

An updated Earth System Impact metric for bridging sub-global pressures and planetary boundaries

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A. ESI Metric Construction

The approach to ESI Construction in this paper is largely consistent with the documentation in the Supplementary Methods of the ESI prototype described by Lade et al. (2021). Here we recap the variables that are essential to feedback modelling and highlight other adjustments and new features. (Note that what we refer to as “sub-global boundaries,” the text of Lade et al.

30 (2021) referred to as “guardrails.”)

State and Pressure Variables and Interaction Matrix

We define state variables for climate change (CC), land cover change (LCC) and runoff (RO) to be represented by atmospheric CO₂ concentrations, land areas covered by different vegetation types, and total runoff density, respectively. Over each region
 35 (as determined by continents and dominant PFTs), water state variables are aggregated using means for runoff density and sums for vegetation land area.

To implement the feedback model, we define a vector x of all the model’s state variables:

$$x = \begin{bmatrix} CC \\ LCC_1 \\ RO_1 \\ LCC_2 \\ RO_2 \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

40

(S1)

where the number subscripts refer to the different regions. The vectors Δx and Δd are similarly structured but represent the impacts or change to each state variable, and the pressures that resulted in that change, respectively.

To calculate Δx in response to Δd , a matrix of interaction strengths, B , is assembled:

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$$B = \begin{bmatrix} 0 & LCC_1 \rightarrow CC & RO_1 \rightarrow CC & LCC_2 \rightarrow CC & RO_2 \rightarrow CC & \dots \\ CC \rightarrow LCC_1 & 0 & RO_1 \rightarrow LCC_1 & LCC_2 \rightarrow LCC_1 & RO_2 \rightarrow LCC_1 & \\ \vdots & & & & & \end{bmatrix} \quad (S2)$$

Interactions along the diagonal (i.e., $CC \rightarrow CC$, $LCC_I \rightarrow LCC_I$, etc.) are 0. Interactions driven by RO (marked in gray in Eq. S2) are also 0 in this study but may be defined in future work. Likewise, interactions that imply teleconnections across regions (e.g. $LCC_2 \rightarrow LCC_I$, also marked in gray in Eq. A2) are beyond the scope of this study and set to 0 but can be estimated in future studies.

Equation (1) in the text is derived from equilibrium assumptions in Eq (S3):

$$\Delta x = B\Delta x + \Delta d \quad (S3)$$

55 Including Barren Land

PFTs in LPJmL are aggregated into five basic classes: boreal forest, temperate forest, tropical forest, C3 / cool grasslands and C4 / warm grasslands. Foliage projected cover (FPC), which represents the fractional vegetation cover of each PFT in LPJmL, is used to determine the dominant vegetation types in each gridcell. The fractional cover of barren land is determined as the residual of the sum of the other types. In the *NoLU* simulations, the entire grid cell is considered as being naturally vegetated, the fractional cover of barren land in each tile would be (Eq. S4):

$$FPC_{barren} = 1 - (FPC_{boreal} + FPC_{temperate} + FPC_{tropical} + FPC_{c3_grass} + FPC_{c4_grass}) \quad (S4)$$

In the *WithLU* simulation, the crop portion of each grid cell is assigned a fraction (FPC_{crop}), distinct from the fraction of the naturally vegetation portion of the grid cell (such that $FPC_{crop} + FPC_{natural} = 1$). The individual fractions of the PFTs are scaled to the fraction of the naturally vegetated area. Hence, the fractional cover of barren land in each tile of the *WithLU* simulation would be (Eq. S5):

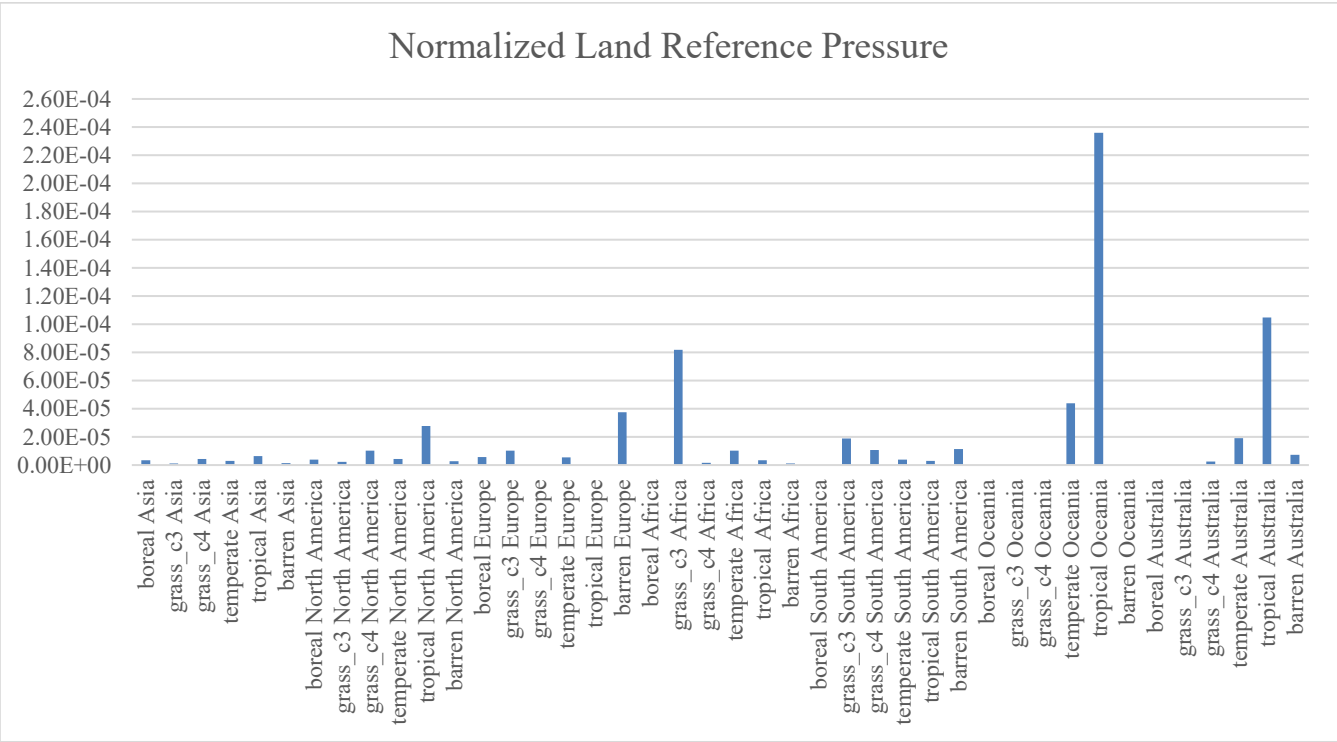
$$FPC_{barren} = FPC_{natural} - (FPC_{boreal} + FPC_{temperate} + FPC_{tropical} + FPC_{c3_grass} + FPC_{c4_grass}) * FPC_{natural} \quad (S5)$$

Given the FPCs, each tile is classified according to the dominant cover type from the seven major classes: boreal forest, temperate forest, tropical forest, C3 / cool grasslands and C4 / warm grasslands, barren land or crop. Tiles of the same dominant cover are then aggregated within each continent to produce the regional clusters used in this paper, with a minimum threshold of 10 grid cells. Output variables for carbon storage and runoff are averaged over full tiles and aggregated within each cluster.

75 Normalized Reference Pressures

The normalized land and water reference pressures (Figs. S1-S2) are indicative of the magnitude of the pressure relative to the available area of natural land cover and the available runoff, respectively. Higher values for normalized land reference pressures indicate smaller land areas. Similarly, higher values for normalized water reference pressures indicate lower

80 availability of surface freshwater, which is also related to the area of the region. (Both are calculated from Eq. 4 in the main
text.)



85 **Figure S1. Normalized land reference pressure determined by dividing the reference pressure of 5 km² natural land cover loss by the difference between the regional boundary and the preindustrial baseline.**

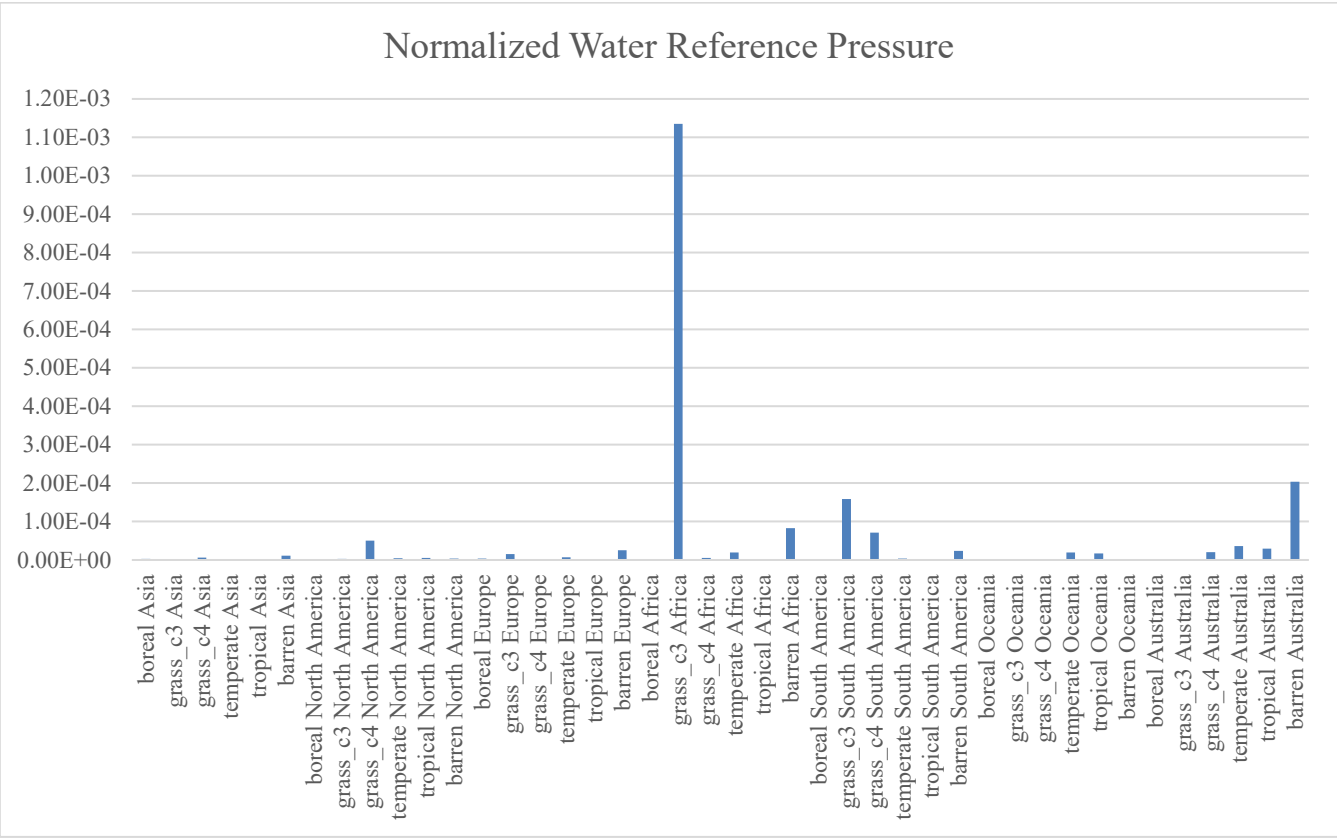
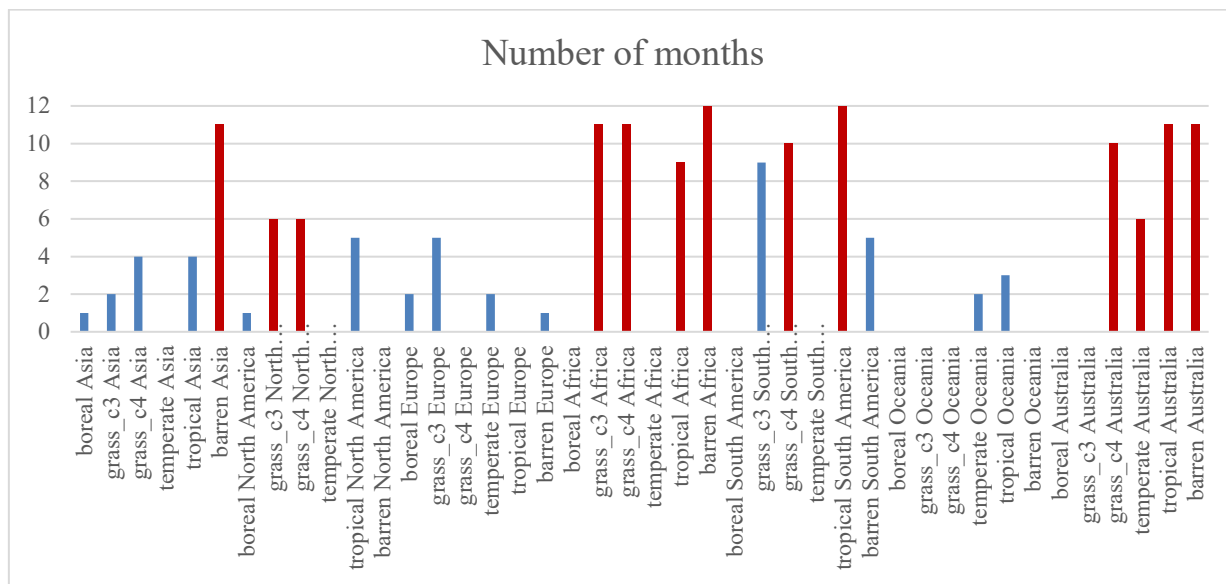


