KIEL Institut

Lotta Thaller, Anthony Harding, Ignacio Saldivia Gonzatti, Clemens Schwingshackl, Michael O'Sullivan, Julia Pongratz and Wilfried Rickels

March 2026

Country social cost of carbon estimates and their application to assess the natural land sink

Kiel Working Paper

No. 2316, ISSN 1862-1155
Kiel Institute for the World Economy

Abstract

Lotta Thaller*, Anthony Harding, Ignacio Saldivia Gonzatti, Clemens Schwingshackl, Michael O'Sullivan, Julia Pongratz and Wilfried Rickels

Climate change damages vary across countries, because of regional variation in climate metrics like temperature and regional variation in economic exposure. This is evident in the breakdown of the social cost of carbon: the country social cost of carbon (CSCC). While for the former a large amount of estimates exists, only few studies provide information on the per country breakdown and among those few, empirically-derived estimates do not well align with model-based derived estimates. Here, we derive a new set of CSCC estimates consistent with macroeconomic growth theory which align with model-based estimates. We obtain a median estimate for the SCC of US dollars (US$) 167 per tCO_2 (2020 prices, 66% CI: 39 to 312) for our main specification. India has the highest median CSCC (US$50 per tCO_2 with 66% CI: 26 to 80), resulting from a relatively high GDP and relatively high projected temperature. Furthermore, we apply the CSCC estimates to assess the wealth contributions resulting from carbon sequestration in land ecosystems globally, nationally, and across borders. Countries both contribute to and benefit from sequestration elsewhere, which is particularly relevant for designing payment schemes. Under a global agreement, Brazil for example would receive median US$202 ha^{-1} yr^{-1} for forest protection. In more plausible bilateral settings, India, the country with the highest CSCC, could offer Brazil a median payment of US$91 ha^{-1} yr^{-1} to preserve primary forests.

Keywords: carbon sequestration, inclusive wealth, land use, social cost of carbon
JELs: Q23, Q54, Q56

Authors

Lotta Thaller
Kiel Institute for the World Economy
lotta.siebert@kielinstitut.de
www.kielinstitut.de

Anthony Harding
Georgia Institute of Technology
aharding6@gatech.edu
www.gatech.edu/

Ignacio Saldivia Gonzatti
Wageningen University & Research
ignacio.saldiviagonzatti@wur.nl
www.wur.nl

Clemens Schwingshackl
Ludwig-Maximilians-Universität München
c.schwingshackl@lmu.de
www.lmu.de

Michael O'Sullivan
University of Exeter
M.OSullivan@exeter.ac.uk
www.exeter.ac.uk

Julia Pongratz
Ludwig-Maximilians-Universität
Max Planck Institute for Meteorology
julia.pongratz@lmu.de
www.lmu.de

Wilfried Rickels
Kiel Institute for the World Economy
Kiel University
wilfried.rickels@kielinstitut.de
www.kielinstitut.de

*Lotta Thaller and Wilfried Rickels acknowledge funding from the Volkswagen AG as part of an endowed professorship via the Stifterverband. Lotta Thaller acknowledges funding from the European Horizon Project SEAO2-CDR.
Corresponding author lotta.siebert@kielinstitut.de (L. Thaller)
We provide an interactive web-based visualization tool as supplementary information, accessible at https://lfsiebert.github.io/carbon-wealth-explorer/. The datasets and code used to generate the figures and produce the results presented in this study will be publicly available at https://github.com/lfsiebert/CarbonWealth upon publication.

I. Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) aims to control anthropogenic greenhouse gases to mitigate climate change. The current, most prominent UNFCCC treaty, the Paris Agreement, aims to limit the increase in global mean temperature to specific values, and, given the natural carbon uptake of the land and the ocean sink, provides the basis to derive emissions budgets. These budgets, usually focusing on anthropogenic CO_2 emissions, determine how much CO_2 can still be emitted to stay below a given temperature target, given a defined exceedance probability. This is a net budget, as it is becoming increasingly clear that methods must be used to remove CO_2 from the atmosphere (carbon dioxide removal, CDR) and thus compensate for emissions that exceed the budget. Reforestation plays an important role in these CDR methods. At the same time, however, about 11 percent of emissions arise from land-use change (Friedlingstein et al., 2024), and reducing emissions from deforestation is a crucial element of climate policy. Both approaches—less deforestation and thus lower gross anthropogenic emissions, and more reforestation and thus lower net anthropogenic emissions—must not be confused with or offset against natural land carbon sinks.

However, the natural land carbon sinks are unevenly distributed across countries. The magnitude of the (gross) land sink is primarily determined by vegetation cover and country size; Russia (∼13%), Brazil (∼11%), and the United States (∼9%) (based on the data by Friedlingstein et al. (2023)) contribute the largest shares to the global land sink of 2.21 gigatons of carbon per year (GtC/yr). At the same time, having a large land carbon sink, i.e. large forests, makes you a likely candidate for having also large CO_2 emissions from deforestation. These emissions are currently particularly high in tropical regions; Brazil, Indonesia and the Democratic Republic of the Congo have the highest levels of land-use change emissions. Together, these three countries emit approximately 0.70 GtC/yr, accounting for almost 60% of net land-use emissions over 2013–2022, partly offsetting or even surpassing their domestic land sink.

While there is a debate over what portion of land-based CO_2 sequestration is allowed to be included in national inventories (Grassi et al., 2018), there is no doubt that it reduces climate-change damages, increases intergenerational well-being, and therefore contributes to “inclusive” wealth (Arrow, Dasgupta and Mäler, 2003; Fenichel et al., 2016; Bastien-Olvera and Moore, 2021; Rickels et al., 2024). As a result, at the recent conference of the parties, an annual conference as part of the UNFCCC, which was the 30th conference, taking place in Brazil, a mechanism and fund was proposed that is supposed to acknowledges also the natural land sink contribution of countries. In a nutshell, the fund, which is supposed to focus on tropical rain forests, provides payments for standing, natural forest, given that deforestation does not exceed specific thresholds. The former therefore acknowledges the natural carbon sink (and all further benefits provided by this forest ecosystems), the latter makes the payment though contingent on anthropogenic action, i.e. mitigation of deforestation. Clearly, such type of incentive structure could be very helpful in developing transboundary climate policies in an increasingly polarized world, especially since one major emitter, the U.S., has withdrawn from both the Paris Agreement and the UNFCCC. These are questions of political economy, which naturally also have to deal with the exact design of such a fund (Harstad, 2025). Our objective here is to quantify the contribution to wealth that comes from the natural and anthropogenic CO_2 fluxes from the land sink and to inform such new payment schemes to mitigate climate change.

For that purpose, we provide estimates for the country social cost of carbon which we apply in a natural capital framework (Arrow, Dasgupta and Mäler, 2003) to assess the global, country-specific and transboundary (net) contribution of land carbon sequestration to inclusive wealth and sustainable development. In this framework, manufactured and natural capital stocks valued in monetary terms are aggregated to obtain an estimate of the wealth of an economy (Arrow, Dasgupta and Mäler, 2003; Arrow et al., 2012; Bastien-Olvera and Moore, 2021). Since also natural capital stocks like for example forest are included, valued with shadow prices to quantify their ecosystem services, the measure is commonly referred to as comprehensive or inclusive wealth (IW). The change in IW over time, e.g., in a year, is denoted as *comprehensive investment* and needs to be non-negative to achieve sustainable development (Arrow, Dasgupta and Mäler, 2003; Rickels, Quaas and Visbeck, 2014). Public bads associated with climate change, like increasing atmospheric carbon concentration, reduce IW by imposing global damages (Fenichel et al., 2016). The social cost of carbon (SCC) and the country-level social cost of carbon (CSCC) serve as the shadow prices used to assess the wealth implications of carbon fluxes at the global and national level. Cost estimates are obtained by multiplying carbon fluxes by the social cost of carbon. These estimates quantify the damages or avoided damages associated with carbon fluxes that increase or decrease the concentration of atmospheric CO_2, respectively.

While studies exist that account for these regional variations (Bertram et al., 2021; Rickels et al., 2024), which estimates to use for the CSCC, to assess the value of coastal and open ocean carbon sinks, remains highly disputed.

Bertram et al. (2021) apply CSCC estimates from Ricke et al. (2018), a multimodel study of climate change impacts. However, four out of five of these CSCC estimates are based on the conceptual framework of Burke, Hsiang and Miguel (2015), which has been criticized for assuming persistent effects of temperature changes on economic growth, which leads to an implausible dispersion across countries over time and a concave global damage function (Tol, 2019; Harding et al., 2025). This is because, at some point, the gains to countries estimated to benefit from climate change will start to dominate the losses of countries estimated to be negatively impacted by climate change. Instead, Rickels et al. (2024) restrict their assessment to the CSCC estimates based on the framework of Dell, Jones and Olken (2012), the only CSCC estimate within Ricke et al. (2018) not based on the Burke, Hsiang and Miguel (2015) framework. They do this because the Dell, Jones and Olken (2012) framework does not generate negative CSCC estimates or a concave damage function. However, it does assume a linear relationship between temperature and economic growth, which has also been criticized. As an additional comparison, Rickels et al. (2024) apply CSCC estimates from Tol (2019), which are derived from integrated-assessment models (IAM). Yet, the magnitude of estimates from Dell, Jones and Olken (2012) and Tol (2019) differs by nearly sevenfold, reflecting the difficulty of aligning empirical-based SCC estimates with those from IAMs. More recent IAM-based estimates produce SCCs more in line with empirical-based estimates (Rennert et al., 2022; Moore et al., 2024). However, they lack information on regional breakdowns that is needed to assess domestic and transboundary wealth contributions of land-based carbon sequestration.

Accordingly, we apply the specification of Harding et al. (2025) to derive a new set of CSCC estimates. The specification of Harding et al. (2025) provides empirically-based growth-convergence-consistent estimates of climate damages, having the the following advantages over the frameworks applied in Ricke et al. (2018) and Tol (2019): i) climate damages from this framework align with IAM-based estimates, ii) estimates allow for a non-linear relationship between temperature and economic growth, and iii) the damage function reflects the convex relationship between climate changes and climate damages one would expect. Yet, uncertainty in estimates is still high, and some countries are still found to benefit from climate change. Applying CSCC estimates derived from this specification in the Ricke et al. (2018) framework, we quantify the global, domestic, and transboundary wealth contributions of land-based carbon fluxes at the country-level, thereby informing IW and sustainable development assessments and providing information to support the design of potential transfer schemes to reduce deforestation.

II. Methods

Wealth contribution of carbon fluxes

Following Arrow et al. (2012), intergenerational well-being is determined by an economy's inclusive wealth, which is defined as the aggregate value of all its capital assets. These assets encompass not only manufactured capital but also human, natural, and resource-based assets, valued either by market prices or, if unavailable, by their shadow prices. Let $V_i(t)$ denote the inclusive wealth of country i at time t, which reflects intergenerational well-being. The change in inclusive wealth over time, $\Delta V_i(t)$, represents comprehensive investment. According to Arrow, Dasgupta and Mäler (2003), comprehensive investment must be non-negative to ensure weak sustainable development[1]:

$$\Delta V_i(t) = r(t)\Delta t + \sum_s p_{i,s}(t)\Delta K_{i,s}(t) + \sum_j g_{i,j}(t)\Delta G_j(t) \tag{1}$$

where $r(t)$ is the global shadow price of time, capturing exogenous factors such as changes in total factor productivity. The term $p_{i,s}(t)$ represents the (shadow) prices corresponding to capital assets $K_{i,s}$, while $g_{i,j}(t)$ denotes the shadow prices associated with public goods or bads G_j.

