available from 2007 onwards. We approximated yearly uncertainties in 2001–2006 by the average uncertainty in 2007–2011.

Russia

Russia indicates LULUCF uncertainties in the same way as Canada, providing percentage uncertainty estimates and information about the GHG for each LULUCF subcategory individually. To obtain the total uncertainty for 2001–2015, we thus follow the approach used for Canada, by summing the uncertainty estimates of all LULUCF subcategories connected to CO_2 fluxes to obtain yearly U_{abs}. The uncertainty estimates of 2014 are erroneous as they are a replication of the 2013 values. We thus approximate the 2014 uncertainty by averaging the U_{perc} of the years 2012, 2013, and 2015. LULUCF uncertainty estimates for Russia are only available from 2007 onwards. We approximated yearly uncertainties in 2001–2006 by the average uncertainty in 2007–2011.

USA

The USA provide confidence intervals for their yearly LULUCF estimates, ranging from the 2.5th to the 97.5th percentile. To obtain the uncertainty of the 2001–2015 net LULUCF, we follow the methodology described above but process each uncertainty bound separately. LULUCF uncertainty estimates for the USA are only available from 2005 onwards. We approximated yearly uncertainties in 2001–2004 by the average uncertainty in 2005–2009.

Brazil

The Brazilian National Communication submissions to UNFCCC state uncertainties for CO_2 emissions from LULUCF of 33% for 2005,[64] of 32% for 2010,[65] and of 73% for 2016.[55] We apply the uncertainty estimates of the 2005 inventory to all years before 2005. The uncertainties of the years 2006–2009 are obtained by linearly interpolating the uncertainty estimates of 2005 and 2010, and the uncertainties of the years 2011–2015 are obtained by linearly interpolating the uncertainty estimates of 2010 and 2016. Uncertainties for Brazil are indicated as 95% confidence intervals.[64,65]

China

In its UNFCCC reports, China indicates LULUCF uncertainties of −21.2%–21.2% for 2010,[52] of 43.2% for 2012,[53] and of −21.1%–21.2% for 2014.[54] We apply the uncertainty estimates of the 2010 inventory to all years before 2010 and the uncertainty estimates of 2014 to the year 2015. To obtain the uncertainty for 2011, we linearly interpolate between the uncertainty estimates of 2010 and 2012. The 2013 uncertainty estimate is obtained in the same way from the values in 2012 and 2014.

DR Congo

DR Congo does not report any uncertainty estimates for LULUCF, but provides net LULUCF estimates in its 3rd NC and, additionally, LULUCF emissions in its REDD+ report.[57,58] We approximate the LULUCF uncertainty in DR Congo as the range between the estimates from the 3rd NC and a combination of the emissions from the REDD+ report with the LULUCF sinks reported in the 3rd NC.

Indonesia

Indonesia reports a LULUCF uncertainty of 20.1% for 2000 and for 2014,[66] which we apply as general uncertainty to the Indonesian LULUCF flux data.

Sensitivity analysis for natural land sink

We perform two sensitivity tests for assessing the robustness of the natural land sink estimates: (1) the weighting field is calculated using all natural land PFTs (including forests, shrubs, savanna, grasslands, etc., but excluding cropland and pasture) instead of only forest PFTs, and (2) the threshold for forest fraction is varied between 10% and 30%. The results are shown in Figure S1.

By calculating the weighting field based on all natural land PFTs instead of forest PFTs, we can test the influence on the natural land sink due to potentially varying definitions of forest PFTs in different DGVMs. Weighting based on all natural land PFTs leads to larger sink estimates in most countries (relative increase of 2%–11%), except for Canada and the USA with almost no change, and the EU27&UK with a relative decrease of −13%. The decrease of the land sink in Europe is likely due to the increase of forest fraction in Europe between pre-industrial times and today, whose effect is diminished if considering the fraction of all natural land cover. The generally consistent results suggest that varying definitions of forest PFTs only have minor impacts on the estimated natural land sink.

Varying the threshold for forest cover between 10% and 30% changes the natural land sink by −18% to +12% relative to the default threshold of 20% in all countries except the EU27&UK, where the estimates vary between an increased sink of 21% and a decreased sink of −26%. In all countries/regions, the variations lie within the uncertainty range of the natural land sink estimated by the spread across DGVMs (as shown in Figure 2), which highlights that the estimated natural land sink is robust to variations of the forest cover threshold between 10 and 30%.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2022.11.009.

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AUTHOR CONTRIBUTIONS

Conceptualization, J.P. and C.S.; methodology, C.S., J.P., and G.G.; formal analysis: C.S., W.A.O., and S.B.; resources, C.S, G.G., T.G., R.A.H., S.S., W.A.K., P.F., and J.G.C.; writing – original draft, C.S., W.A.O., S.B., J.P., G.G., and T.G.; writing – revised version, C.S., J.P., W.A.O., W.A.K., T.G., G.G., P.F., and S.B.; visualization, C.S.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We support inclusive, diverse, and equitable conduct of research.

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