Figure S2. Normalized water reference pressure determined by dividing the reference pressure of 10^6 m^3 water withdrawal by the difference between the regional lower bound and the preindustrial baseline.

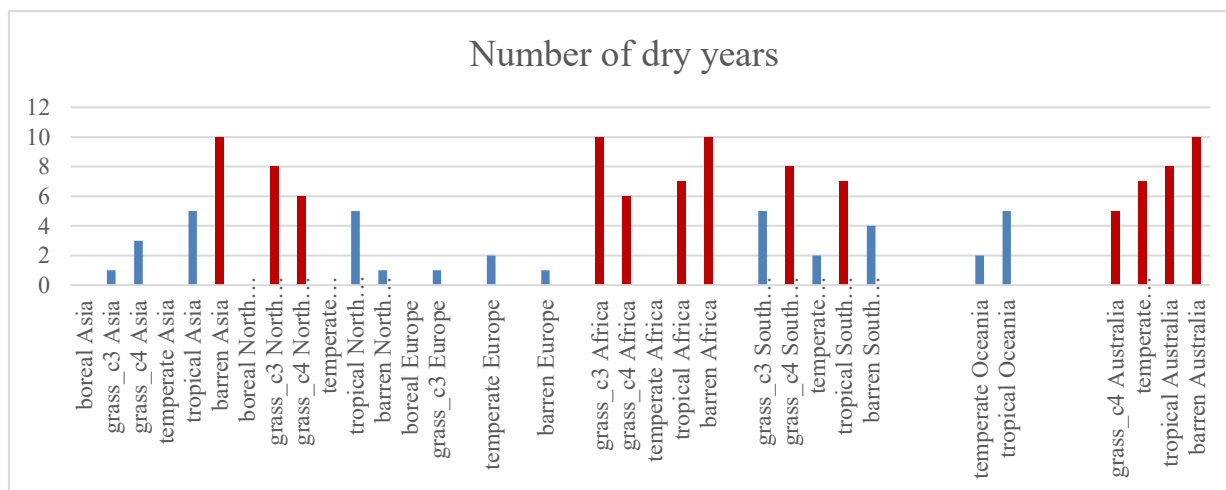
90 **Water ESI Weighting**

The weighting approach to produce the final Water ESI coefficients is based on either the fraction of dry months within the year as averaged over the past 10 years (an indicator of intra-annual variability), or the fraction of dry years over the past 10 years (an indicator of inter-annual variability). Figures S3 and S4 tally the counts of dry months and dry years, respectively,

95 for each region:



100 **Figure S3. Number of months within the year that are drier than their respective preindustrial monthly average. Bars in red are regions where the current state is overall drier compared to the preindustrial baseline when aggregated annually; blue, wetter.**



105 **Figure S4. Number of years in the last 10 years of the simulation that are drier than the annual preindustrial baseline. Bars in red are regions where the current state averaged over the last 10 years is overall drier; blue, wetter. Vegetation boundaries are determined by cover averaged over the last 10 years of the NoLU simulation.**

Based on these data, weighting options derived for the different regions are as shown in Table S1. The higher weight is applied to generate the final Water ESI scores.

110 **Table S1. Weights for the Water ESI coefficients based on number of dry months and number of dry years. The higher number was applied to yield the final Water ESI coefficients. Where both weights are 0, the Water ESI coefficient likewise becomes 0. Regions with NA have undefined coefficients due to not meeting the minimum threshold for number of grid cells.**

Region	Weight based on number of dry months (x/12)	Weight based on number of dry years (x/10)
boreal Asia	0.08	0
grass_c3 Asia	0.17	0
grass_c4 Asia	0.33	0.4
temperate Asia	0.00	0
tropical Asia	0.33	0.5
barren Asia	0.92	1
boreal North America	0.08	0
grass_c3 North America	0.50	0.9
grass_c4 North America	0.50	0.5
temperate North America	0.00	0
tropical North America	0.42	0.4
barren North America	0.00	0
boreal Europe	0.17	0
grass_c3 Europe	0.42	0
grass_c4 Europe	NA	NA
temperate Europe	0.17	0.2
tropical Europe	NA	NA
barren Europe	0.08	0
boreal Africa	NA	NA
grass_c3 Africa	0.92	0.9
grass_c4 Africa	0.92	0.6
temperate Africa	0.00	0
tropical Africa	0.75	0.6
barren Africa	1.00	1
boreal South America	NA	NA
grass_c3 South America	0.75	0.8
grass_c4 South America	0.83	0.9
temperate South America	0.00	0.2
tropical South America	1.00	0.7

Region	Weight based on number of dry months (x/12)	Weight based on number of dry years (x/10)
barren South America	0.42	0.2
boreal Oceania	NA	NA
grass_c3 Oceania	NA	NA
grass_c4 Oceania	NA	NA
temperate Oceania	0.17	0.2
tropical Oceania	0.25	0.5
barren Oceania	NA	NA
boreal Australia	NA	NA
grass_c3 Australia	NA	NA
grass_c4 Australia	0.83	0.8
temperate Australia	0.50	0.7
tropical Australia	0.92	0.6
barren Australia	0.92	1

115 Carbon ESI Scaling

The Carbon ESI coefficient is intended to be applied to cumulative emissions, but an alternative Carbon ESI metric is provided for cases in which only annual emission rates are available. This alternative is calculated by applying a scaling factor to the Carbon ESI based on the share of the annual emissions in the global fossil fuel emissions. As of 2023, the last year of our simulations, global fossil fuel emissions were estimated at 38 GtCO₂ / 10.354 GtC/year (Friedlingstein et al., 2025).

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Given the original reference pressure of 0.1MtC, the equivalent in atmospheric CO₂ concentration is approximately CCref_{original} = 2.36*10⁻⁵ppm, assuming an airborne fraction of 0.5 and given a conversion factor of 2.12 GtC = 1ppm CO₂. This reference pressure results in the Carbon ESI of 40*10⁻⁸.

125 We now consider a new reference pressure of 1 KtC/year = 0.001MtC/year. We apportion to this a responsibility for the historical increase in atmospheric CO₂ concentration from preindustrial (280ppm) to current (420ppm) state, based on share in annual emissions (38 GtCO₂/year = 10,354 MtC/year). This yields:

$$CCref_{new} = \frac{reference\ annual\ emission}{global\ annual\ emissions} (Current\ Atm\ Conc - Preindustrial\ Atm\ Conc) \quad (S6)$$

$$CCref_{new} = 1.35*10^{-5}ppm$$

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By applying simple ratio and proportion between CCref_{original}, which had resulted in a Carbon ESI coefficient of 40*10⁻⁸, and CCref_{new}, we derive a corresponding Carbon ESI for the latter of approximately 23*10⁻⁸.

B. Approximation of Albedo Effect

Previous studies (e.g. Carrer et al., 2018; Hasler et al., 2024; Wang et al., 2023b; Zhu et al., 2024) have expressed the climate impact of albedo change as equivalent carbon emissions (CO_2e) for surface darkening, or carbon sequestration for surface brightening. We can incorporate the albedo effect of LCC→CC in the ESI analysis using a similar approach. Several methods estimate CO_2e of albedo change (Bright et al., 2016; Bright and Lund, 2021): emissions equivalent of shortwave forcing (EESF), time-dependent emissions equivalent (TDEE), and the Global Warming Potential (GWP). We used the GWP of albedo (GWP_A) with a 100-year time horizon consistent with the GWP_{100} typically used in climate policy to report emissions (Intergovernmental Panel On Climate Change (Ipcc), 2023). Hammerschlag (2022) proposes albedo-GHG fungibility using GWP_A measured in kgCO_2 reduction per unit area per 0.01 brightening. As a cumulative measure, land use change studies using GWP_A often divide by the number of time steps to approximate an annual CO_2 flux comparable to annual productivity (Bright and Lund, 2021; Carrer et al., 2018; Sciusco et al., 2020).

We compile estimates of GWP_A from the literature (see below), but propose, for general use when no site-specific measurement is available, the value of $2.59 \frac{\text{kgCO}_2}{(\text{m}^2)(0.01 \text{ reduction in albedo})}$ over a time horizon of 100 years. This estimate, from Wang et al., (2023b), represents a composite of transition scenarios between different land use types and is comparable with other literature values. A limitation is that the study site was in China and lacks geographic diversity, and GWP_A can vary greatly between geographic locations and biomes, land use transitions and management practices (Chen et al., 2024).

Given this above expression for GWP_A , the CO_2e of albedo change can be estimated by:

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$$\text{CO}_2\text{e of albedo change} = \text{GWP}_A * \frac{\Delta \text{albedo}}{0.01} * \text{land area of change} \quad (\text{S7})$$

Treating this similarly to the carbon pressure, the appropriate Carbon ESI coefficient can then be applied to compare the impact of albedo change to the impact of actual carbon emissions, as demonstrated in Section G.