Among these public goods and bads, we specifically focus on the transnational externality arising from increasing atmospheric CO_2 concentration and the resulting climate change, i.e. we solely focus on G_{Catm}. The change in atmospheric CO_2 concentration, $\Delta G_{\text{Catm}}(t)$, is determined by several CO_2 fluxes. For those countries negatively affected by climate change, fluxes increasing or decreasing atmospheric CO_2 concentration reduce or increase comprehensive investment, respectively. Accordingly, for countries negatively affected by climate change, the shadow price $g_{i,\text{Catm}}$ is negative, measuring the marginal present-value damage of climate change for country i, commonly discussed as a cost, namely the country social cost of carbon (CSCC) with $g_{i,\text{Catm}} = -\text{CSCC}_i$.

[1] Since sustainable development is assessed based on the aggregation of monetary capital stocks, this framework allows for their substitution, i.e., a decrease in natural capital can be compensated by an increase in manufactured capital. However, as natural capital becomes increasingly scarce, its shadow price rises, thereby requiring more manufactured capital for substitution. In contrast, strong sustainability explicitly limits substitution possibilities by applying a different functional form to the aggregation of capital stocks (Rickels, Quaas and Visbeck, 2014).

Following Bertram et al. (2021) and Rickels, Quaas and Visbeck (2014), we distinguish between global, domestic, outbound, and inbound contribution of carbon fluxes to comprehensive investment, CCI. The global CCI of a carbon flux F_k in country i is given by

$$\mathrm{CCI}_{k,i}^{\mathrm{global}} = F_{k,i} \cdot -\mathrm{SCC}, \tag{2}$$

with $\mathrm{SCC} = \sum \mathrm{CSCC}_i$, i.e. the (global) social cost of carbon. Part of the global contribution is incurred at home, i.e., the domestic contribution, given as:

$$\mathrm{CCI}_{k,i}^{\mathrm{domestic}} = F_{k,i} \cdot -\mathrm{CSCC}_i. \tag{3}$$

Obviously, $\mathrm{CCI}_{k,i}^{\mathrm{global}} - \mathrm{CCI}_{k,i}^{\mathrm{domestic}}$, of the contribution to comprehensive investment is incurred abroad, i.e. the outbound contribution, given by:

$$\mathrm{CCI}_{k,i}^{\mathrm{out}} = F_{k,i} \cdot -(\mathrm{SCC} - \mathrm{CSCC}_i). \tag{4}$$

At the same time, CO_2 fluxes abroad also contribute to comprehensive investment at home. This inbound contribution is given by:

$$\mathrm{CCI}_{k,i}^{\mathrm{in}} = (F_k - F_{k,i}) \cdot -\mathrm{CSCC}_i, \tag{5}$$

where F_k is the global flux of type k, calculated as the sum of fluxes across all countries $\left(\sum_i F_{k,i}\right)$. Netting the out- and inbound contributions allows deriving the balance of CCI, which we denote as balance of transboundary carbon flux contributions to comprehensive investment ($\mathrm{CCI}^{\mathrm{BT}}$):

$$\mathrm{CCI}_{k,i}^{\mathrm{BT}} = \mathrm{CCI}_{k,i}^{\mathrm{out}} - \mathrm{CCI}_{k,i}^{\mathrm{in}}. \tag{6}$$

A country with a positive $\mathrm{CCI}_{k,i}^{\mathrm{BT}}$ contributes more to comprehensive investment to the rest of the world than it receives in return. By assessing (national) carbon flux data with climate change metrics, our analysis reveals the distributional impacts of carbon fluxes on global wealth. A schematic overview of the calculations for the different fluxes is provided in Figure B.1 in Appendix B. A positive balance requires that a country's share in the carbon flux exceeds its share in the global SCC (i.e, $F_{k,i}/F_k > \mathrm{CSCC}_i/\mathrm{SCC}$).

Carbon flux data

We use country-level estimates for five types of carbon fluxes: three measures of the natural land sink—the land sink as it has been commonly defined by global annual assessments of the anthropogenic carbon budget, i.e. on all land covers using the pre-industrial land cover distribution (S_{LAND}); the land sink based on current forest cover ($S_{\mathrm{LAND}}^{\mathrm{tF}}$); and the land sink based on managed forest area ($S_{\mathrm{LAND}}^{\mathrm{mF}}$)—as well as net anthropogenic carbon emissions and sequestration from land use, land-use change, and forestry (LULUCF) (E_{LUC}), and fossil and industrial CO_2 emissions (E_{FOS}).

Data for S_{LAND}, $S_{\mathrm{LAND}}^{\mathrm{tF}}$, and $S_{\mathrm{LAND}}^{\mathrm{mF}}$ were obtained from the Global Carbon Budget (GCB) 2023, which includes estimates from 20 Dynamic Global Vegetation Models (DGVMs) within the TRENDY intercomparison project. These models simulate carbon dynamics in response to environmental drivers, such as rising atmospheric CO_2 levels, nitrogen deposition, and climate-driven changes in ecosystem processes, while holding the land cover fixed at its pre-industrial distribution. Country-level data for E_{LUC} and E_{FOS} were sourced from the GCB 2024[2] release (Friedlingstein et al., 2024). E_{LUC} quantifies net emissions from LULUCF activities, including deforestation, forest regrowth and wood harvest, calculated using four bookkeeping models (BLUE, H&C2023, OSCAR, LUCE) that incorporate historical land-use data and peatland drainage and fires from external datasets. E_{FOS}, which primarily reflects emissions from fossil fuel combustion, cement production, and carbonation uptake, is derived from global energy and industrial statistics. While generally robust, these estimates tend to underrepresent minor sources, such as lime production and carbonate decomposition in glass manufacturing (Friedlingstein et al., 2024).

The natural land sink (S_{LAND}) represents the net atmospheric CO_2 uptake by natural ecosystems, including forests, grasslands, and soils, as estimated by DGVMs under the assumption of pre-industrial land cover conditions

[2]We use the GCB 2024 release because it increased the number of bookkeeping models from three in the GCB 2023 to four. For completeness, we also report and discuss the results based on the E_{LUC} data from GCB 2023 in the Supplementary Information as a robustness check.

(Friedlingstein et al., 2024). As a sink, S_{LAND} typically has a negative sign, indicating net removal of carbon from the atmosphere.

To more accurately reflect contemporary land cover, we focus on $S^{\mathrm{tF}}_{\mathrm{LAND}}$, which is based on present-day forest area. Following Schwingshackl et al. (2022), $S^{\mathrm{tF}}_{\mathrm{LAND}}$ is obtained by applying a gridded weighting field to S_{LAND}, wherein each grid cell is scaled by the ratio of current to pre-industrial forest cover. This adjustment mitigates the systematic overestimation of carbon uptake inherent in S_{LAND} due to the greater forest extent in pre-industrial times compared to present-day. $S^{\mathrm{mF}}_{\mathrm{LAND}}$ is derived using the same methodology, but restricted to forest areas classified as managed, thereby isolating the carbon uptake attributable to actively managed forest land.

Distinguishing between $S^{\mathrm{tF}}_{\mathrm{LAND}}$ (or S_{LAND}) and E_{LUC} remains challenging due to the inherent difficulty of quantifying the interacting effects of processes such as CO_2 fertilization, nitrogen deposition, land management practices, and climate variability. To account for these uncertainties and ensure a robust assessment, we focus on the net land carbon flux, defined as:

$$N^{\mathrm{tF}}_{\mathrm{LAND}} = S^{\mathrm{tF}}_{\mathrm{LAND}} + E_{\mathrm{LUC}}. \tag{7}$$

Including also fossil fuel emissions, we obtain the net total carbon flux:

$$N^{\mathrm{tF}}_{\mathrm{TOT}} = S^{\mathrm{tF}}_{\mathrm{LAND}} + E_{\mathrm{LUC}} + E_{\mathrm{FOS}}. \tag{8}$$

Our main analysis considers carbon fluxes within the terrestrial boundaries of each country, while we separately report the additional contributions that several countries derive from their overseas territories.

For all fluxes, we use decadal averages for the period 2013–2022 to minimize the influence of interannual variability and associated uncertainties in flux estimates (Friedlingstein et al., 2023, 2024). For the land sink fluxes, S_{LAND}, $S^{\mathrm{tF}}_{\mathrm{LAND}}$, and $S^{\mathrm{mF}}_{\mathrm{LAND}}$, this results in 20 estimates, corresponding to outputs from the 20 DGVMs. For E_{LUC}, we derive four estimates based on the four bookkeeping models. For E_{FOS}, a single estimate per country represents the decadal average fossil and industrial emissions.

Valid data are available for 194 countries for $S^{\mathrm{tF}}_{\mathrm{LAND}}$, 197 countries for E_{LUC}, and 214 countries for E_{FOS}. The combined net land carbon flux ($N^{\mathrm{tF}}_{\mathrm{LAND}}$) is available for 174 countries, and the net total carbon flux ($N^{\mathrm{tF}}_{\mathrm{TOT}}$) for the same set of countries.

Carbon price data: country social cost of carbon

We derive estimates of CSCC following the framework of Ricke et al. (2018), but we incorporate an updated climate-economy relationship (often referred to as the damage function) from Harding et al. (2025). Harding et al. (2025) apply climate econometrics methods to assess how changes in temperature and precipitation causally affect economic growth at the country-level. Their approach closely follows the approach of Burke, Hsiang and Miguel (2015), which informs the baseline estimates of Ricke et al. (2018), but with two key updates. First, Harding et al. (2025) use updated data, spanning 1960 to 2017, with economic growth data sourced from the World Bank and temperature and precipitation measures sourced from Willmott and Matsuura (2018). Second, and more importantly, they derive and apply an estimating equation consistent with neoclassical growth theory that incorporates a convergence term–accounting for the tendency of poorer countries to grow faster than richer ones.

This gives an estimation equation of:

$$\Delta y_{i,t} = -\lambda y_{i,t-1} + \beta_T T_{i,t} + \beta_{T2} T^2_{i,t} + \beta_P P_{i,t} + \beta_{P2} P^2_{i,t} + \gamma_i(t) + \eta_i + \nu_t + \epsilon_{i,t}. \tag{9}$$

Here, $y_{i,t}$ measures the log of Gross Domestic Product (GDP) per capita for country i in year t. The term $-\lambda$ estimates the convergence effect. T and P measure population-weighted annual mean temperature and precipitation, respectively. The coefficients on temperature (β_T and β_{T2}) and precipitation (β_P and β_{P2}), estimate a non-linear effect of temperature and precipitation on economic growth. Country and year fixed effects η_i and ν_t, respectively, control for unobserved country- and year-specific factors. $\gamma_i(t)$ is a country-specific time trend, capturing long-run steady state growth trends. $\epsilon_{i,t}$ is the error term.

Harding et al. (2025) find a non-linear effect of temperature on economic growth. Warming can benefit colder countries up to a point, while hotter countries experience an increasingly negative effect as temperatures rise. This is consistent with the findings of Burke, Hsiang and Miguel (2015), but Harding et al. (2025) also find a moderating convergence effect (see Table A.1 in Appendix A). We use their estimates for equation (9) to derive estimates for the

CSCC following the framework of Ricke et al. (2018). Our analysis focuses on the Shared Socioeconomic Pathway (SSP) 2 and the Representative Concentration Pathway (RCP) 6.0 scenario, i.e. SSP2-RCP6.0. This represents a middle-of-the-road socioeconomic pathway combined with a moderate concentrations trajectory. As our primary specification, we apply a 2.5% discount rate, in line with central rates used in other SCC estimates and observed real market interest rates. Given the importance of this parameter to estimates of CSCC, we examine the sensitivity of our results to this choice by considering three additional discount rates: two higher fixed discount rates of 3%, 5%, and one endogenous discounting approach with a pure rate of time preference (prtp) of 2% and an elasticity of marginal utility (elasmu) of 1.5.

Bootstrapping framework and uncertainty analysis

To account for both cross-model and econometric uncertainty in our CSCC estimates, we use a bootstrapping procedure. We pair each of 1,000 draws of the damage function, sampling across econometric uncertainty, with a randomly drawn climate model, sampled across 210 climate models from CMIP5, to estimate CSCC values. The same sequence of model selection is applied across all countries within each draw to preserve global consistency. Aggregate SCC estimates are then obtained by summing country-level outcomes for each draw. An analogous approach is used for natural land sink estimates (S_{LAND}, $S^{\mathrm{tF}}_{\mathrm{LAND}}$, and $S^{\mathrm{mF}}_{\mathrm{LAND}}$) and land-use change emissions (E_{LUC}), drawing 1,000 realizations to capture model uncertainty while ensuring consistency across countries. All reported statistics, including the CCIs estimates (global, domestic, inbound, outbound, and transboundary balance), are based on these bootstrapped datasets, ensuring internally consistent uncertainty estimates. Fossil fuel emissions (E_{FOS}), which rely on a single estimate per country, are incorporated directly without bootstrapping.

III. Results

Natural Land Sink, Land-Use Change Emissions, and Fossil Emissions

Table 1 shows the global mean carbon fluxes and the corresponding net carbon fluxes, with our main specification based on $S^{\mathrm{tF}}_{\mathrm{LAND}}$ highlighted in bold. For all three land sink estimates, even after accounting for net E_{LUC} emissions, the net land carbon flux remains negative, i.e., terrestrial ecosystems continue to remove carbon from the atmosphere. However, this balance reverses once fossil fuel emissions (E_{FOS}) are included, resulting in a net flux to the atmosphere.

Table 1
Global mean carbon fluxes (GtC/yr), 2013–2022.

Land sink	S_{LAND}	E_{LUC}	E_{FOS}	N_{LAND}	N_{TOT}
S_{LAND}	−3.37 (0.84)			−2.19 (0.84)	7.19 (0.84)
$\boldsymbol{S^{\mathrm{tF}}_{\mathrm{LAND}}}$	−2.21 **(0.73)**	**1.18** (0.22)	**9.49**	−1.03 **(0.72)**	8.34 **(0.72)**
$S^{\mathrm{mF}}_{\mathrm{LAND}}$	−1.71 (0.54)			−0.53 (0.55)	8.84 (0.55)

Notes: Values are decadal means for 2013–2022. Values in parentheses indicate standard deviations. S_{LAND} denotes the natural land sink based on pre-industrial land cover (GCB baseline); $S^{\mathrm{tF}}_{\mathrm{LAND}}$ the natural land sink based on present-day forest cover (main scenario); $S^{\mathrm{mF}}_{\mathrm{LAND}}$ the natural land sink based on managed forest area. E_{LUC} denotes emissions from land-use change; E_{FOS} fossil fuel and industrial emissions. $N_{\mathrm{LAND}} = S_{\mathrm{LAND}} + E_{\mathrm{LUC}}$ is the net land carbon flux, and $N_{\mathrm{TOT}} = N_{\mathrm{LAND}} + E_{\mathrm{FOS}}$ the net total carbon flux.

Carbon fluxes vary considerably from region to region. Figure 1 shows the decomposition of flux components for the ten countries with the largest net land carbon flux ($N^{\mathrm{tF}}_{\mathrm{LAND}}$), along with Brazil and Indonesia, which are included due to the substantial carbon sink associated with their humid tropical primary forests and the substantial carbon losses from the degradation of these ecosystems through land-use change. The figure shows the large carbon sinks provided by forests in Russia, the U.S., China, Canada, the Democratic Republic of the Congo (DR Congo), Brazil, and Indonesia, largely reflecting their extensive land areas and forest cover. Together, these seven countries' natural carbon sink provided by forests accounted for almost 60% of the global $S^{\mathrm{tF}}_{\mathrm{LAND}}$, which is estimated at -2.21 GtC/yr (see Table 1).

The large natural sinks in the DR Congo, Brazil, and Indonesia are offset by high land-use change emissions, particularly from deforestation, with mean emissions of 0.15 GtC/yr (SD: 0.01), 0.31 GtC/yr (SD: 0.10) and 0.23 GtC/yr (SD: 0.02), respectively. As a result, the net land carbon sink in the DR Congo is reduced to -0.03 GtC/yr (SD:

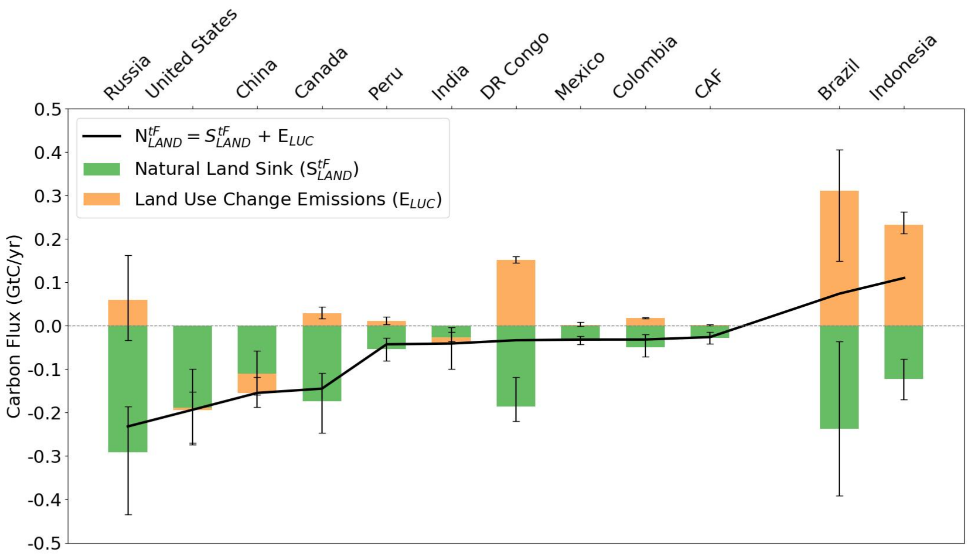

Figure 1: Carbon flux breakdown for major land sinks (2013–2022).

Notes: Mean carbon fluxes (GtC/yr) are shown for the ten countries with the largest net land carbon flux ($N^{\mathrm{tF}}_{\mathrm{LAND}} = S^{\mathrm{tF}}_{\mathrm{LAND}} + E_{\mathrm{LUC}}$) based on today's total forest area, with Brazil and Indonesia also included due to their substantial tropical forest sinks and comparatively large associated emissions from anthropogenic deforestation and forest degradation. Green bars indicate natural land sinks ($S^{\mathrm{tF}}_{\mathrm{LAND}}$), and orange bars represent land-use change emissions (E_{LUC}). The black line denotes $N^{\mathrm{tF}}_{\mathrm{LAND}}$. Error bars reflect the 66% confidence (17th–83rd percentiles), capturing multi-model variability. Positive values indicate carbon emissions, while negative values represent carbon uptake by the land. (CAF: Central African Republic.)

0.06), while both Brazil and Indonesia even emerge as net carbon sources, with net land carbon fluxes of 0.07 GtC/yr (SD: 0.22) and 0.11 GtC/yr (SD: 0.06), respectively.

After accounting for E_{LUC} emissions, 109 of the 174 countries considered in our study remain net land carbon sinks, i.e. removing more carbon from the atmosphere than they emitted over the period. However, once fossil and industrial carbon emissions (E_{FOS}) are included, this pattern reverses: even countries with the three largest net land carbon sinks, Russia, the U.S., and China, all become net emitters, with mean net total carbon fluxes of 0.23 GtC/yr (SD: 0.18), 1.23 GtC/yr (SD: 0.12) and 2.70 GtC/yr (SD: 0.06), respectively (see Figure B.2 in Appendix B). Despite this shift towards emissions, 31 countries retain a negative net carbon flux with the atmosphere and would therefore be classified as net carbon negative from an inclusive wealth perspective. Peru, the Democratic Republic of the Congo, and the Central African Republic are particularly notable, remaining net negative even after fossil emissions are considered. As shown in Figure B.2 in Appendix B, this is because their substantial land carbon sinks outweigh comparatively low fossil fuel emissions. Obviously, such flux-based assessments should not be confused with the concept of anthropogenic net zero or net negative CO_2 emissions, which are required to limit global warming (Allen et al., 2025).

Figure B.3 in Appendix B presents the same information as Figure 1, but uses the natural land sink estimate based on pre-industrial land cover (S_{LAND}), as reported in the GCB 2023, rather than present-day forest area. Using pre-industrial land cover generally increases the estimated land sink across nearly all countries, most notably for China, Russia, and India, where the sink strengthens by roughly 0.11–0.14 GtC/yr (Table A.2 in Appendix A).

In total, 52 countries, including Iceland, Israel, Burkina Faso, and Western Sahara, report zero values for $S^{\mathrm{tF}}_{\mathrm{LAND}}$, indicating no detectable forest-based land sink under present-day forest cover. In contrast, only Antarctica exhibits a zero value under the GCB S_{LAND} specification. In addition, eight countries with positive S_{LAND} values in the original GCB data (indicating net emissions from natural land) shift to zero or slight sinks when recalculated using present-day forest area. Full country-level details are assessed in the Supplementary Information.

Our main analysis considers carbon fluxes within the terrestrial boundaries of each country; however, several nations maintain overseas territories where land carbon fluxes occur. As illustrated in Figure B.4 in Appendix B, the United States and France show the largest absolute gains from overseas sinks, with forest carbon uptake in their overseas territories enhancing their national $S^{\mathrm{tF}}_{\mathrm{LAND}}$ by –0.34 MtC/yr and –0.17 MtC/yr, respectively, corresponding

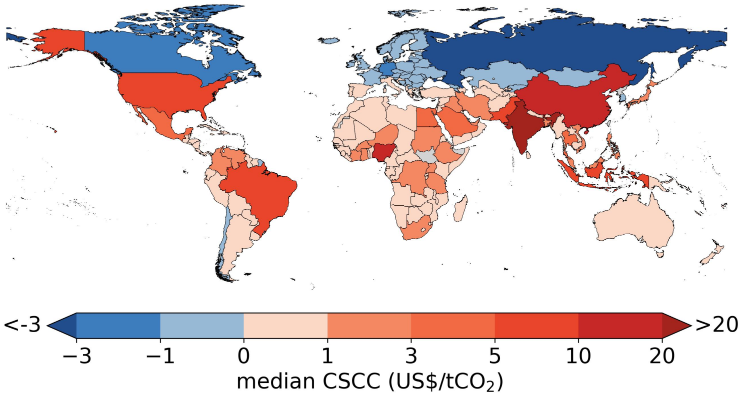

Figure 2: Median country-level social cost of carbon (CSCC).

Notes: This map shows median CSCC (US$/tCO$_2$) for the SSP2–RCP6.0 scenario with a 2.5% discount rate. Countries with projected net economic damages from climate change are shaded red (positive CSCC), while those with net economic benefits are shaded blue (negative CSCC). Regions without data are shown in grey.

to only +0.18% and +2.18% of their national land sinks. If instead the land sink is calculated using S_{LAND} values as reported in the GCB 2023, Denmark sees the largest contribution from its overseas territories (Greenland and the Faroe Islands) amounting to –0.58 MtC/yr in total.

Country Social Cost of Carbon

We obtain a median estimate for the SCC of US dollars (US$) 166.69 per tCO$_2$ (2020 prices, 66% CI: 39.08 to 312.01) for our reference scenario SSP2-RCP6.0, with a 2.5% discount rate. For the alternative discounting assumptions, we find median SCC values of US$121.32 (66% CI: 24.87 to 232.02) with a 3% rate, US$46.33 (66% CI: 3.51 to 92.60) with a 5% rate, and US$31.51 (66% CI: –6.59 to 74.81) using an endogenous approach with a 2% pure rate of time preference and an elasticity of marginal utility of 1.5.