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This simplified approach is useful for an initial approximation but carries important caveats. Albedo is sensitive to location, vegetation and soil characteristics, local climate, and land management, so general estimates over broad tracts of land carry some uncertainty. The cooling from albedo brightening is also not equivalent to actual emissions reductions: albedo-driven climate perturbations are more localized and reversible over shorter time scales than CO_2 emissions, which mix and persist in the atmosphere (Bright and Lund, 2021). Changes in atmospheric CO_2 concentrations would also modify the carbon fertilization effect, which does not apply to CO_2 equivalents of albedo change. Incorporating albedo CO_2e into the carbon pressure could therefore over- or under-estimate the CO_2 effect (over-estimating for surface darkening; underestimating for surface brightening). The cooling effect of brightening land cover should also not be read as a motivation to deforest in favour

of higher-albedo, carbon sequestering croplands: deforestation carries other impacts on local climate, biodiversity, and other ecosystem services that a narrow albedo-carbon comparison would miss.

Albedo Output from LPJmL5.7.9

From LPJmL output of the *WithLU* simulation, we derive cluster-specific (continent-PFT) estimates for the albedo of vegetation types including barren land and crops (Table S2).

Table S2. Estimates of Albedo from LPJmL5.7.9 simulations with human land use

Region	Albedo
boreal Asia	0.26
grass_c3 Asia	0.45
grass_c4 Asia	0.22
temperate Asia	0.16
tropical Asia	0.15
barren Asia	0.36
crop Asia	0.29
boreal North America	0.25
grass_c3 North America	0.43
grass_c4 North America	0.22
temperate North America	0.16
tropical North America	0.15
barren North America	0.55
crop North America	0.25
boreal Europe	0.25
grass_c3 Europe	0.43
grass_c4 Europe	0.20
temperate Europe	0.17
tropical Europe	NA
barren Europe	0.53
crop Europe	0.26
boreal Africa	NA
grass_c3 Africa	0.23
grass_c4 Africa	0.21
temperate Africa	0.17
tropical Africa	0.15
barren Africa	0.29

Region	Albedo
crop Africa	0.21
boreal South America	0.23
grass_c3 South America	0.23
grass_c4 South America	0.21
temperate South America	0.17
tropical South America	0.15
barren South America	0.28
crop South America	0.20
boreal Oceania	NA
grass_c3 Oceania	NA
grass_c4 Oceania	0.17
temperate Oceania	0.16
tropical Oceania	0.14
barren Oceania	NA
crop Oceania	0.19
boreal Australia	NA
grass_c3 Australia	0.25
grass_c4 Australia	0.23
temperate Australia	0.16
tropical Australia	0.15
barren Australia	0.25
crop Australia	0.23

Albedo Values from Literature

In this section, we compare the model-estimated albedo to some albedo values compiled from literature:

- 175 • BOREAL FOREST
 - From literature:
 - 0.10 - 0.18 General estimates of forest albedo by Khokhlov et al. (2023) and Myhre and Myhre (2003)
 - 0.168 – 0.264 Arctic woodland (depends on species) estimated by Petzold and Rencz (1975)
 - 180 ▪ 0.09 – 0.11 for shortwave albedo depending on the species in the boreal forest Alibakhshi et al. (2020)
 - 0.1635 for boreal pine in Kuusinen et al. (2014) averaged across different times
 - 0.1188 for boreal spruce in Kuusinen et al. (2014) averaged across different times
 - 0.2215 for boreal broadleaved in Kuusinen et al. (2014) averaged across different times
 - 185 ▪ 0.10 – 0.15 for coniferous forests in Komilov (2020)
 - 0.08 – 0.12 for evergreen coniferous forests in Sieber et al. (2019)
 - 0.156 for no-snow aspen, 0.214 with snow in Betts and Ball (1997)

- 0.086 for no-snow jack pine across sites, 0.15 with snow in Betts and Ball (1997)
- 0.081 for no-snow spruce/poplar across sites, 0.108 with snow in Betts and Ball (1997)

- The albedo values for boreal forests derived from LPJmL do not distinguish seasons with snow cover vs. those without. However, even considering the with-snow values from literature, the estimates from LPJmL5 tend to be higher, which implies brighter surfaces. If boreal forests are converted to bright or reflective built-up areas, then a higher albedo for boreal forests might underestimate the equivalent carbon emissions reduction.

- TEMPERATE FOREST

- From literature:

- 0.10 - 0.18 General estimates of forest albedo by Khokhlov et al. (2023) and Myhre and Myhre (2003)
- 0.09 – 0.12 for shortwave albedo depending on the species in the temperate forest (Alibakhshi et al., 2020)
- Approximately 0.12 – 0.32 across different species and seasons (winter, summer) in temperate forest plantations in Vatani et al. (2019)
- 0.10 – 0.15 for coniferous forests in Komilov (2020)
- 0.13 – 0.18 for deciduous broadleaf forests in Sieber et al. (2019)

- The LPJmL5-derived estimates are slightly higher but within the general estimates from literature.

- TROPICAL FOREST

- From literature:

- 0.10 - 0.18 General estimates of forest albedo by Khokhlov et al. (2023) and Myhre and Myhre (2003)
- 0.124 as an average from studies reviewed by Culf et al. (1995) for the Amazon
- 0.1275 as an average of the studies reviewed by Giambelluca et al. (1997)
- 0.09 – 0.12 for shortwave albedo depending on the species in the tropical forest (Alibakhshi et al., 2020)
- 0.13 – 0.18 for deciduous broadleaf forests in Sieber et al. (2019)

- The LPJmL5-derived estimates are within the estimates from literature.

- COOL GRASS (C3)

- From literature:

- 0.26 as a general estimate from Khokhlov et al. (2023)
- 0.18 – 0.20 as a general estimate from Myhre and Myhre (2003)
- 0.15 – 0.23 as general estimate for grassland in Sieber et al. 2019
- 0.15 – 0.25 for meadows in Komilov (2020)
- 0.172 for unimproved grasslands in Sweden in Sieber et al. (2022)
- 0.197 for no-snow grass, 0.75 with snow in Betts and Ball (1997)

- The albedo estimates of C3_grass in LPJmL5 are generally higher, especially in clusters where we might expect some snow at some time of the year. Thus, the potential impact of snowfall on average albedo over human land uses must also be taken into account when considering conversions from C3 grasslands.

- WARM GRASS (C4)

- From literature:

- 0.26 as a general estimate from Khokhlov et al. (2023)
- 0.18 – 0.20 as a general estimate from Myhre and Myhre (2003)
- 0.15 – 0.23 as general estimate for grassland in Sieber et al. (2019)
- 0.15 – 0.25 for meadows in Komilov (2020)
- 0.175 as an average across tall and short savannahs and grasses in Nigeria in Giambelluca et al. (1997)

- The LPJmL5-derived estimates are within the estimates from literature.

- BARREN LAND

- We use “bare soil” from literature as a comparison. Estimates of albedo of bare soil can also vary widely based on the type of soil.

- 0.14 for bare soil in Nigeria (Giambelluca et al., 1997)
- 0.17 for exposed soils (Giambelluca et al., 1997)
- 0.05 – 0.15 for dark soils (Komilov 2020)
- 0.10 – 0.20 for wet gray soils (Komilov 2020)
- 0.20 – 0.35 for dry clayey or grey soils (Komilov 2020)
- 0.35 – 0.40 for dry light sandy soils (Komilov 2020)
- 0.134 in a Europe-based study (Sieber et al., 2022b)
- 0.15 – 0.19 in an urban context (Gardi et al., 2007)
- 0.35 in an urban context (Ramirez and Muñoz, 2012)
- 0.27 – 0.43 for deserts (Sieber et al., 2019)
- 0.70 – 0.87 for snow and ice cover (Sieber et al., 2019)

- Excluding snow and ice, the LPJmL5-derived albedo values for bare soil are high compared to most estimates from literature but fit into the range for deserts. Since these are based on annual averages of monthly albedo, higher latitudes could have been influenced by snow. If barren land is converted to built-up surfaces, the impact would depend on the specific characteristics of the latter. If the conversion is from barren land in North America to dark asphalt or to crops, the effect would be akin to contributing carbon emissions rather than reducing them. However, this contribution might be overestimated if the albedo values for barren land.

- CROP
 - From literature: crop albedo can vary depending on types of crop and location. There are general ‘crop’ estimates in literature, but ranges can be broad, e.g:
 - 0.10-0.25 rye and wheat fields (Komilov 2020)
 - 0.15-0.25 potato fields (Komilov 2020)
 - 0.20-0.25 cotton fields (Komilov 2020)
 - 0.15 - 0.20 (Myhre and Myhre, 2003)
 - 0.17 for crops in Nigeria (Giambelluca et al., 1997)
 - 0.176 in Giambelluca et al. (1997)
 - Averaged at 0.18-0.19 (but range from 0.13-0.20) between Sieber et al. (2022b, a)
 - In comparison, the crop albedo estimates from LPJmL5 are higher, which might result in overestimation of equivalent emissions reduction when darker forests are converted to crop lands.

Albedo of Other Human Land Use Types

Built-up land use types and mining/excavation land use types are not represented in LPJmL. We compile (in Table S3) the following values from literature, namely Ramirez and Muñoz (2012), Gardi et al. (2007), and Petzold and Rencz (1975):

Table S3. Other Estimates of Surface Albedo from Literature

Type of Surface	Albedo
Asphalt	0.05 to 0.200 (color fades with age)
Concrete - New	0.35 to 0.40
Concrete - Old	0.25 to 0.30
Concrete with Slag or White Cement	0.7
Corrugated Roof	0.10-0.15
Highly Reflective Roof	0.60-0.70
Brick/Stone	0.20-0.40
Red/Brown Tile	0.10-0.35
Light density residential	0.2
Medium density residential	0.23

High density residential	0.25
Parks	0.16
Industrial Area	0.26
Freeway	0.3
Mud/silt (wet, subarctic)	0.066
Boulders (Ore, wet, subarctic)	.086
Slate bedrock (dry, subarctic)	0.12
Gravel <2cm (wet, subarctic)	0.98
Gravel <2cm (dry, subarctic)	0.17
Frost scar (dry, subarctic)	0.139