Figure 2 shows the regional distribution of the SCC, i.e. the CSCC estimates. The three countries with the highest median CSCC are India (US$49.64 per tCO$_2$ with 66% CI: 25.82 to 80.15), China (US$13.80 per tCO$_2$ with 66% CI: -6.46 to 35.17), and Nigeria (US$13.38 per tCO$_2$ with 66% CI: 7.23 to 21.28), resulting from a relatively high GDP and relatively high projected temperature increase in these countries. The empirically derived GDP-based estimates usually yield negative CSCC values for colder countries, consistent with the non-linear, inverted-U relationship between temperature and economic growth. The lowest median CSCC values are found in Russia (-US$6.08 per tCO$_2$ with 66% CI: -9.67 to -2.74), Canada (-US$2.21 per tCO$_2$ with 66% CI: -3.70 to -0.76), and Germany (-US$1.28 per tCO$_2$ with 66% CI: -2.84 to 0.23). Figure B.5 in Appendix B presents results under alternative discounting assumptions, indicating that changing the discount rate shifts the absolute CSCC levels but leaves their spatial distribution largely unchanged. Median CSCC values for the five countries with the highest and lowest estimates across all discounting scenarios are reported in Table A.3 in Appendix A.

Contribution of carbon fluxes to global comprehensive investment

Under the SSP2–RCP6.0 scenario with a 2.5% discount rate, the median $\mathrm{CCI}_k^{\mathrm{global}}$ amounts to US$1,240.39 B/yr for the natural land sink ($k = S_{\mathrm{LAND}}^{\mathrm{tF}}$), US$495.24 B/yr for the net land carbon flux ($k = N_{\mathrm{LAND}}^{\mathrm{tF}}$), and -US$5,066.96 B/yr for the net total carbon flux ($k = N_{\mathrm{TOT}}^{\mathrm{tF}}$). In Table 2 we report the corresponding values under alternative discount rates and natural land sink estimates. Changes in the discounting assumptions affect the magnitude of global CCI estimates, reflecting the respective social cost of carbon. As expected, higher discount rates reduce the estimated global CCI. Additionally, the definition of the natural land sink has a considerable impact, using present-day forest cover results in substantially lower global CCI compared to estimates based on pre-industrial land cover, reflecting both the reduced extent of present-day forests and the exclusion of other vegetation types.

Across 194 countries with valid data, 120 exhibit a positive median $\mathrm{CCI}_{k,i}^{\mathrm{global}}$ for the natural land sink ($k = S_{\mathrm{LAND}}^{\mathrm{tF}}$), one country has a negative value, and 73 register zero (i.e., no net contribution). This changes once factoring in land-use

Table 2
Global carbon flux contributions to comprehensive investment under alternative discount rates.

Discount rate	Land cover	Natural land carbon sink (billion US$/yr)	Net land carbon flux (billion US$/yr)	Net total carbon flux (billion US$/yr)
2.5 percent	S_{LAND}	1953.01 [474.81, 3983.10]	1236.68 [240.52, 2593.07]	−4318.49 [−8166.35, −1039.09]
	$\boldsymbol{S^{\mathrm{tF}}_{\mathrm{LAND}}}$	**1240.39 [272.82, 2663.21]**	**495.24 [−11.44, 1336.37]**	−5066.96 [−9320.41, −1187.76]
	$S^{\mathrm{mF}}_{\mathrm{LAND}}$	964.71 [220.11, 2026.61]	217.88 [−50.69, 767.65]	−5372.73 [−9956.02, −1275.47]
3 percent	S_{LAND}	1430.07 [278.99, 2951.67]	908.46 [152.04, 1922.33]	−3150.68 [−6026.97, −649.00]
	$S^{\mathrm{tF}}_{\mathrm{LAND}}$	913.57 [171.59, 1982.68]	357.39 [−13.52, 992.83]	−3682.93 [−6919.81, −744.84]
	$S^{\mathrm{mF}}_{\mathrm{LAND}}$	710.69 [138.33, 1506.94]	157.27 [−40.09, 570.91]	−3918.08 [−7391.23, −800.01]
5 percent	S_{LAND}	538.98 [47.24, 1182.45]	335.86 [22.08, 789.98]	−1192.65 [−2415.56, −87.72]
	$S^{\mathrm{tF}}_{\mathrm{LAND}}$	345.93 [25.31, 799.85]	125.77 [−14.97, 400.96]	−1397.71 [−2776.16, −101.36]
	$S^{\mathrm{mF}}_{\mathrm{LAND}}$	272.34 [20.70, 612.40]	53.68 [−20.74, 228.61]	−1480.54 [−2976.19, −110.64]
Endogenous	S_{LAND}	373.18 [−76.30, 955.57]	228.54 [−44.23, 635.54]	−813.57 [−1959.90, 178.17]
	$S^{\mathrm{tF}}_{\mathrm{LAND}}$	236.54 [−49.36, 640.85]	83.64 [−27.85, 320.49]	−962.31 [−2250.27, 203.37]
	$S^{\mathrm{mF}}_{\mathrm{LAND}}$	183.26 [−37.55, 496.70]	32.60 [−24.39, 178.56]	−1031.03 [−2407.96, 219.12]

Notes: Entries report median global comprehensive investment contributions, followed by the 66 percent confidence interval in brackets. Estimates are shown for three carbon flux measures, three land-cover scenarios, and four discount-rate specifications (three fixed and one endogenous). The endogenous specification uses $\varepsilon = 1.5$ and a pure rate of time preference of 2 percent. Bold values highlight the preferred specification discussed in the main text.

change emissions (Figure 3). Indonesia, Brazil, and Sudan record the most negative median CCIs for the net land carbon flux ($k = N^{\mathrm{tF}}_{\mathrm{LAND}}$), at -US$54.77 B/yr (66% CI: -123.52 to -5.76), -US$18.20 B/yr (66% CI: -210.50 to 93.58), and -US$6.65 B/yr (66% CI: -12.19 to -1.59), respectively, driven by their high land-use change emissions. Nevertheless, 103 (107) out of 174 countries still exhibit positive global median (mean) $\mathrm{CCI}^{\mathrm{global}}_{k,i}$ for $k = N^{\mathrm{tF}}_{\mathrm{LAND}}$ (Figure 3). Even after factoring in fossil fuel emissions, 25 (30) countries still have a positive median (mean) $\mathrm{CCI}^{\mathrm{global}}_{k,i}$ for $k = N^{\mathrm{tF}}_{\mathrm{TOT}}$ (Figure B.6, panel (c), in Appendix B), i.e. indicating that these countries positively contribute to global wealth through their carbon fluxes.

Balance of transboundary carbon flux contributions to comprehensive investment

Countries' global CCI scales linearly with carbon fluxes, since all fluxes are valued using the global SCC. In contrast, domestic, outbound, and inbound CCI incorporate regional variation in climate change impacts by decomposing the global SCC into country-level SCC (CSCC). Countries with a high CSCC benefit greatly from domestic land-based carbon sequestration and carbon sequestration abroad, while countries with a low CSCC gain relatively little from their own sequestration, with much of the domestic carbon sequestration contributing to comprehensive investment abroad. Figure 4 shows the five countries with the highest and lowest median $\mathrm{CCI}^{\mathrm{BT}}$ for the net land carbon flux, $N^{\mathrm{tF}}_{\mathrm{LAND}}$, restricted to countries with a positive CSCC.

Among those countries with a positive CSCC, the United States have the highest annual median $\mathrm{CCI}^{\mathrm{BT}}_{k,i}$ for $N^{\mathrm{tF}}_{\mathrm{LAND}}$, at US$69.11 B/yr (66% CI: 13.58 to 161.99). This reflects the composition of its carbon flux contributions: the U.S. mean net land carbon flux of -0.19 GtC/yr implies a median global CCI of US$84.99 B/yr (66% CI: 6.59 to 233.26) of which only US$3.14 B/yr (66% CI: -2.76 to 12.98) accrues as median domestic CCI, while US$82.95 B/yr (66% CI: 9.10 to 217.07) are accounted as median outbound CCI, benefiting other countries. Conversely, the global mean net land carbon flux excluding the U.S contributions (-0.84 GtC/yr) translates into a median inbound CCI for the U.S. of US$13.74 B/yr (66% CI: -15.47 to 65.92). The balance between the outbound and inbound CCI determines the positive transboundary CCI for the United States.

India has the lowest median $\mathrm{CCI}^{\mathrm{BT}}_{k,i}$ for $k = N^{\mathrm{tF}}_{\mathrm{LAND}}$, at -US$143.61 B/yr (66% CI: -338.90 to -7.76). India's relatively low mean net land carbon flux of -0.04 GtC/yr yields a domestic CCI of US$4.47 B/yr (66% CI: 0.93 to 15.24) and an outbound CCI of US$7.98 B/yr (66% CI: 0.01 to 39.51). However, India's high CSCC implies that carbon fluxes abroad are valued particularly highly. As a result, India receives an inbound CCI of US$166.42 B/yr (66% CI: 12.90 to 351.63), implying the negative $\mathrm{CCI}^{\mathrm{BT}}_{k,i}$ mentioned above.

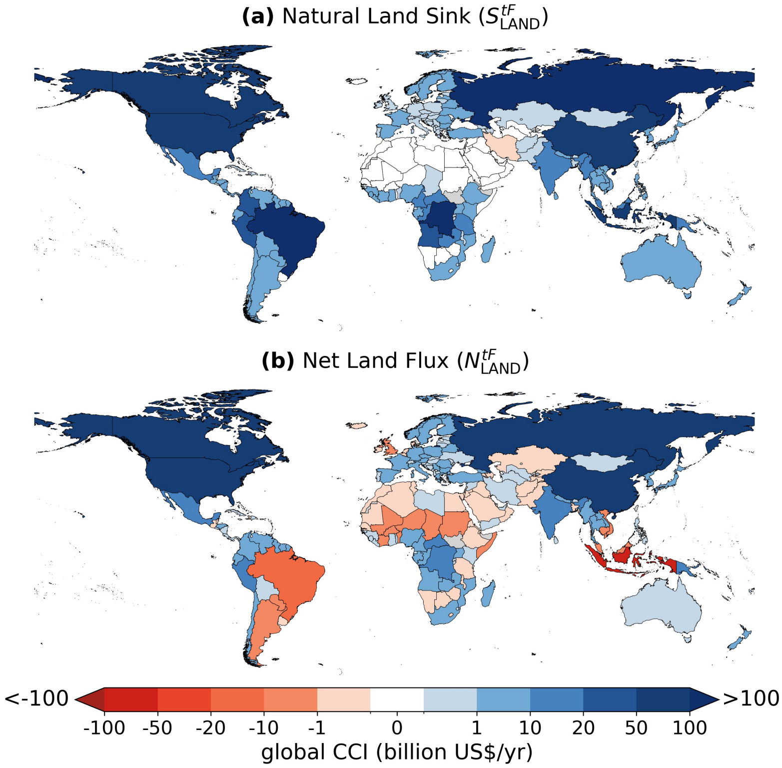

Figure 3: Country-level global carbon flux contributions to comprehensive investment (CCI).

Notes: The figure shows the median country-level $\mathrm{CCI}^{\text{global}}_{k,i}$ (billion US$/yr) for two carbon fluxes: (a) the natural land sink based on present-day forest area ($S^{\text{tF}}_{\text{LAND}}$), (b) the net land carbon flux ($N^{\text{tF}}_{\text{LAND}} = S^{\text{tF}}_{\text{LAND}} + E_{\text{LUC}}$). Negative values, representing reductions in global CCI, are shown in red, while positive values, indicating contributions to global CCI, are shown in blue. Countries with zero values are shown in white, and those without data are displayed in light grey.

The difference between the United States and India in $\mathrm{CCI}^{\text{BT}}_{N^{\text{tF}}_{\text{LAND}},i}$ reflects both differences in their physical carbon fluxes and in the valuation of those fluxes, the latter determined by the CSCC. India's CSCC is US$49.64 per tCO_2, representing roughly 30% of the global SCC, whereas the U.S. CSCC is considerably lower at US$6.85 per tCO_2, or roughly 4% of the global SCC.