Global Warming Potential (GWP) of Albedo

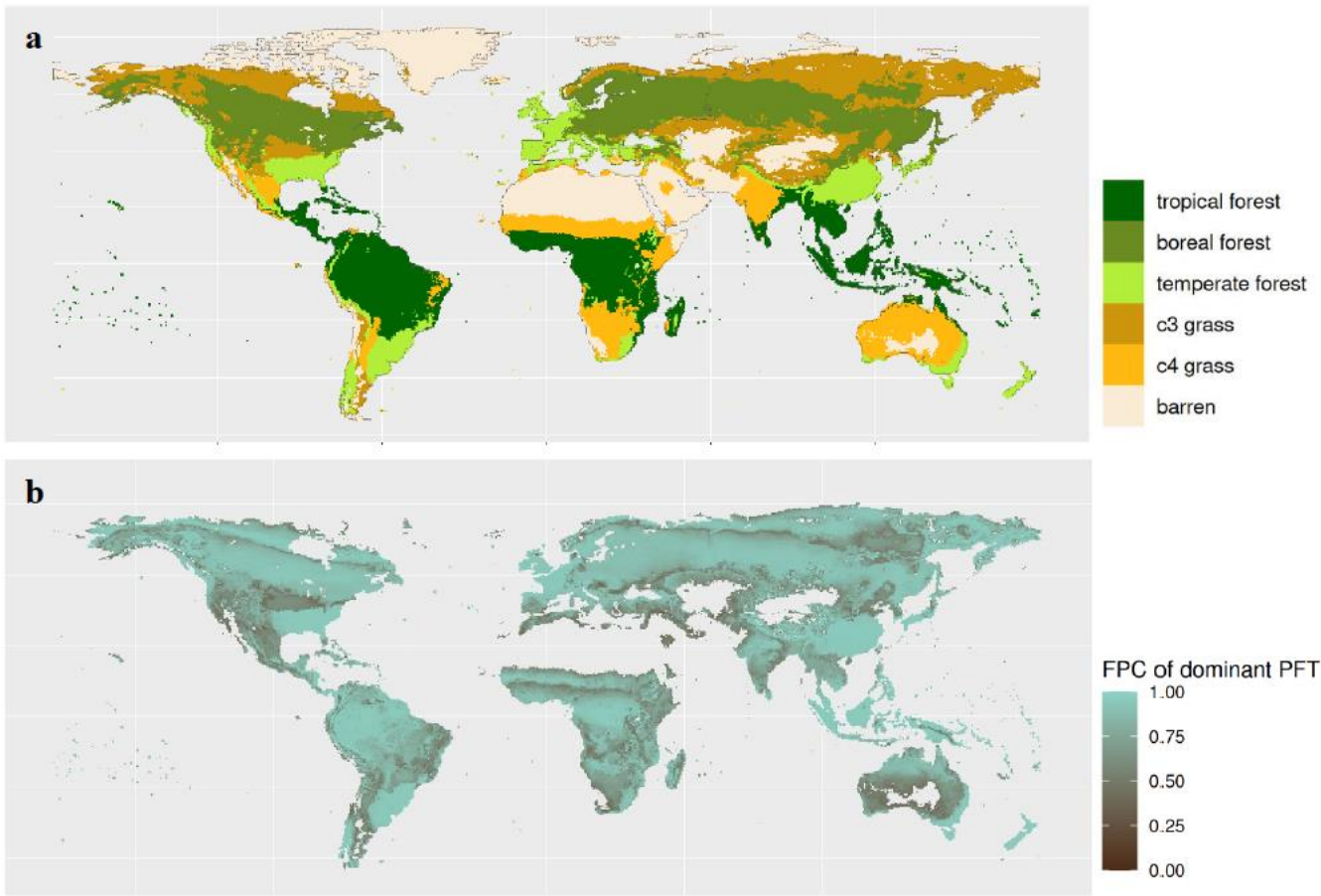
For reference, we include here a table (Table S4) that compiles studies with estimates of GWP_A over a time horizon of 100 years. The estimate from Wang et al. (2023) used in Section G of the Supplementary Information (0.0259 $\frac{kgCO_2}{(m^2)(0.01 \text{ change in albedo})(year)}$, from 2.59 over a time horizon of 100 years) is comparable to other studies and represents a more conservative estimate.

Table S4. Estimates of GWP_A

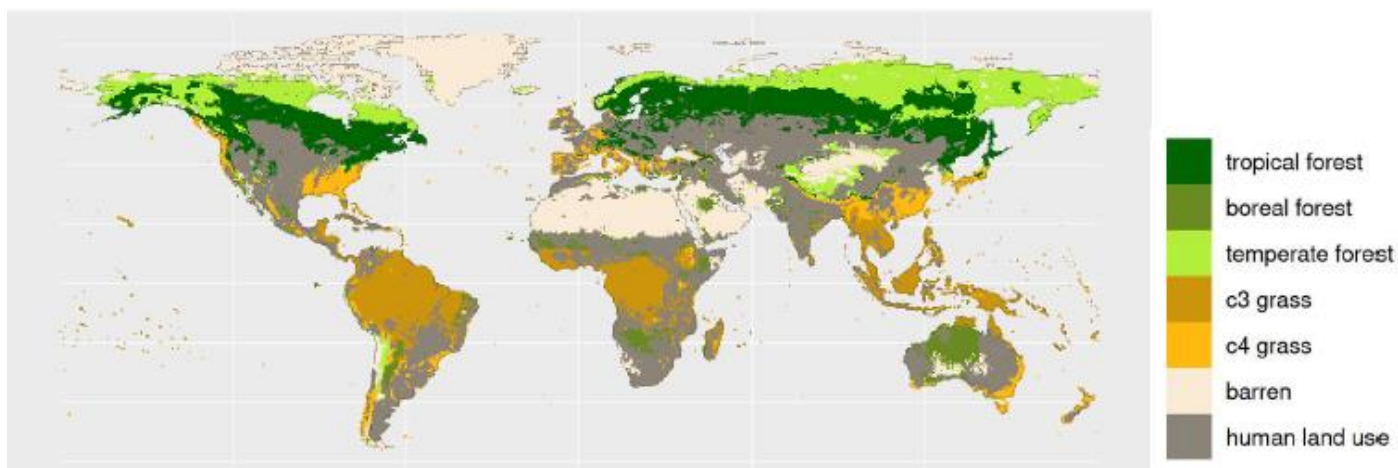
Study	GWP_A $kgCO_2 / m^2$, per 0.01 albedo change	Land Use Change and Other Notes
Akbari et al. (2009)	2.55	Increasing urban albedo (e.g. switching to reflective roofs / paved surfaces)
Carrer et al. (2018)	6.41	Fallow land to cover crops in Europe, considering an area of 4,422,217 km^2 of which 4.49% is cropland Method 1 EESF with 100 TH, constant AF: 3.16 $MtCO_2e/year$ (mitigation potential of 15.91 $gCO_2e/year/m^2$)
Carrer et al. (2018)	5.93	As above but: Method 2 GWP: 2.92 $MtCO_2e/year$ 14.71 $gCO_2e/year/m^2$)

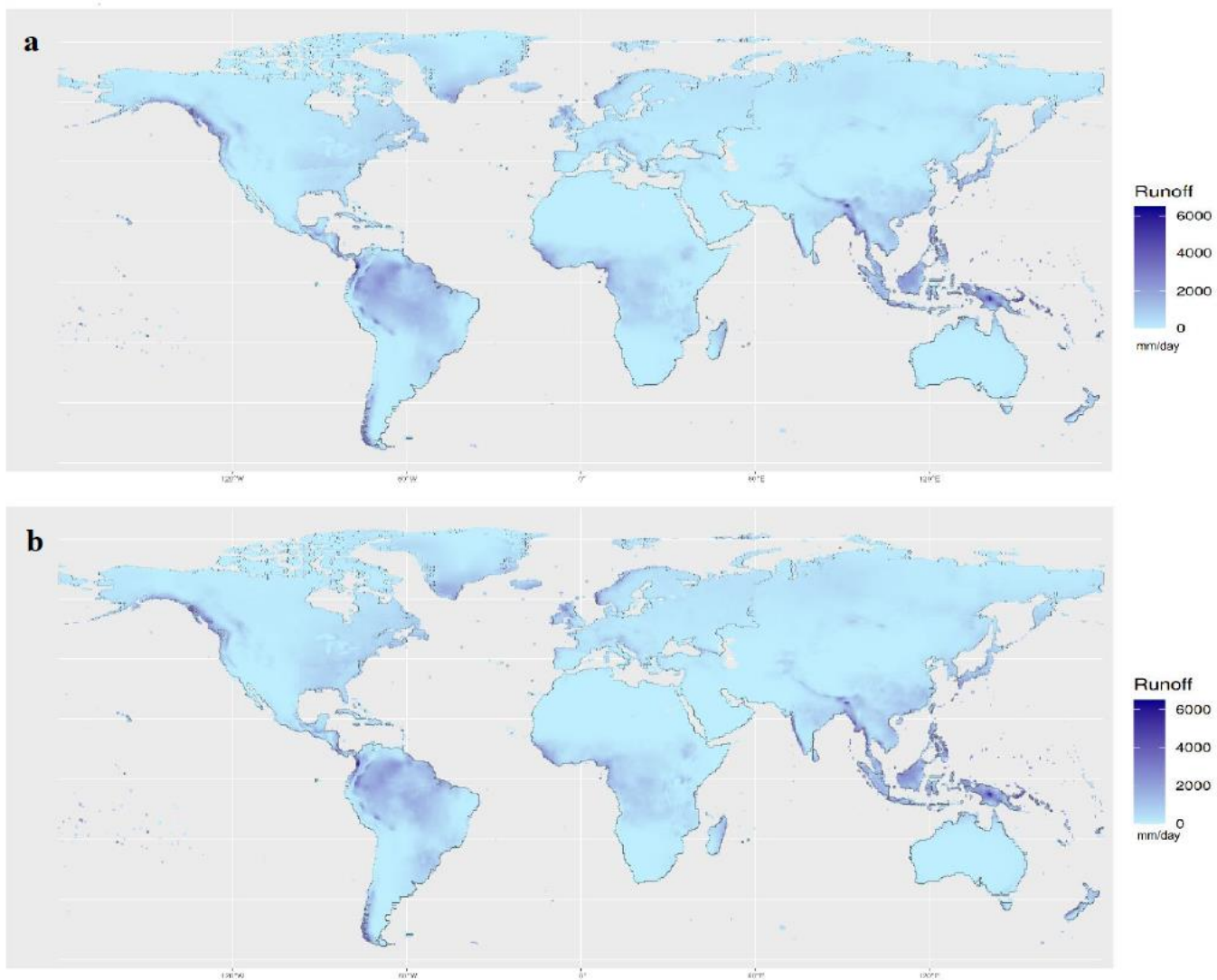
Chen (2021)	3.70 (corn or mixed prairies) 7.31 (switchgrass)	Forest to crop, in southwest Michigan
Muñoz et al. (2010) As cited and recalculated in (Hammerschlag, 2022)	3.76	Native land to reflective plastic cover of greenhouses in Southern Spain
Sieber et al. (2022a)	1.54	Grassland to crop (averaged across crops) in Sweden
Sieber et al. (2022b)	1.37	Bare soil to crop (averaged across crops) in Northern Europe
Sieber et al. (2019)	1.33 1.25	Fallow to Willow Coniferous Forest to Clear-cut Both in Southwestern Sweden
Wang et al., 2023b)	2.59	Vegetation restoration on the Loess Plateau, China, considering different transitions of land cover types

C. Additional Maps



305 **Figure S5. (a) Recent vegetation cover map representing potential natural vegetation without human land use based on the last 30 years of with *NoLU* simulation. (b) Foliar projective cover (FPC), expressed as a fraction, of the dominant vegetation type in each cell in the vegetation cover map in (a).**





315 **Figure S7. (a) Early 20th century runoff map, assuming no human land use change, based on the first 30 years of the *NoLU* simulation using LPJmL. This was used as the preindustrial estimate. (b) Recent runoff map, based on the last 10 years of the *WithLU* simulation, used to estimate current state of water.**