Potential payment scheme for forest preservation

A detailed breakdown of the $\mathrm{CCI}^{\text{BT}}_{k,i}$ can inform the design of potential payment schemes for the provision of public carbon sequestration by land sinks. While we focus primarily on the net land sink, these insights are particularly relevant to the natural land sink, and changes thereof, which is inadequately addressed in current climate policy incentive schemes.

As an illustrative example, consider the loss of humid tropical primary forests in Brazil. Between 2002 and 2024, Brazil had a reduction of 33.50 million hectares (Mha) of humid tropical primary forests (World Resources Institute, 2024). This considerable loss has spurred calls to develop financial incentive schemes aimed at primary forest preservation.

Applying the global mean CCI of the natural land sink provided by Brazil's total forest area (US$149.83 B/yr, 66% CI: -7.34 to 313.44) and an estimated total forest area of 496.62 Mha in 2020 (FAO, 2020) yields a CCI of US$301.70 per ha per year (66% CI: -14.77 to 631.15). However, using this figure to derive a payment claim under an international agreement would ignore the fact that Brazil itself benefits from the carbon sequestration by its domestic natural land sink. Alternatively, using Brazil's mean outbound wealth contribution (US$291.24 per ha per year, 66% CI: -14.28 to 610.23) still ignores the fact that Brazil also benefits from carbon sequestration occurring in natural land sinks outside its borders. Accordingly, the balance of transboundary contribution to comprehensive investment, which accounts for

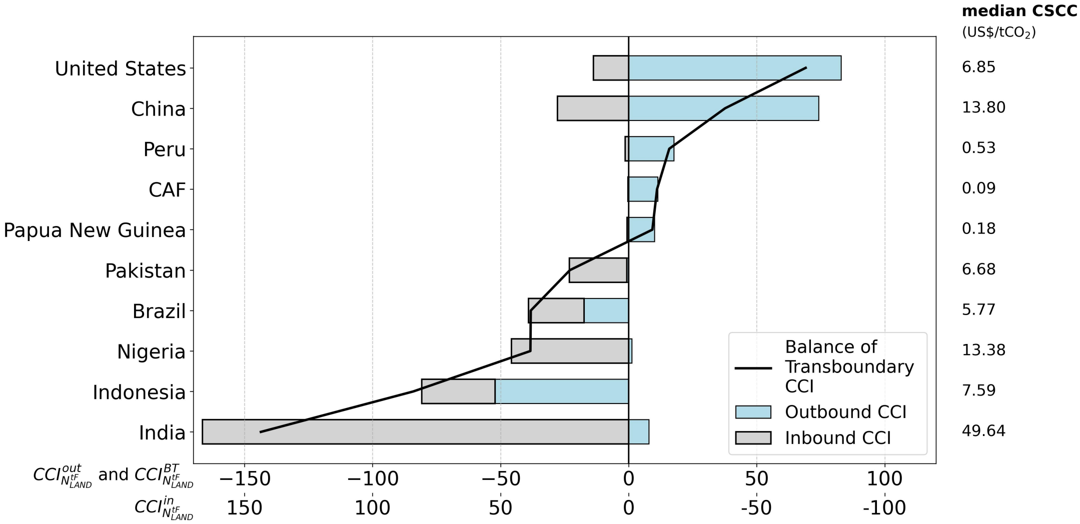

Figure 4: Top and bottom five countries by balance of transboundary CCI from the net land carbon flux $N^{\mathrm{tF}}_{\mathrm{LAND}}$.

Notes: The figure shows the five countries with the highest and lowest median balance of transboundary carbon flux contributions to comprehensive investment ($\mathrm{CCI}^{\mathrm{BT}}_{k,i}$) associated with net land carbon fluxes ($N^{\mathrm{tF}}_{\mathrm{LAND}}$), restricted to countries with a positive CSCC. Bars decompose each country's balance into outbound CCI (blue; contributions of a country's net land carbon flux to others) and inbound CCI (grey; contributions received from fluxes in other countries), with all values expressed in billion US$/yr. Positive inbound CCI values are plotted as bars extending to the left; the mirrored secondary x-axis provides the corresponding scale. The black solid line represents the transboundary wealth contribution, $\mathrm{CCI}^{\mathrm{BT}}_{k,i}$, equal to outbound minus inbound CCI, and median CSCC values are listed on the right-hand side.

both inbound and outbound flows, represents a more appropriate figure. This implies a mean value of US$201.86 per ha per year for protecting forests in Brazil.

Of course, this balance of global transboundary contributions would only emerge if all countries participated in a global agreement. Perhaps more likely, two countries or small groups of countries may participate in bilateral or multilateral agreements. For example, considering a bilateral relationship between Brazil and India, the country with the largest inbound CCI, based on their transboundary wealth balance, India could offer the mean net value of US$91.13 per ha per year (66% CI: 6.23 to 178.45) for the preservation of primary forest in Brazil.

Figure 5 illustrates such bilateral wealth flows, showing the outbound and inbound CCI fluxes resulting from $S^{\mathrm{tF}}_{\mathrm{LAND}}$ for the seven countries with the largest CSCC, the rest aggregated as rest of world (ROW). For example, one can see the outbound contributions from Brazil to India in dark blue. Note this calculation does not incorporate other inclusive wealth contributions of the land sink sources, such as other ecosystem services. Nevertheless, it shows that a global agreement might not necessarily be required. Rather, monetizing the CCI for some main beneficiary or willing countries could be sufficient to develop a payment system where a willing group of countries could utilize the outbound CCI of recipient countries.

IV. Discussion and Conclusion

Land-based carbon sequestration provides global benefits to inclusive wealth. Countries differentially benefit from land-based carbon sequestration. Large countries, such as Russia, Brazil, the United States, Democratic Republic of the Congo, and Canada contribute the most to natural, land-based carbon sequestration. Tropical countries, such as Brazil, Indonesia, and the Democratic Republic of the Congo contribute significantly to natural land sinks, but they also lead in emissions from land-use changes, particularly deforestation of carbon-dense forests, resulting in small net carbon sequestration or even net carbon release to the atmosphere. Countries that experience large losses from climate change (and therefore have high CSCC), such as India, Nigeria, Indonesia, China, and Pakistan, benefit the most from land-based carbon sequestration abroad.

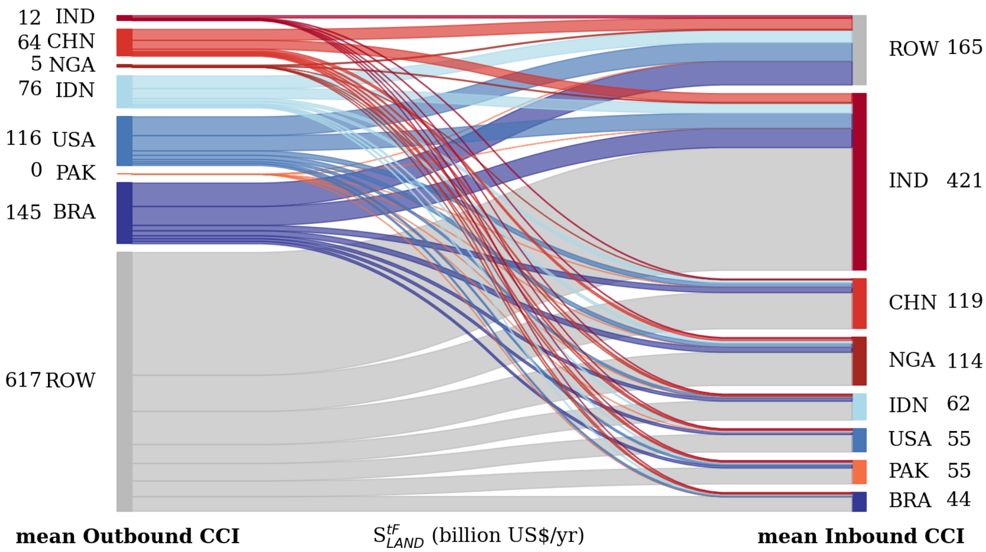

Figure 5: Outbound and inbound CCI from the natural land sink ($S^{\mathrm{tF}}_{\mathrm{LAND}}$) for the seven countries with the highest CSCC.

Notes: Shown are mean outbound and inbound CCI flows (billion US$/yr) for India, China, Nigeria, Indonesia, the United States, Pakistan, and Brazil, with the rest of the world (ROW) aggregated. Flow widths are proportional to the magnitude of contributions, while colors indicate each country's balance of transboundary CCI (outbound minus inbound): blue shades represent net contributors and red shades net beneficiaries.

Properly attributing land-based carbon sequestration to natural versus anthropogenic processes remains challenging, and multiple approaches are used to estimate these fluxes. Dorgeist et al. (2024) show that DGVM-based estimates in the GCB overestimate the natural land carbon sequestration (i.e., the natural land sink) by about 23% for 2012–2021, because pre-industrial instead of present-day land cover is assumed in the modeling. We combine the bookkeeping-based E_{LUC} estimates from the GCB with the natural land sink provided by present-day total forest area, yielding a global mean net land-based carbon sequestration of -1.03 GtC/yr (SD 0.72). This value aligns closely with the estimated -1.2 GtC/yr [min: -2.1, max -0.5] reported by Dorgeist et al. (2024).

In monetary terms, this translates to a global aggregated median contribution to comprehensive investment of US$495.24 B/yr (66% CI: -11.44 to 1,336.37). If one would instead estimate the contribution of the net land sink to comprehensive investment using pre-industrial land cover or managed forest area, the estimate would increase to US$1,236.68 B/yr (66% CI: 240.52 to 2593.07) or decrease US$217.88 B/yr (66% CI: -50.69 to 767.65), respectively. This range demonstrates the importance of having accurate (i.e. not using the pre-industrial land cover) and robust estimates of the land sink in order to properly assess its contribution to wealth.

Note that we assess the annual contribution to comprehensive investment using the current annual land-based carbon fluxes obtained as average over the period 2013 to 2022. We do not provide an estimate of the present value of all future land-based carbon fluxes. Not only would this provide a different wealth metric—informing us about the value of the stock rather than the flow—but it would also considerably increase the uncertainty in the assessment. This includes the possibility that the land carbon sink becomes a carbon source instead of a sink, for example as a result of net-negative anthropogenic CO_2 emissions scenarios and therefore a reduced CO_2 fertilization effect (Brienen et al., 2015; Gidden et al., 2023). Additionally, climate change itself is projected to strongly reduce net land carbon sequestration due to more frequent and intense wildfires (Jain et al., 2024), insect outbreaks (Hicke et al., 2012), drought stress (Park Williams et al., 2013), and windthrow caused for example by hurricanes (Tumber-Dávila et al., 2024). Nevertheless, our framework could also be applied to assess the wealth implications of such single events like for example the reduction in comprehensive investment resulting from wildfires in Canada.

Estimating the implications for comprehensive investment resulting from such a single land-based event like the wild-fires in Canada or, as in our study, the contribution of the (net) land sink hinges crucially on the carbon price data. Here, we employ an empirical approach to estimate the marginal economic impacts of climate change on countries, based on observed historical relationships between weather fluctuations and economic outcomes. Such empirically grounded methods are increasingly used to calibrate integrated assessment models and inform government estimates of climate damages (e.g., Hogan and Schlenker, 2024). However, because these estimates leverage short-term weather variation to identify a causal relationship, they may not fully capture the effects of long-term climate changes. Consequently, the derived impacts may underestimate the role of adaptation and unforeseen changes in weather outcomes under future climate conditions (Tol, 2019; Hogan and Schlenker, 2024).

Empirical studies also differ in whether they estimate climate impacts on the level or the growth rate of economic output. Models assuming persistent impacts on economic growth rates project far greater long-term economic damages from climate change than those assuming only transitory or level effects (Moore and Diaz, 2015; Tol, 2019; Hogan and Schlenker, 2024). For example, Kalkuhl and Wenz (2020) and Newell, Prest and Sexton (2021) find that temperature primarily affects GDP levels, without persistent effects on growth. Recent studies by Casey, Fried and Goode (2023) and Nath, Ramey and Klenow (2024) identify temporary impacts on economic growth, projecting damages that exceed estimates based only on level effects but fall below those assuming persistent growth effects.

We adopt the impact function derived by Harding et al. (2025), which aligns with recent findings of Casey, Fried and Goode (2023) and Nath, Ramey and Klenow (2024). Harding et al. (2025) find that accounting for the macroeconomic feature of convergence in economic growth — which was not considered in any of the estimates used by Ricke et al. (2018) — has little effect on the estimated relationship between temperature, precipitation, and economic growth. However, it has important implications for projected climate damages. Using convergence-consistent estimates considerably reduces the dispersion and magnitude of projected climate damages because the convergence effect mitigates the economic impacts of climate change. We demonstrate the importance of accounting for this when applying empirically derived damage functions to estimate CSCC.

Using the impact function from Harding et al. (2025), we estimate a median SCC of US$166.69 per tCO_2 (66% CI: 39.08 to 312.01) under our main specification, which applies a constant discount rate of 2.5% and projects economic growth and climate change according to a SSP2-RCP6.0 scenario. This is less than half the estimate of Ricke et al. (2018) and the spread of CSCCs across countries is similarly reduced. This estimate aligns with the multi-model SCC synthesis by Moore et al. (2024), which reports a median of US$62.61 and a mean of US$250.87 per tCO_2, reflecting the skewness of published SCC estimates. Note that the mean SCC in Moore et al. (2024) is inflated by an extreme outlier, reporting a SCC estimate near US$75,000 per tCO_2; excluding the top and bottom 0.1% of estimates yields a mean SCC of US$175.85 per tCO_2. Higher discount rates (3%, and 5%) and endogenous discounting (with a pure rate of time preference of 2% and an elasticity of marginal utility of 1.5) result in considerably lower mean SCC estimates of US$128.74, 49.06, and 36.06 per tCO_2, respectively. Accordingly, the median global CCI declines from US$495.24 B/yr (66% CI: -11.44 to 1336.37) at a 2.5% discount rate to US$357.39 B/yr (66% CI: -13.52 to 992.83) at 3%, US$125.77 B/yr (66% CI: -14.97 to 400.96) at 5%, and US$83.64 B/yr (66% CI -27.85 to 320.49) under endogenous discounting.

Our estimates account for uncertainty in projected climate damages resulting not only from the econometric estimates but also from climate system uncertainty (Burke et al., 2015). Using a bootstrap framework, we sample 1,000 CSCC estimates across each of 210 CMIP5 climate models that were included in Ricke et al. (2018) for RCP6.0, and across uncertainty in the empirically derived damage function from Harding et al. (2025). We find that uncertainty in the damage function is the primary driver of variation in CSCC estimates, exceeding the effect of variation across climate model predictions. This is reflected not only in the width of the 66% confidence intervals but also in the extremes of the distribution: the maximum SCC in our sample is US$901.59 per tCO_2, while the minimum is -US$221.75 per tCO_2, suggesting a net global benefit from climate change. Although this wide uncertainty range complicates robust assessments of the wealth contribution of land carbon sinks, these extreme values represent the outer bounds across CSCC distributions, and therefore the global SCC.

Furthermore, the distribution we obtained for the CSCC across countries is consistent with earlier estimates, such as estimates based on integrated assessment models provided by Tol (2019), although with differences in absolute values. India and China have the highest CSCC, consistent with Tol's findings, while Nigeria stands out with a relatively large CSCC compared with Tol's results but remains consistent with Ricke et al. (2018). While the estimation accounts for time-invariant historical, institutional, and technological factors through the use of fixed effects, it does not account for trade and price feedback. In turn, countries such as Canada and Russia are estimated to benefit from warming, as found in other empirical estimates that allow for a non-linear relationship between temperature and economic outcomes (Burke, Hsiang and Miguel, 2015). Incorporating trade and price feedbacks, however, may alter the estimated impacts of climate change on GDP—and by extension, CSCC—relative to those inferred from historical weather–economy relationships (Calzadilla et al., 2013; Aaheim et al., 2015). Accordingly, we focus on countries with a positive CSCC (i.e., countries estimated to be negatively affected by climate change). For countries with a negative CSCC (i.e., countries estimated to be positively affected by climate change), meaningful insights can still be derived with respect to the global and outbound contribution to comprehensive investment since our aggregated SCC estimate is well supported by the broader literature.

The accompanying database for this study provides, for all four discount rate specifications, the median, minimum and maximum values, 66% and 95% confidence intervals (derived from the 17th–83rd and 2.5th–97.5th percentiles, respectively), as well as the mean and standard deviation of the contribution of various carbon fluxes to comprehensive investment, allowing one to assess the wealth contribution including uncertainties and different discount rate scenarios. Our analysis includes multiple specifications, including three land-based carbon fluxes and two net carbon fluxes also incorporating fossil fuel emissions, different treatment of carbon fluxes from overseas territories, and varying specifications for the carbon price data. Beyond quantifying the contribution of land-based carbon sequestration to inclusive wealth, this framework generates a comprehensive database to assess, for example, the foregone wealth contribution from carbon sequestration due to primary forest destruction. The data also enable estimation of each country's net gains from preserving these forests, accounting for the contributions of their own domestic sinks. Together, these insights provide a foundation for designing incentive schemes to protect primary forests and reduce land-use emissions.

References

Aaheim, Asbjørn, Bård Romstad, Taoyuan Wei, Jón Egill Kristjánsson, Helene Muri, Ulrike Niemeier, and Hauke Schmidt. 2015. "An economic evaluation of solar radiation management." *Science of The Total Environment*, 532: 61–69.

Allen, Myles R, David J Frame, Pierre Friedlingstein, Nathan P Gillett, Giacomo Grassi, Jonathan M Gregory, William Hare, Jo House, Chris Huntingford, Stuart Jenkins, et al. 2025. "Geological Net Zero and the need for disaggregated accounting for carbon sinks." *Nature*, 638(8050): 343–350.

Arrow, Kenneth J, Partha Dasgupta, and Karl-Göran Mäler. 2003. "Evaluating projects and assessing sustainable development in imperfect economies." *Environmental and Resource Economics*, 26: 647–685.

Arrow, Kenneth J, Partha Dasgupta, Lawrence H Goulder, Kevin J Mumford, and Kirsten Oleson. 2012. "Sustainability and the measurement of wealth." *Environment and development economics*, 17(3): 317–353.

Bastien-Olvera, Bernardo A, and Frances C Moore. 2021. "Use and non-use value of nature and the social cost of carbon." *Nature Sustainability*, 4(2): 101–108.

Bertram, Christine, Martin Quaas, Thorsten BH Reusch, Athanasios T Vafeidis, Claudia Wolff, and Wilfried Rickels. 2021. "The blue carbon wealth of nations." *Nature Climate Change*, 11(8): 704–709.

Brienen, Roel JW, Oliver L Phillips, Ted R Feldpausch, Emanuel Gloor, Tim R Baker, Jon Lloyd, Gabriela Lopez-Gonzalez, Abel Monteagudo-Mendoza, Yadvinder Malhi, Simon L Lewis, et al. 2015. "Long-term decline of the Amazon carbon sink." *Nature*, 519(7543): 344–348.

Burke, Marshall, John Dykema, David B Lobell, Edward Miguel, and Shanker Satyanath. 2015. "Incorporating climate uncertainty into estimates of climate change impacts." *Review of Economics and Statistics*, 97(2): 461–471.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel. 2015. "Global non-linear effect of temperature on economic production." *Nature*, 527(7577): 235–239.

Calzadilla, Alvaro, Katrin Rehdanz, Richard Betts, Pete Falloon, Andy Wiltshire, and Richard S. J. Tol. 2013. "Climate change impacts on global agriculture." *Climatic Change*, 120(1): 357–374.

Casey, Gregory, Stephie Fried, and Ethan Goode. 2023. "Projecting the Impact of Rising Temperatures: The Role of Macroeconomic Dynamics." *IMF Economic Review*, 71(3): 688–718.

Dell, Melissa, Benjamin F Jones, and Benjamin A Olken. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics*, 4(3): 66–95.

Dorgeist, Lea, Clemens Schwingshackl, Selma Bultan, and Julia Pongratz. 2024. "A consistent budgeting of terrestrial carbon fluxes." *Nature Communications*, 15(1): 7426.

FAO. 2020. "FAOSTAT: Forest Area (SDG Indicator 15.1.1) for All Countries, 2020." Data retrieved from FAOSTAT SDG Indicators (SDGB) database, licensed under CC BY 4.0.

Fenichel, Eli P, Joshua K Abbott, Jude Bayham, Whitney Boone, Erin MK Haacker, and Lisa Pfeiffer. 2016. "Measuring the value of groundwater and other forms of natural capital." *Proceedings of the National Academy of Sciences*, 113(9): 2382–2387.

Friedlingstein, Pierre, Michael O'Sullivan, Matthew W. Jones, and et al. 2023. "Global Carbon Budget 2023." *Earth System Science Data*, 15(12): 5301–5369. Publisher: Copernicus GmbH.

Friedlingstein, Pierre, Michael O'Sullivan, Matthew W. Jones, and et al. 2024. "Global carbon budget 2024." *Earth System Science Data*.

Gidden, Matthew J, Thomas Gasser, Giacomo Grassi, Nicklas Forsell, Iris Janssens, William F Lamb, Jan Minx, Zebedee Nicholls, Jan Steinhauser, and Keywan Riahi. 2023. "Aligning climate scenarios to emissions inventories shifts global benchmarks." *Nature*, 624(7990): 102–108.

Grassi, Giacomo, Jo House, Werner A Kurz, Alessandro Cescatti, Richard A Houghton, Glen P Peters, Maria J Sanz, Raul Abad Viñas, Ramdane Alkama, Almut Arneth, et al. 2018. "Reconciling global-model estimates and country reporting of anthropogenic forest CO2 sinks." *Nature Climate Change*, 8(10): 914–920.

Harding, Anthony, Juan Moreno-Cruz, Martin Quaas, Wilfried Rickels, and Sjak Smulders. 2025. "Distribution of climate damages in convergence-consistent growth projections." *Energy Economics*, 108705.

Harstad, Bard. 2025. "Improving tropical forest financing." Stanford Institute for Economic Policy Research (SIEPR) Policy Brief.

Hicke, Jeffrey A, Craig D Allen, Ankur R Desai, Michael C Dietze, Ronald J Hall, Edward H Hogg, Daniel M Kashian, David Moore, Kenneth F Raffa, Rona N Sturrock, et al. 2012. "Effects of biotic disturbances on forest carbon cycling in the U nited S tates and C anada." *Global Change Biology*, 18(1): 7–34.

Hogan, Dylan, and Wolfram Schlenker. 2024. "Chapter 2 - Empirical approaches to climate change impact quantification." In . Vol. 1 of *Handbook of the Economics of Climate Change*, , ed. Lint Barrage and Solomon Hsiang, 53–111. North-Holland.

Jain, Piyush, Quinn E Barber, Stephen W Taylor, Ellen Whitman, Dante Castellanos Acuna, Yan Boulanger, Raphaël D Chavardès, Jack Chen, Peter Englefield, Mike Flannigan, et al. 2024. "Drivers and impacts of the record-breaking 2023 wildfire season in Canada." *Nature Communications*, 15(1): 6764.

Kalkuhl, Matthias, and Leonie Wenz. 2020. "The impact of climate conditions on economic production. Evidence from a global panel of regions." *Journal of Environmental Economics and Management*, 103: 102360.

Moore, F.C., M.A. Drupp, J. Rising an S. Dietz, I. Rudik, and G. Wagner. 2024. "Synthesis of evidence yields high social cost of carbon due to structural model variation and uncertainties." *PNAS*, 121(52): e2410733121.

Moore, Frances C., and Delavane B. Diaz. 2015. "Temperature impacts on economic growth warrant stringent mitigation policy." *Nature Climate Change*, 5(2): 127–131. Publisher: Nature Publishing Group.