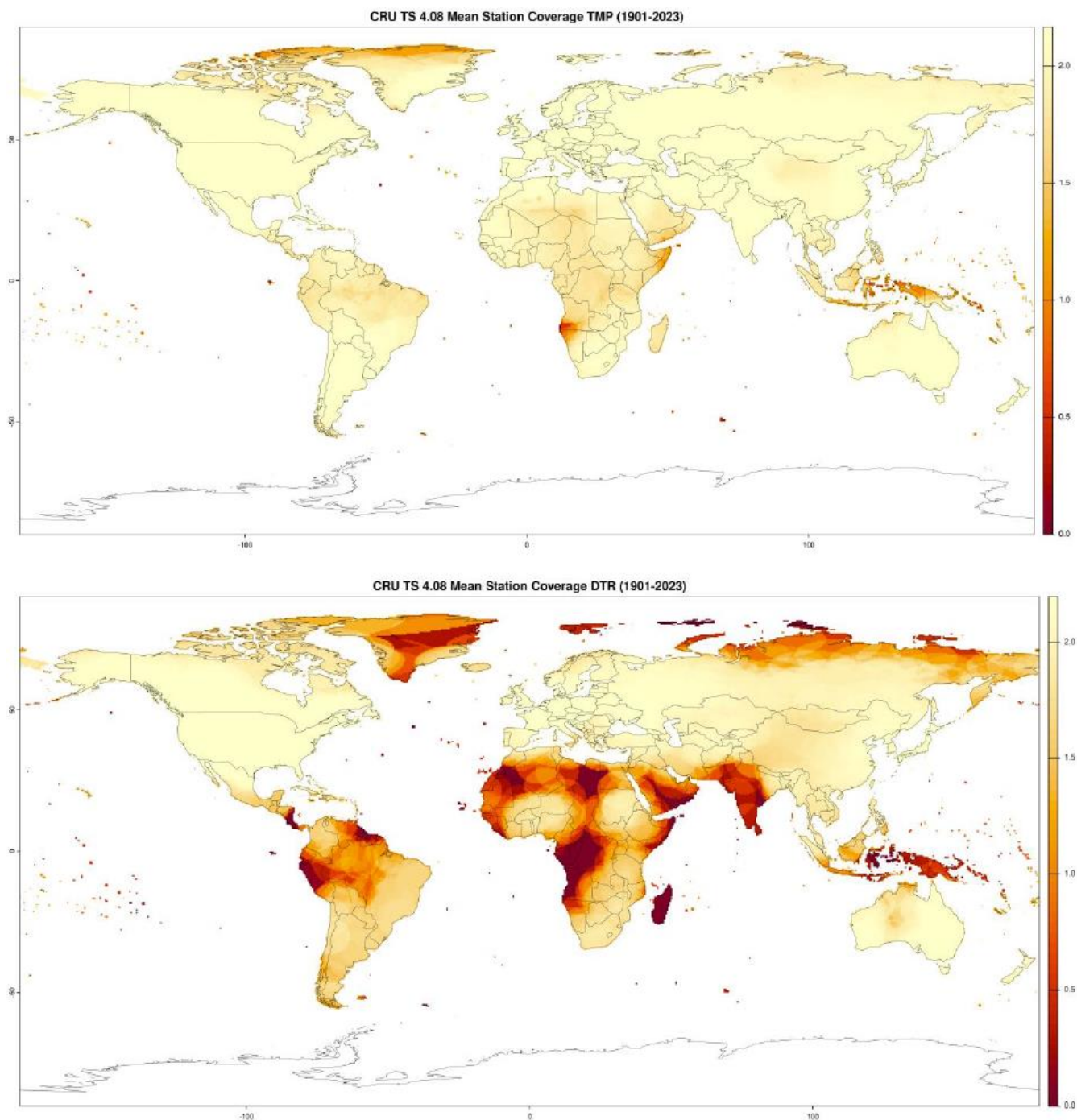
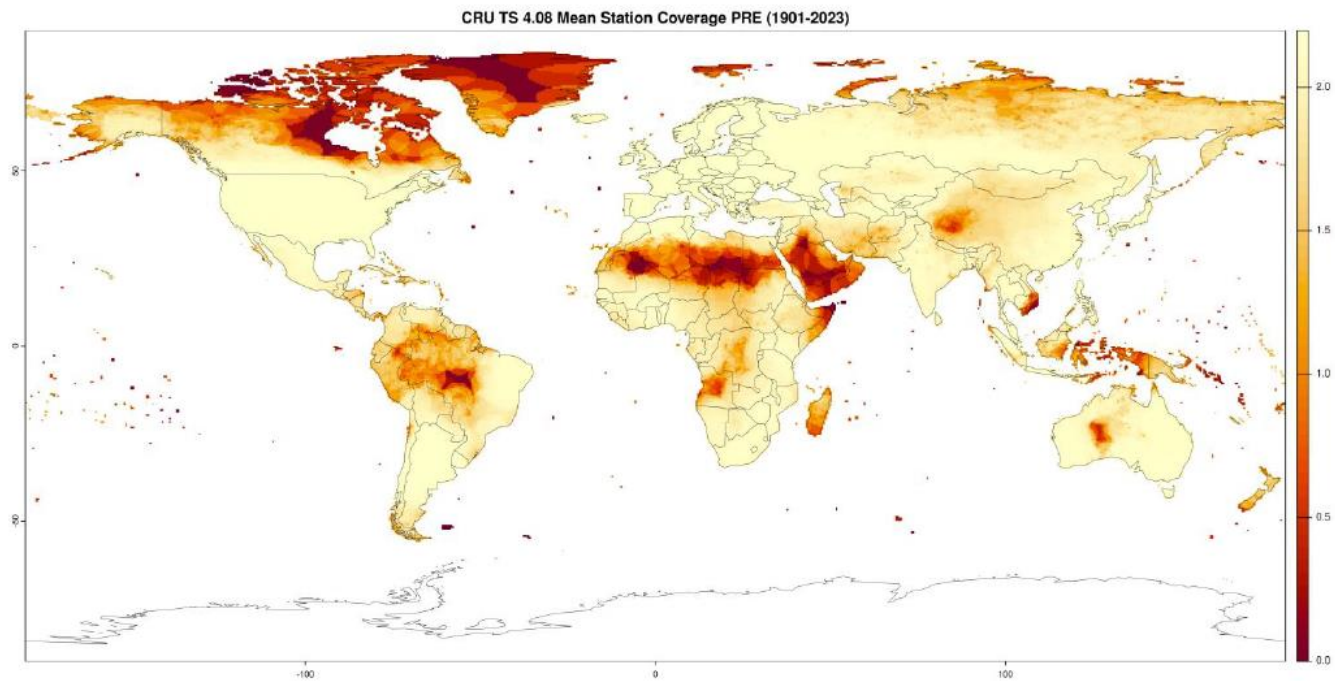
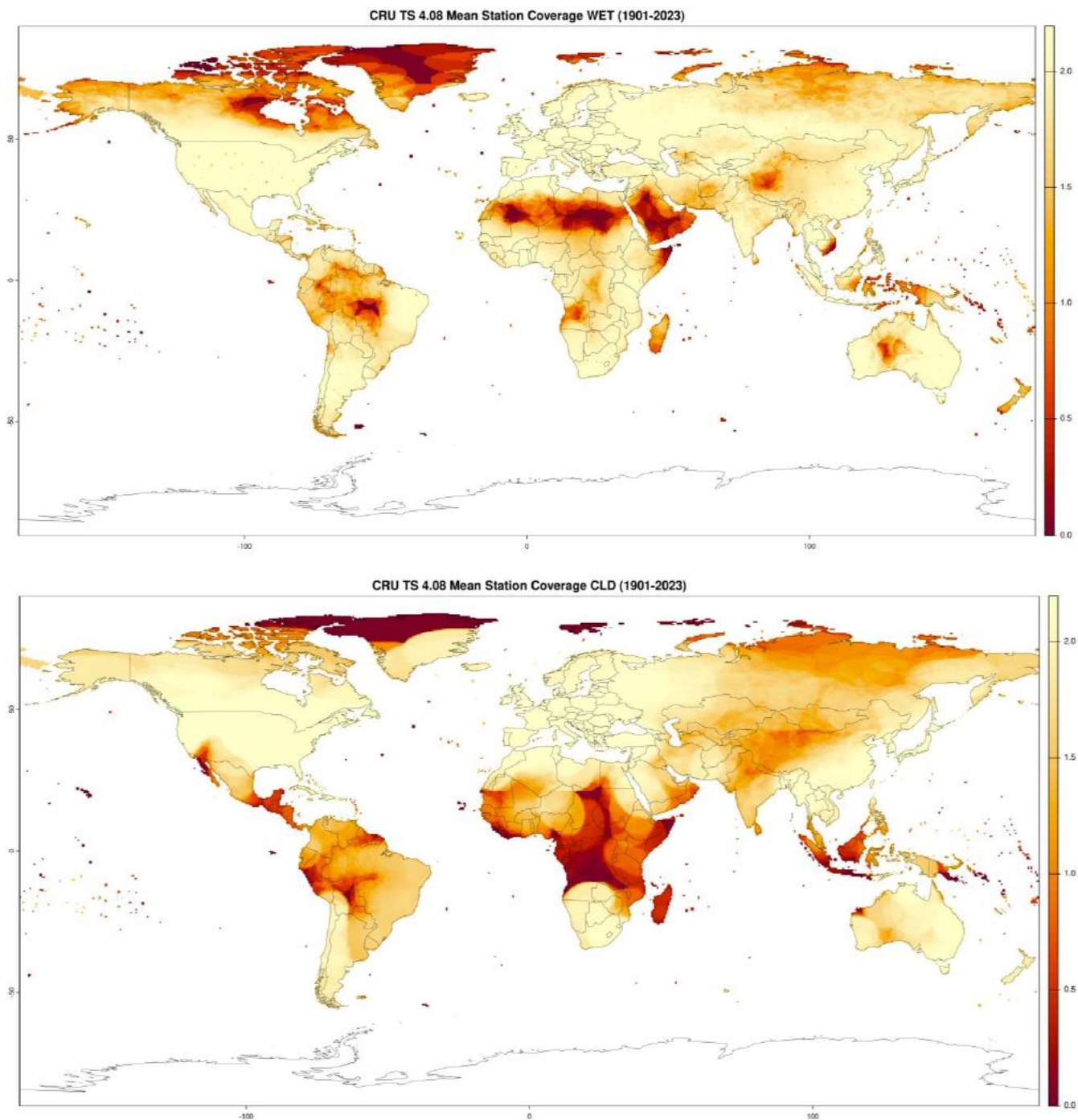


Figure S8. Station coverage underlying the CRU TS4.08 dataset (Harris et al. (2020)). The station cover of a variable in a grid cell at a point in time is being defined as the number of stations within the correlation decay distance of that cell that were reporting a valid value for the variable at that point in time. Maps display the log-scaled station cover averaged across 1901-2023 for the variables of (top) mean temperature (TMP) and (bottom) diurnal temperature range (DTR).



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Figure S9. Station coverage underlying the CRU TS4.08 dataset (Harris et al. (2020)). The station cover of a variable in a grid cell at a point in time is being defined as the number of stations within the correlation decay distance of that cell that were reporting a valid value for the variable at that point in time. Maps display the log-scaled station cover averaged across 1901-2023 for the variable total precipitation (PRE).



335 **Figure S10. Station coverage underlying the CRU TS4.08 dataset (Harris et al. (2020)).** The station cover of a variable in a grid cell at a point in time is being defined as the number of stations within the correlation decay distance of that cell that were reporting a valid value for the variable at that point in time. Maps display the log-scaled station cover averaged across 1901-2023 for the variables of (top) rainday counts (WET) and (middle) cloud cover (CLD).