Nath, Ishan B., Valerie A. Ramey, and Peter J. Klenow. 2024. "How much will global warming cool global growth?"

Newell, Richard G., Brian C. Prest, and Steven E. Sexton. 2021. "The GDP-Temperature relationship: Implications for climate change damages." *Journal of Environmental Economics and Management*, 108: 102445.

Park Williams, A, Craig D Allen, Alison K Macalady, Daniel Griffin, Connie A Woodhouse, David M Meko, Thomas W Swetnam, Sara A Rauscher, Richard Seager, Henri D Grissino-Mayer, et al. 2013. "Temperature as a potent driver of regional forest drought stress and tree mortality." *Nature climate change*, 3(3): 292–297.

Rennert, Kevin, Frank Errickson, Brian C Prest, Lisa Rennels, Richard G Newell, William Pizer, Cora Kingdon, Jordan Wingenroth, Roger Cooke, Bryan Parthum, et al. 2022. "Comprehensive evidence implies a higher social cost of CO2." *Nature*, 610(7933): 687–692.

Ricke, Katharine, Laurent Drouet, Ken Caldeira, and Massimo Tavoni. 2018. "Country-level social cost of carbon." *Nature Climate Change*, 8(10): 895–900.

Rickels, Wilfried, Felix Meier, Sonja Peterson, Sina Rühland, Sneha Thube, Johannes Karstensen, Conny Posern, Claudia Wolff, Athanasios T Vafeidis, Patricia Grasse, et al. 2024. "The ocean carbon sink enhances countries' inclusive wealth and reduces the cost of national climate policies." *Communications Earth & Environment*, 5(1): 513.

Rickels, Wilfried, Martin F Quaas, and Martin Visbeck. 2014. "How healthy is the human-ocean system?" *Environmental Research Letters*, 9(4): 044013.

Schwingshackl, Clemens, Wolfgang A. Obermeier, Selma Bultan, Giacomo Grassi, Josep G. Canadell, Pierre Friedlingstein, Thomas Gasser, Richard A. Houghton, Werner A. Kurz, Stephen Sitch, and Julia Pongratz. 2022. "Differences in land-based mitigation estimates reconciled by separating natural and land-use CO2 fluxes at the country level." *One Earth*, 5(12): 1367–1376.

Tol, Richard SJ. 2019. "A social cost of carbon for (almost) every country." *Energy Economics*, 83: 555–566.

Tumber-Dávila, Shersingh Joseph, Taylor Lucey, Emery R Boose, Danelle Laflower, Agustín León-Sáenz, Barry T Wilson, Meghan Graham MacLean, and Jonathan R Thompson. 2024. "Hurricanes pose a substantial risk to New England forest carbon stocks." *Global Change Biology*, 30(4): e17259.

Willmott, Cort J., and Kenji Matsuura. 2018. "Terrestrial air temperature and precipitation: monthly and annual time series (1900-2017) v. 5.01."

World Resources Institute. 2024. "The Top 10 Countries for Humid Tropical Primary Forest Loss (2002–2024)."

Appendix

A. Additional Tables

Table A.1
Regression results from Harding et al. (2025).

Dependent variable	Δy_{it}
Level effects	
Temperature	0.00901
	(0.00363)
Temperature^2	−0.000332
	(0.000138)
Precipitation	0.000756
	(0.00959)
Precipitation^2	−0.00149
	(0.00198)
Implied λ	0.149
	(0.0112)
Peak growth temperature	13.6
Country-specific time trend	Linear
Observations	8,046

Notes: The model includes country and year fixed effects. Standard errors (in parentheses) are clustered at the country level. Temperature is measured in degrees Celsius, and precipitation is measured in micrometers per year. The model is estimated using instrumental variables, instrumenting lagged income with its two-period lag.

Table A.2
Change in natural land sink estimates when using pre-industrial land cover.

Country	S_{LAND}	$S^{\text{tF}}_{\text{LAND}}$	$\Delta = S_{\text{LAND}} - S^{\text{tF}}_{\text{LAND}}$	Relative Δ
China	−0.2482	−0.1100	−0.14	−56 percent
Russia	−0.4026	−0.2916	−0.11	−28 percent
India	−0.1365	−0.0264	−0.11	−81 percent
United States	−0.2967	−0.1880	−0.11	−37 percent
Argentina	−0.0515	−0.0100	−0.04	−81 percent
Canada	−0.2139	−0.1734	−0.04	−19 percent
Brazil	−0.2772	−0.2379	−0.04	−14 percent
Ethiopia	−0.0503	−0.0153	−0.04	−70 percent
Kenya	−0.0353	−0.0061	−0.03	−83 percent
Indonesia	−0.1512	−0.1224	−0.03	−19 percent

Notes: The table reports mean natural land carbon sink estimates (GtC/yr) for the ten countries most affected by switching from present-day forest cover estimates ($S^{\text{tF}}_{\text{LAND}}$) to estimates based on pre-industrial land cover (S_{LAND}, GCB baseline). The difference Δ measures the additional sink implied by using pre-industrial land cover. Relative changes are expressed as percentages of $S^{\text{tF}}_{\text{LAND}}$.

Table A.3
Top and bottom five countries by median CSCC across discounting scenarios.

Country	dr = 2.5	dr = 3	dr = 5	Endogenous
Top five countries (highest CSCC)				
India	49.64 (25.82, 80.15)	36.92 (19.39, 59.85)	14.99 (7.66, 24.17)	7.53 (3.64, 12.96)
China	13.80 (−6.46, 35.17)	10.62 (−5.47, 28.05)	4.91 (−3.29, 13.57)	3.18 (−2.02, 8.94)
Nigeria	13.38 (7.23, 21.28)	9.26 (4.98, 14.67)	2.85 (1.52, 4.50)	1.05 (0.53, 1.79)
Indonesia	7.59 (3.85, 12.45)	5.75 (2.90, 9.44)	2.46 (1.23, 4.02)	1.20 (0.58, 2.05)
United States	6.85 (−5.54, 19.45)	5.19 (−4.75, 15.08)	2.15 (−2.85, 7.23)	4.77 (−4.15, 14.46)
Bottom five countries (lowest CSCC)				
Sweden	−0.62 (−1.03, −0.25)	−0.49 (−0.81, −0.20)	−0.24 (−0.40, −0.11)	−0.34 (−0.52, −0.15)
United Kingdom	−0.92 (−2.22, 0.29)	−0.75 (−1.75, 0.20)	−0.40 (−0.89, 0.06)	−0.54 (−1.19, 0.11)
Germany	−1.28 (−2.84, 0.23)	−1.08 (−2.32, 0.14)	−0.61 (−1.26, 0.02)	−0.82 (−1.67, 0.07)
Canada	−2.21 (−3.70, −0.76)	−1.77 (−2.94, −0.63)	−0.91 (−1.48, −0.37)	−1.33 (−2.11, −0.53)
Russia	−6.08 (−9.67, −2.74)	−4.86 (−7.76, −2.28)	−2.54 (−4.00, −1.25)	−2.17 (−3.30, −1.09)

Notes: The table reports median country-level social cost of carbon (CSCC) estimates in US dollars per metric ton of CO_2, with 66 percent confidence intervals in parentheses. Results are shown for discount rates of 2.5, 3, and 5 percent, as well as an endogenous discounting specification with a pure rate of time preference of 2 percent and an elasticity of marginal utility of 1.5.

B. Additional Figures

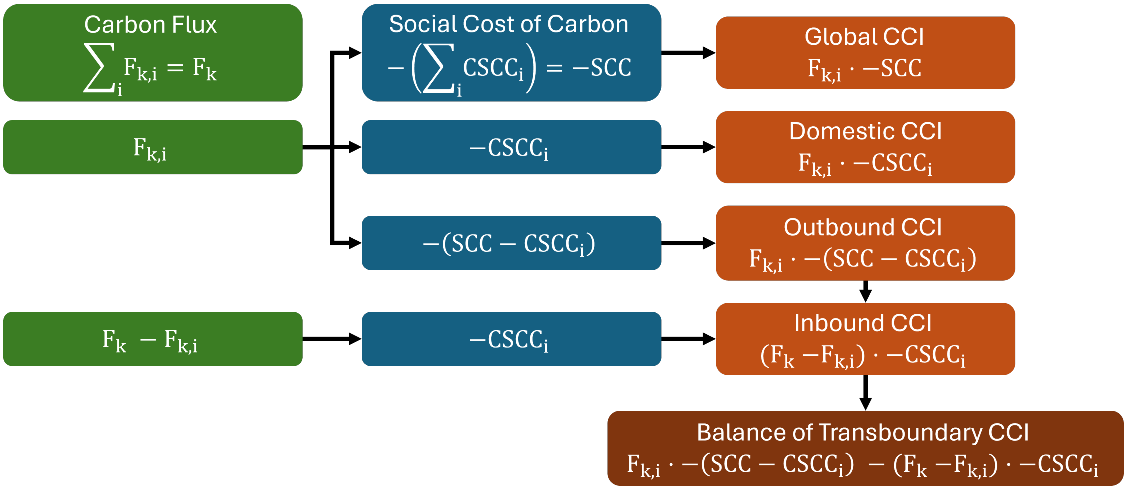

Figure B.1: Schematic overview of carbon flux contributions to comprehensive investment (CCI).

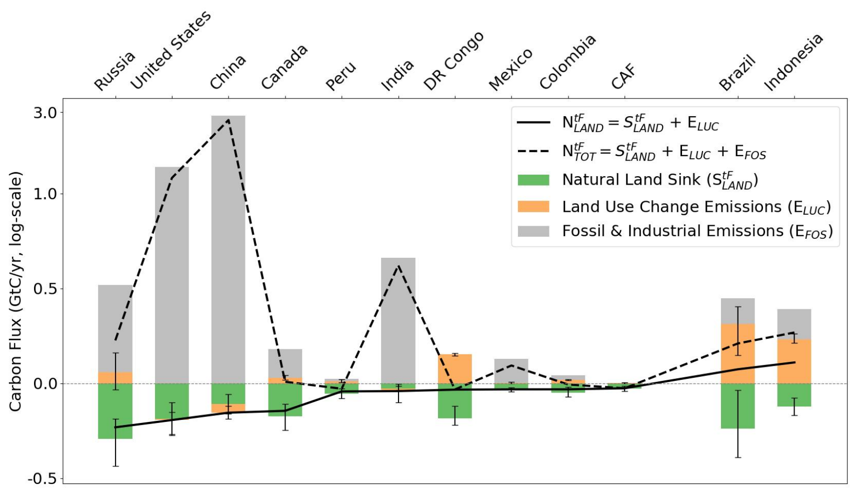

Figure B.2: Carbon flux breakdown for major land sinks (2013–2022).

Notes: Mean carbon fluxes (GtC/yr) are shown for the ten countries with the largest net land carbon flux based on today's total forest area ($N^{tF}_{LAND} = S^{tF}_{LAND} + E_{LUC}$), with Brazil and Indonesia also included due to their significant tropical forest sinks and comparatively large associated losses. Green bars indicate natural land sinks (S^{tF}_{LAND}), orange bars represent land-use change emissions (E_{LUC}) and gray bars show fossil and industrial emissions (E_{FOS}). The black solid line denotes N^{tF}_{LAND}, while the black dashed line indicates N^{tF}_{TOT}. Error bars reflect the interquartile range (17th–83rd percentiles), capturing multi-model variability. Positive values indicate emissions, while negative values represent net carbon uptake. (CAF: Central African Republic, DR Congo: Democratic Republic of the Congo)

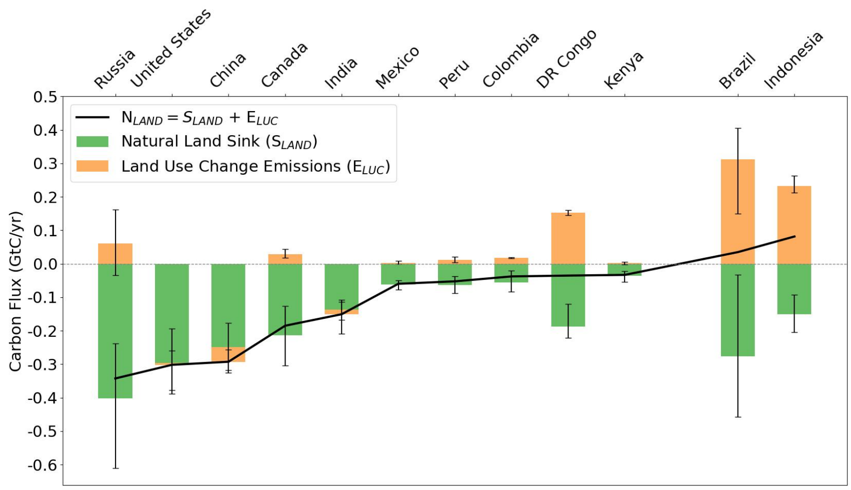

Figure B.3: Carbon flux breakdown for major land sinks (2013–2022).

Notes: Mean carbon fluxes (GtC/yr) are shown for the ten countries with the largest net land carbon flux based on pre-industrial forest area ($N_{\text{LAND}} = S_{\text{LAND}} + E_{\text{LUC}}$), with Brazil and Indonesia also included due to their significant tropical forest sinks and comparatively large associated emissions from their degradation. Green bars indicate natural land sinks (S_{LAND}), and orange bars represent land-use change emissions (E_{LUC}). The black line denotes N_{LAND}. Error bars reflect the interquartile range (17th–83rd percentiles), capturing multi-model variability. Positive values indicate emissions, while negative values represent net carbon uptake. (CAF: Central African Republic, DR Congo: Democratic Republic of the Congo)

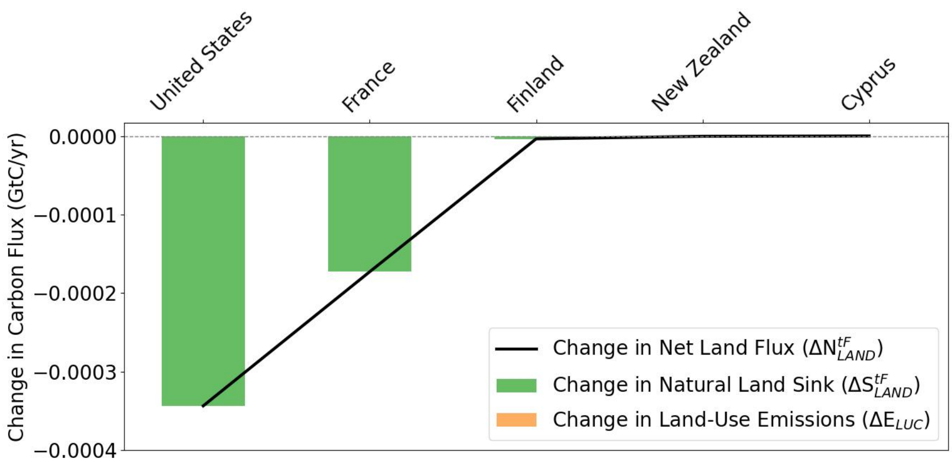

Figure B.4: Effect of attributing overseas territories on national carbon flux estimates.

Notes: This figure shows the change in mean natural land sink ($\Delta S^{tF}_{\text{LAND}}$, green) and land-use change emissions (ΔE_{LUC}, orange) for countries with overseas territories when fluxes from these territories are aggregated with those of the sovereign state (GtC/yr). The black line indicates the resulting change in the net land carbon flux ($\Delta N^{tF}_{\text{LAND}}$). Positive values denote additional emissions, while negative values indicate increased carbon uptake due to the attribution of overseas fluxes.

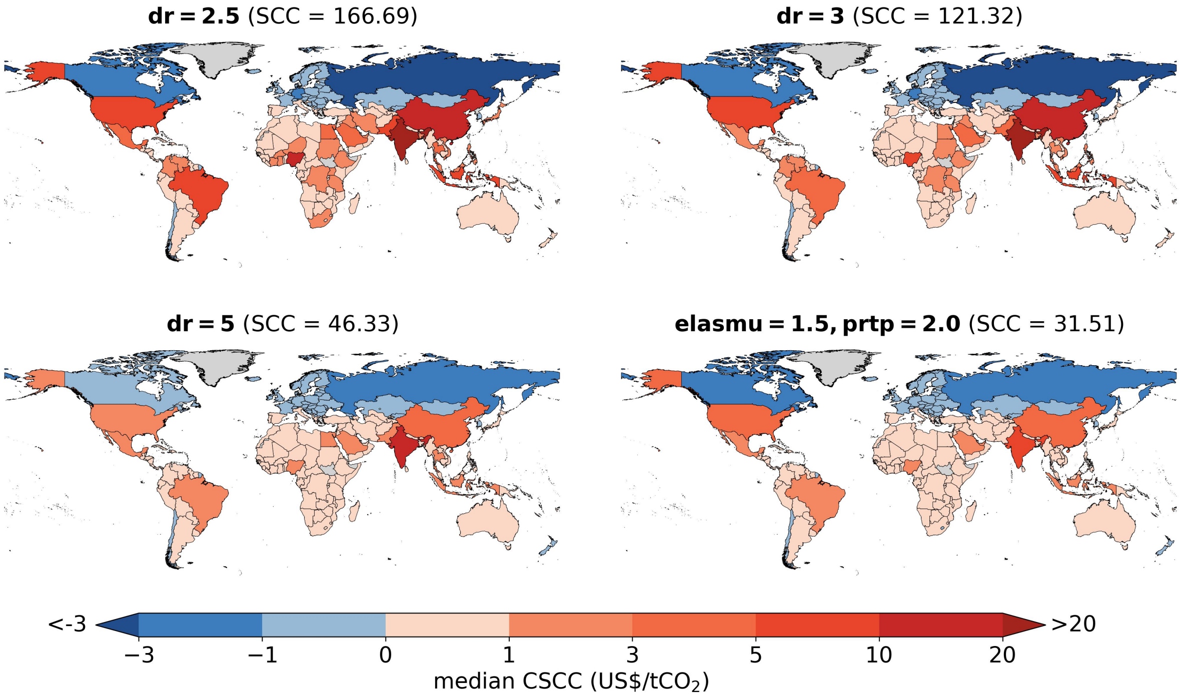

Figure B.5: Median country-level social cost of carbon (CSCC) under alternative discounting assumptions.

Notes: Shown are median estimates of the CSCC (US$/$tCO_2$) for the SSP2–RCP6.0 scenario. Results are presented for a 2.5% discount rate (primary specification), fixed discount rates of 3% and 5%, and an endogenous discounting approach with a pure rate of time preference of 2% and an elasticity of marginal utility of 1.5. Countries with positive CSCC (net damages) are shown in orange to red, while countries with negative CSCC (net benefits) appear in blue. Grey indicates no data.

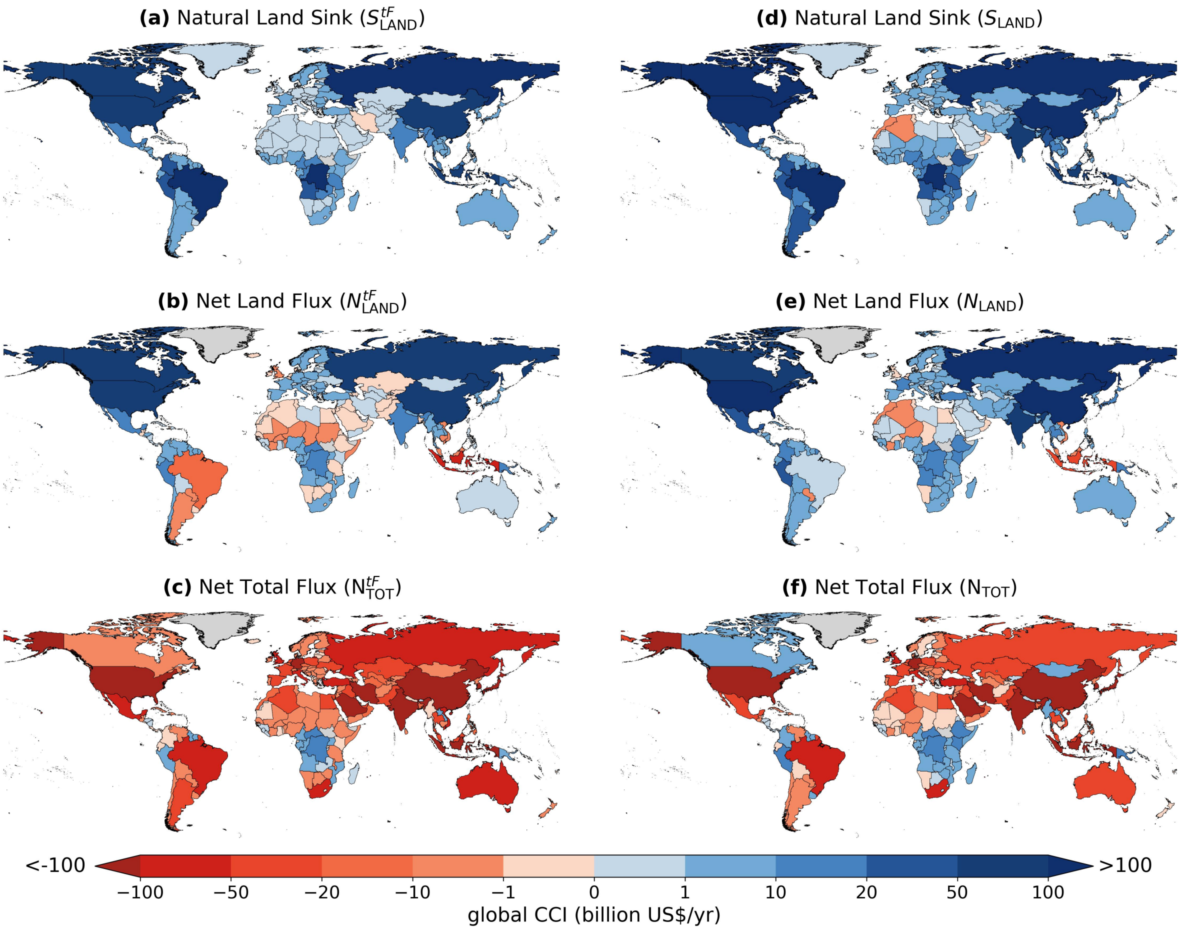

Figure B.6: Global carbon flux contributions to comprehensive investment based on present-day forest area and pre-industrial land covers.

Notes: Panels (a-c) show median global contributions to comprehensive investment ($\mathrm{CCI}^{\mathrm{global}}_{k,i}$) in billion US$/yr, for three carbon fluxes, using present-day forest area as the basis for the natural land sink (S^{tF}_{LAND}): (a) natural land sink (S^{tF}_{LAND}), (b) net land carbon flux ($N^{tF}_{\mathrm{LAND}} = S^{tF}_{\mathrm{LAND}} + E_{\mathrm{LUC}}$), and (c) net total carbon flux ($N^{tF}_{\mathrm{TOT}} = S^{tF}_{\mathrm{LAND}} + E_{\mathrm{LUC}} + E_{\mathrm{FOS}}$). Panels (d–f) present the corresponding results when the natural land sink is instead based on pre-industrial land cover (S_{LAND}): (d) natural land sink (S^{tF}_{LAND}), (e) net land carbon flux (N_{LAND}), and (f) net total carbon flux (N_{TOT}). Values are derived by multiplying each country's carbon flux ($F_{k,i}$) by the global social cost of carbon (SCC). Blue shades indicate a positive contribution to global wealth (net carbon uptake), while red shades denote a negative contribution (net emissions). Countries without data are shown in grey.