340 For Figs. S8 to S10: See Harris et al. (2020) for more details on the computation of the station coverage.
This data set contains the station coverage data from Harris et al., (2024): University of East Anglia Climatic Research Unit;
Harris, I.C.; Jones, P.D.; Osborn, T. (2024): CRU TS4.08: Climatic Research Unit (CRU) Time-Series (TS) version 4.08 of
high-resolution gridded data of month-by-month variation in climate (Jan. 1901- Dec. 2023). NERC EDS Centre for
Environmental Data Analysis, *accessed 16/02/2026*. <https://catalogue.ceda.ac.uk/uuid/715abce1604a42f396f81db83aeb2a4b>

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D. Interaction Strengths at Grid-Cell Resolution

We estimated interaction strength at a grid-cell level based on the historical simulation runs of LPJmL driven by CRU TS reanalysis data. First, we closely followed the procedure described in *Methods* and extracted the following variables per year and per 0.5° by 0.5° grid cell for the simulations with and without human-driven land use change: the percentage of the cell area covered by natural vegetation as a proxy of land use, the total runoff density (mm yr⁻¹) as a proxy of water availability, and the carbon storage density (gm⁻²) as one of the proxies of climate. The CRU TS time series of global atmospheric CO₂ served as the second proxy of climate. At this point, instead of aggregating simulation outcomes by continent and vegetation zone, we applied difference quotients and conducted linear regressions per grid cell to quantify the effects of land use and climate change, respectively.

Note that, if the average vegetation cover in a grid cell is the same for the last 30 years of the scenarios with and without human-driven land use change, effects of land use change could not be quantified. Furthermore, in alignment with Zoller et al. (2026), we excluded grid cells whose difference in vegetation cover is less than 0.1% of the total area of the cell, assuming that such marginal changes do not reflect change in human land use but noise in the simulation and can therefore be neglected. To diminish the effect of outliers in clustering and cluster validation, we "clipped" each of the four data sets to interaction-dependent upper and lower boundaries. The boundaries were set to +/-350 (LCC → RO), +/- 40000 (LCC → CC), +/- 3 (CC → RO), and +/- 0.005 (CC → LCC).

Figure S11 displays normalized interaction strengths for all four effects. We observe that areas of high heterogeneity in interaction strength ("salt-and-pepper pattern") coincide with areas of low station coverage in at least one of the CRU TS driving variables, such as in central South America and northern Europe and Asia (compare Appendix B Station coverage). This phenomenon indicates data insecurity, and corresponding interaction strengths at grid-cell level should be interpreted with caution.

To assess the quality of the applied aggregation by continent and vegetation zone, we compared its ability to capture the derived spatial patterns of interaction strength against 32 alternative spatial aggregations. All aggregations are based on a set of established Earth divisions and encompass a wide range of classification criteria and sizes. They include a classification by continent, the Köppen-Geiger climate classification, a classification by dominant plant functional type as defined by LPJmL, the applied coarser classification by dominant main plant functional type, realms (Udvardy, 1975), and biomes (Dinerstein et al., 2017). See the Methods in Zoller et al. (2026) for a detailed description of the selected Earth divisions.

Our cluster validity assessment is based on the *Banfield-Raftery* index. This variant of the classical within-cluster sum of squares is better suited to handle large differences in cluster size (Todeschini et al., 2024). Assume that n objects are being

380 clustered in K disjoint clusters. Let d be the number of variables (i.e., the dimension of the feature space) and $\mathbf{x}$ the d -dimensional feature vector of object x . Here, $\mathbf{m}$ denotes the d -dimensional vector of variable means, $\mathbf{m}_k$ the d -dimensional vector of cluster means. We denote by n_k the number of objects of the cluster k . We use the notation $\|\cdot\|$ for the Euclidean norm of a vector. Then, the Banfield-Raftery-index (BR) is defined as (Eq. S8):

$$BR = \sum_{k=1}^K n_k \cdot \log(\sum_{i=1}^{n_k} \|\mathbf{x}_i - \mathbf{m}_k\|^2 / n_k). \quad (\text{S8})$$

385 We computed the Banfield-Raftery index both univariately (Fig. S12) for each interaction separately ($d = 1$) and multivariately (Fig. S13) for all four interactions ($d = 4$). Beforehand, we reduced the data space to tiles for which all four interaction strengths could be estimated. This pre-processing step reduces a potential bias towards certain interaction types in the multivariate cluster validity index. Furthermore, we normalized the data set for each interaction to $[-1, +1]$ by dividing each value by the maximal absolute value of the respective interaction strength.

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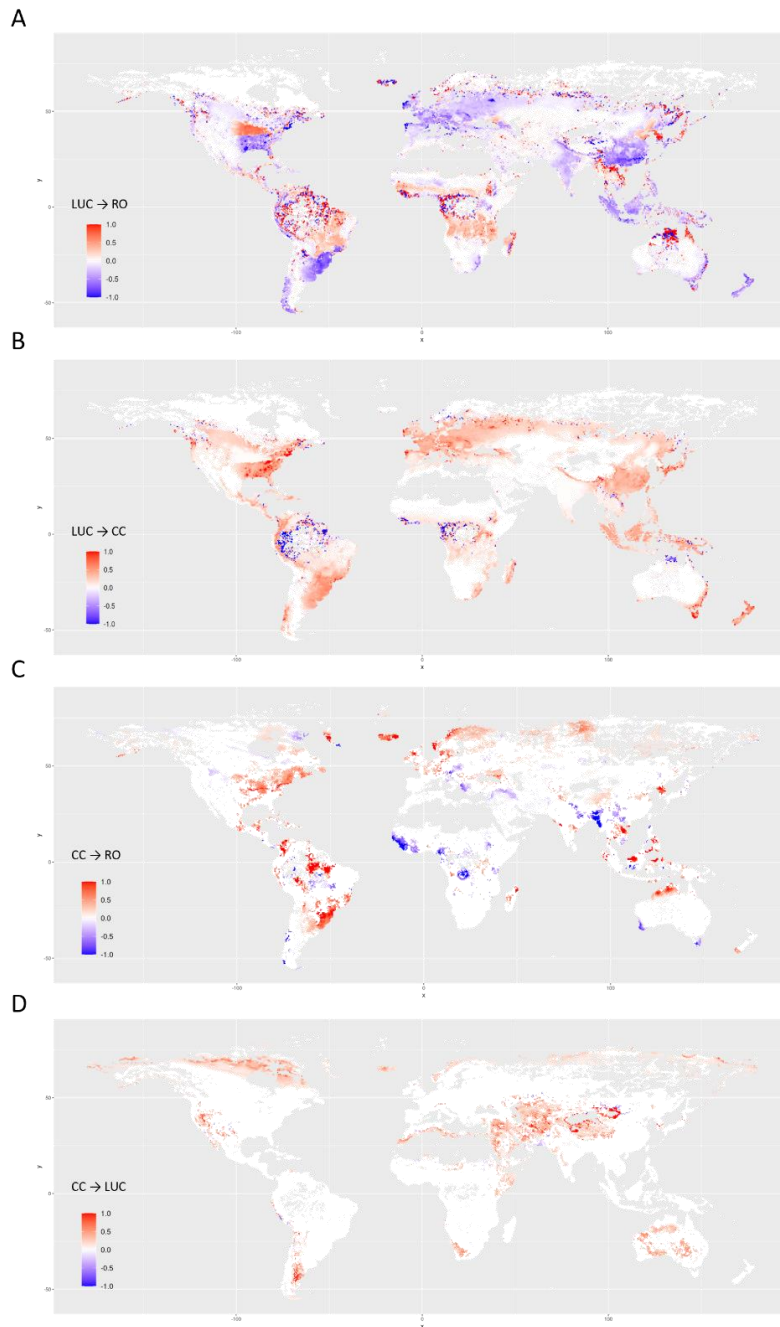


Figure S11. Interaction strengths at grid-cell resolution. The maps display the normalized interaction strength for the effects of natural vegetation cover change on (A) surface water runoff and on (B) carbon storage, as well as the interaction strength for the effects of changes in carbon dioxide concentration on (C) water runoff and on (D) natural vegetation cover. Positive interaction strength (red) indicates that an increase in one Earth system process (e.g., increased natural vegetation cover) causes an increase in another Earth system process (e.g., increased surface water runoff). Analogously, negative interaction strength (blue) indicates that an increase in one process leads to a decrease in another process. All maps are restricted to grid cells in which the human-induced land-use change exceeds 0.1 % of the cell area.

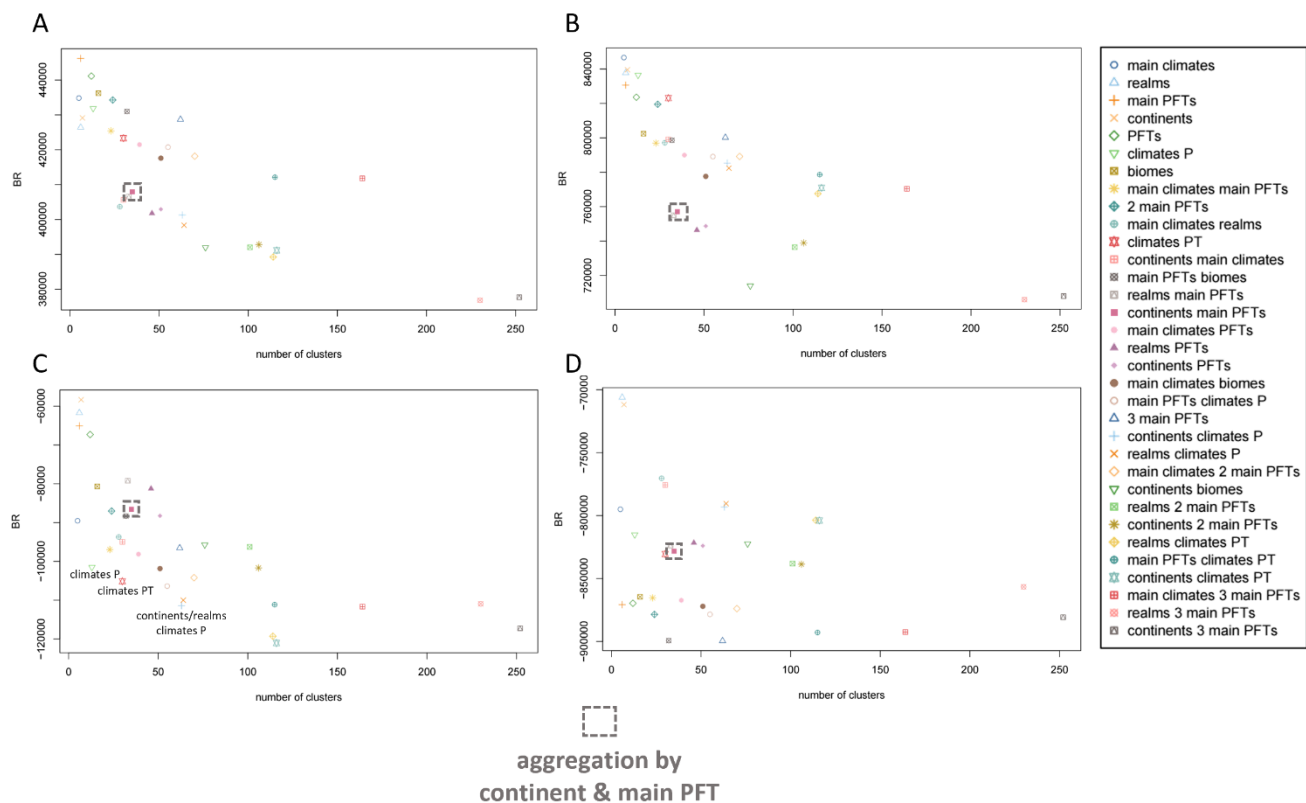


Figure S12. Clustering performance of different aggregations. The Banfield-Raftery index (BR) measures the within-cluster sum-of-squares of 33 political, climatic, and biological Earth partitions for the strengths of the effects of natural vegetation cover on (A) water runoff and (B) carbon storage, as well as the effects of change in carbon dioxide concentration on (C) water runoff and (D) natural vegetation cover. The partitions are sorted by their number of clusters. The ESI score uses the highlighted aggregation by continent and main PFT.

PFT = dominant plant functional type, main PFT = dominant main plant functional types (both as derived by LPJmL for the last 30 years in the simulation without human-driven land-use), main climates = main Köppen-Geiger (KG) climates, climates P = main KG climates including precipitation conditions, climates PT = main KG climates including precipitation and temperature conditions.

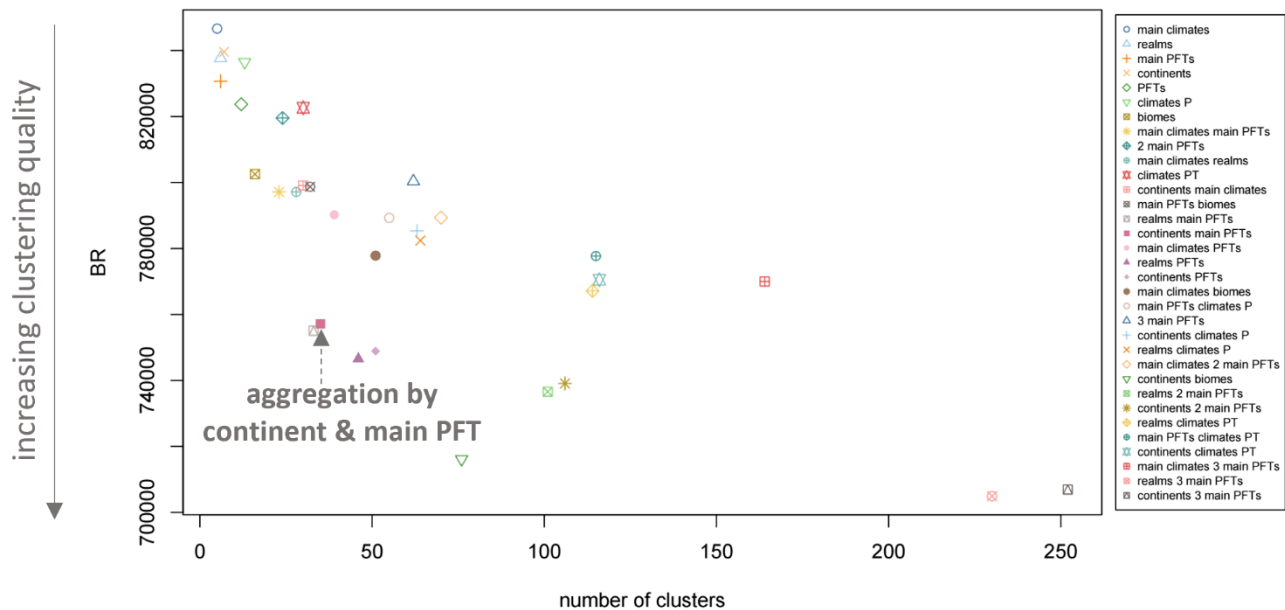


Figure S13. Multivariate clustering performance of different aggregations. The Banfield-Raftery index (BR) measures the within-cluster sum-of-squares of 33 political, climatic, and biological Earth partitions for the strengths of the effects of natural vegetation cover on water runoff and carbon storage, as well as the effects of change in carbon dioxide concentration on surface water runoff and natural vegetation cover. The partitions are sorted by their number of clusters. The ESI score uses the highlighted aggregation by continent and main PFT.

PFT = dominant plant functional type, main PFT = dominant main plant functional types (both as derived by LPJmL for the last 30 years in the simulation without human-driven land-use), main climates = main Köppen-Geiger (KG) climates, climates P = main KG climates including precipitation conditions, climates PT = main KG climates including precipitation and temperature conditions.

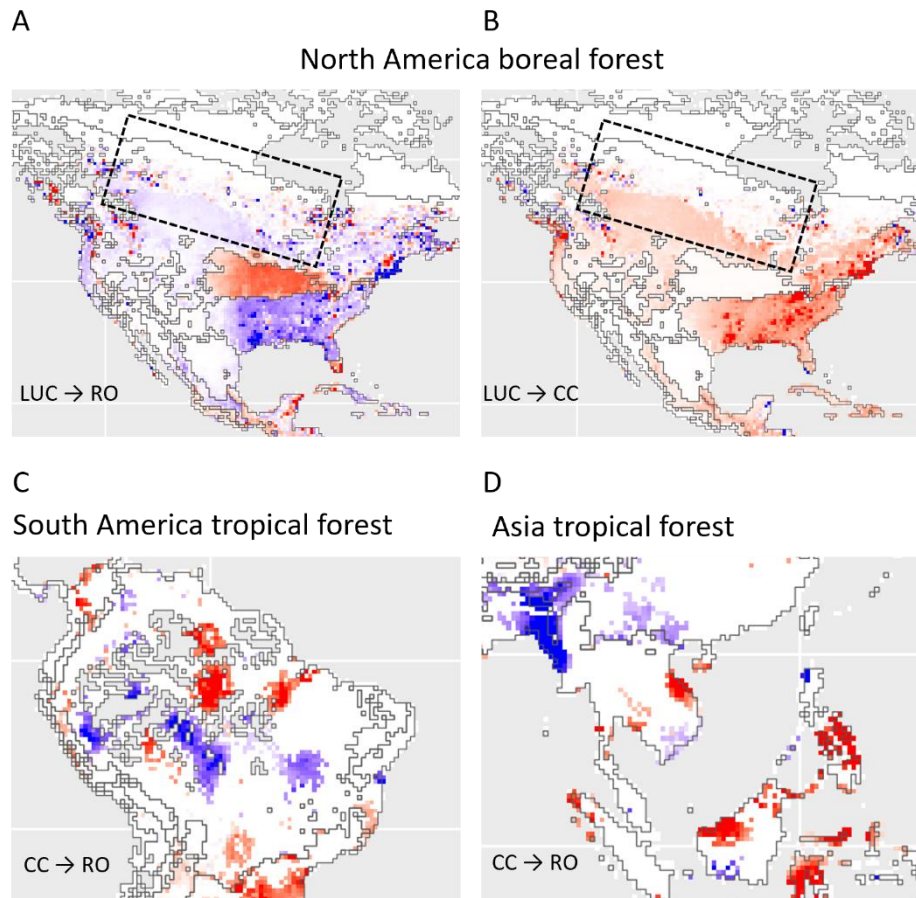


Figure S11. Limitations of the aggregation by continent and main PFT. (A) and (B) display mismatches between the spatial pattern of interaction strength and the North American boreal forest cluster for the effects of land use change on water runoff and on carbon storage, respectively. (C) and (D) display mismatches between the spatial pattern of interaction strength for the effect of climate change on water runoff in the South American and Asian tropical, respectively. (Respective colour bars as in Fig. S11.)

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The planetary boundaries (PBs) for blue water prescribe a 5th to 95th percentile envelope relative to the preindustrial baseline (Porkka et al., 2024). These benchmarks are used here to calculate the lower (dry) and upper (wet) sub-global boundaries under the PB framework. The Earth system Safe and Just boundaries (SJBs) recommend a $\pm 20\%$ flow alteration (Gupta et al., 2024; Stewart-Koster et al., 2023), which we also apply to an estimate of the preindustrial baseline, to determine the lower and upper sub-global boundaries under the SJB framework. Both sets of boundaries (Figs. S15 and S16) are calculated based on the first 30 years of the *NoLU* simulation (1901-1930) as an estimate of preindustrial conditions. The SJB framework results in tighter envelopes (higher dry bounds and lower wet bounds) over all regions, except in the tropical forests of South America (however, the difference is minimal and does not impact final Water ESI score).

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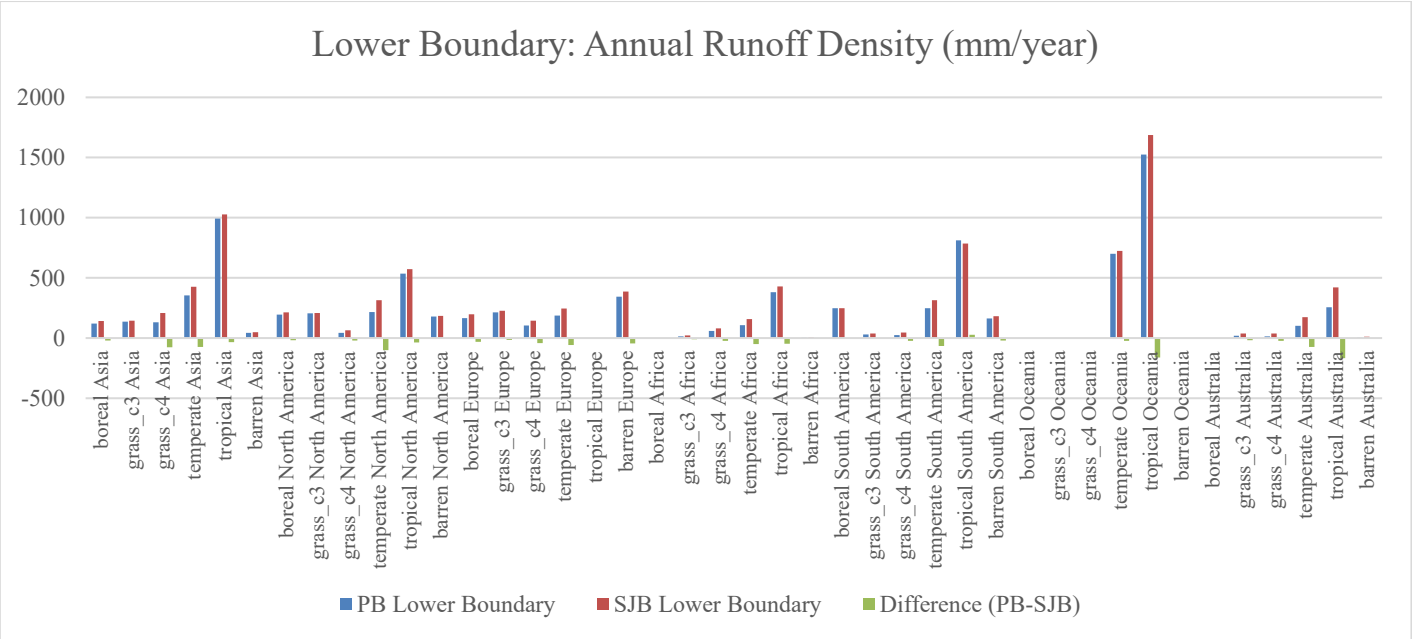


Figure S15. Comparison of the lower bounds for runoff density (representing the lower boundary for flow alteration) using the PB vs the SJB.

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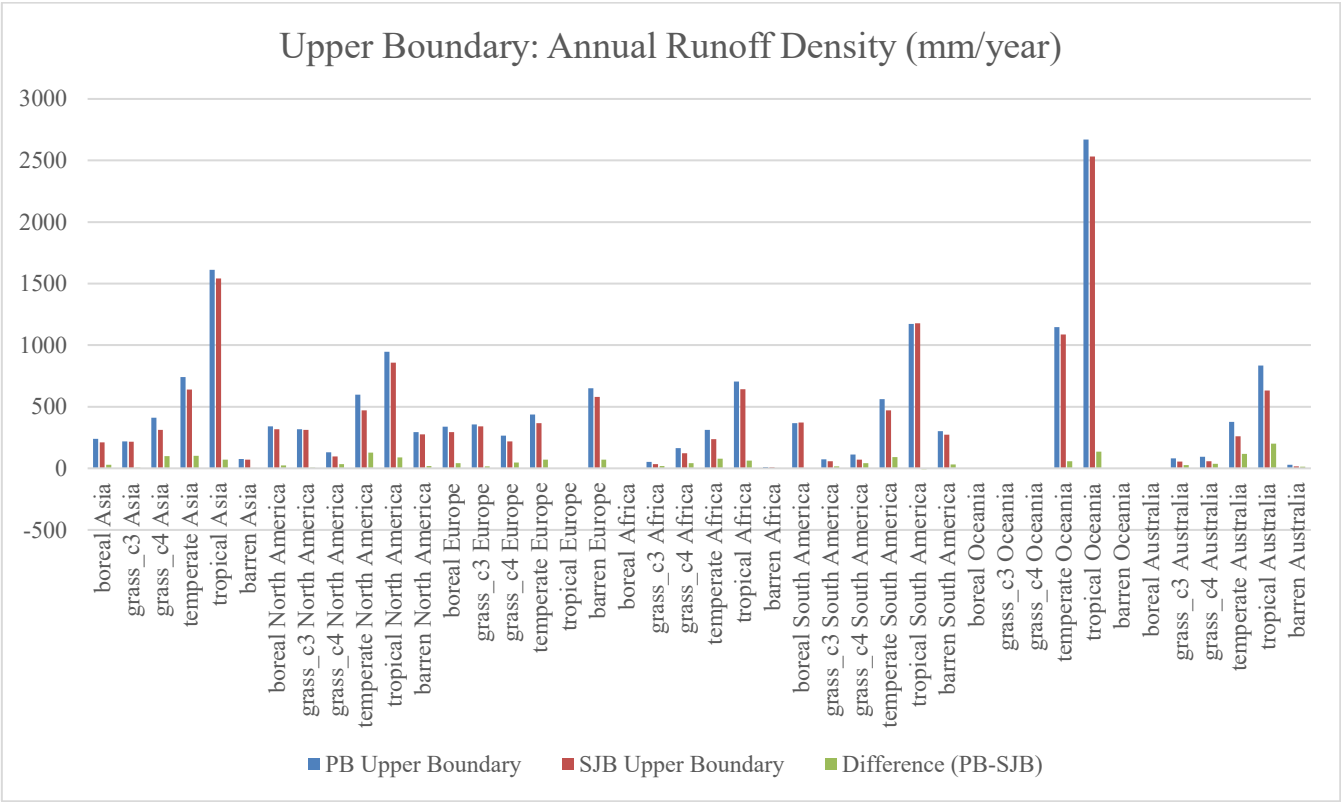


Figure S16. Comparison of the upper bounds for runoff density (representing the upper boundary for flow alteration) using the PB vs the SJB.

F. Uncertainty Analysis

455 ESI coefficients and amplification factors were calculated for different climate scenarios until 2099, using the model MPI-ESM1-2-LR. For the Carbon ESI-C, the CRU-driven outcome represents the most stringent measure. The amplification factors for carbon emissions (Fig. S17, Table S5) were all above one but slightly decreasing in the scenarios with increasing emissions in simulations until 2099 (1.26 in original CRU-driven simulation down to 1.05 in SSP5-8.5 scenario, with a relative standard deviation of 8.2%). Likewise, the Carbon ESI-C scores, ranged from 39.6×10^{-8} , the highest using CRU-driven data, down to
460 34.9×10^{-8} in SSP5-8.5 (with a 5.4% relative standard deviation). This decreasing metric is contrary to the findings in Lade et al. (2021) and to the expectations that feedback (e.g., as described in Anderies et al., 2013; Lenton et al., 2025; Schneider, 2004) associated with increasing emissions would lead to higher amplification factors and Carbon ESI coefficients in the SSP5-8.5 scenario. However, a disadvantage of the simulation timelines is that delayed impacts of climate change occurring beyond this century are not captured by the uncertainty analysis.

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The Land ESI coefficients across scenarios were mixed, with CRU-driven metrics being higher than SSP-driven metrics for some regions (e.g., grasslands in Africa and Europe; temperate forests in Asia, Europe and the Americas; tropical forest in North America; barren lands of North America and Australia), but lower and less stringent in others (e.g. C3 grassland in South America, C4 grassland in North America, temperate forests of Oceania and Asia, and Asian tropical forest) (Fig. S18).
470 Over the forest areas, the relative standard deviation across scenarios was within 12% except for temperate forests in North America (15.5%) and temperate forests in Australia (20.6%). For C3 grassland in Africa and tropical forest in Australia, only one scenario produced a score in each case (CRU and SSP2-4.5, respectively). In the case of C3 grassland in Africa, the SSP-driven LPJmL vegetation distribution did not meet the minimum threshold value. In the case of tropical forest in Australia, only SSP2-4.5 produced a significant $LCC \rightarrow RO$ interaction (Fig. S19). Similar patterns were found in the amplification factors
475 for land cover change (Fig. S18), with the relative standard deviation also within 12% across all vegetation types except for barren land in Africa (16.0%) and temperate forest in Europe (17.0%).

Despite the variations in the magnitudes of the Land ESI coefficients across scenarios, the results generally reflected the same trends across continents and vegetation types in terms of ranking (e.g. which vegetation type has the highest coefficient within
480 a continent, or which regions have higher coefficients). This lends confidence that the application of the ESI metric to generate scores that businesses can use for ranking and prioritization is robust to changes in scenarios.

The Water ESI coefficients across scenarios also reflected the same general trends except for the high score for C3 grasslands in Africa. This region did not meet the minimum threshold for grid cells in scenarios other than the historical. Results showed
485 no variation across SSP-driven outputs since the feedback model does not include changes in land cover and climate due to

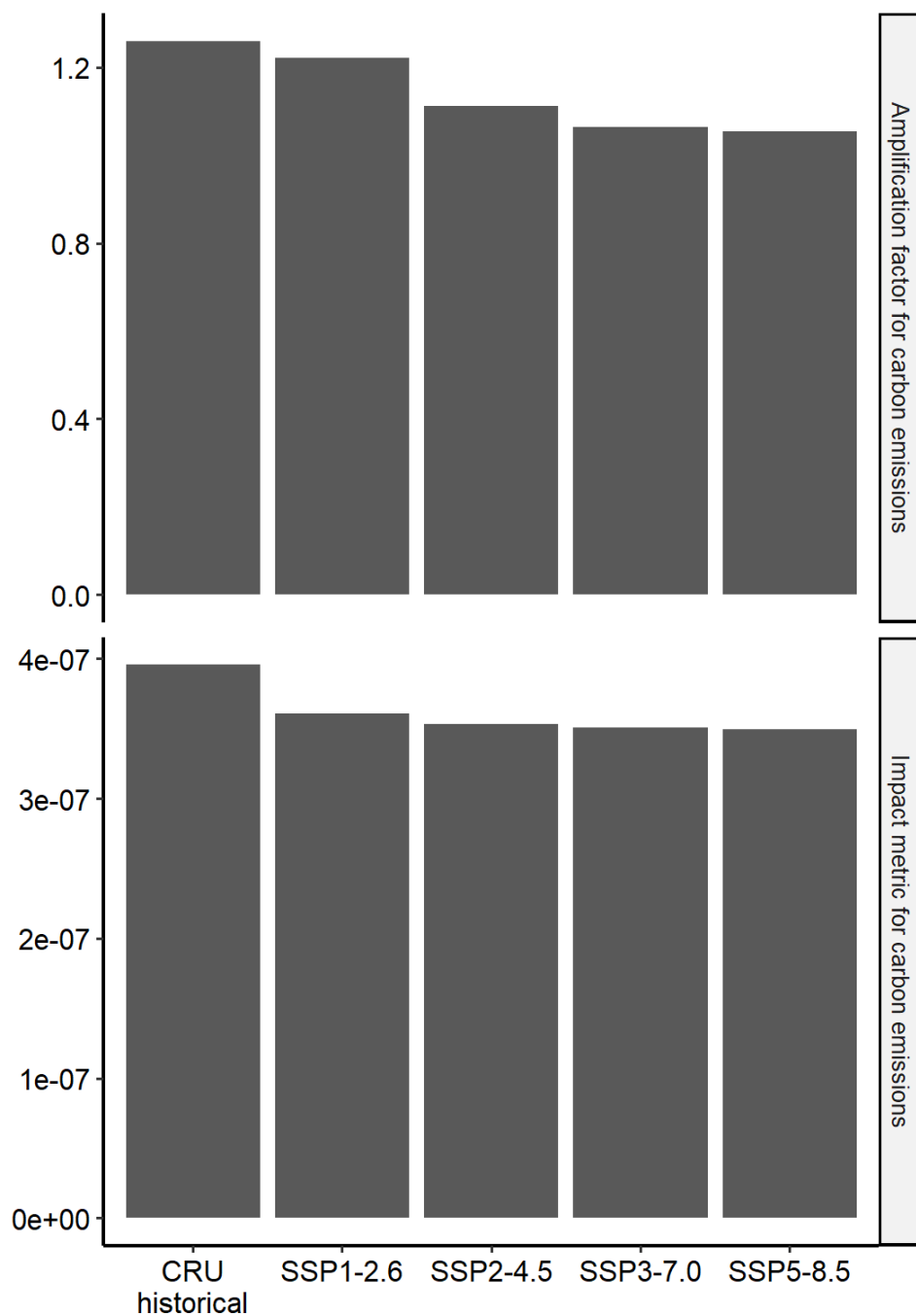
changes in runoff. The differences between the CRU-derived metrics and the SSP-derived metrics were due mainly, again, to variations in vegetation distribution which affects which regions are included in the analysis of total Earth system impacts.

490 Interaction strengths were calculated both for different climate scenarios from 1901 to 2099, as well as across LPJmL outputs driven by different climate models from 1901 to 2023. Outputs gave similar variations in interaction strengths across scenarios (Fig. S19) as across models (Fig. S20). For runoff, unnormalized interactions strengths across models was also plotted to better identify the direction of change in each interaction (Fig. S21).

The $LCC \rightarrow CC$ and $LCC \rightarrow RO$ interactions were comparable across models and reflected the same trends across regions as those based on CRU-driven LPJmL output. For the $LCC \rightarrow CC$ interactions, the relative standard deviation of interaction strengths across boreal forests were within 10.5%; temperate forests, 9.5%; and tropical forests, 7% For the $LCC \rightarrow RO$ interactions. The relative standard deviation of interaction strengths across boreal forests were within 11%; temperate forests, 13%; and tropical forests, 13%. Exceptions were the boreal and tropical forests of North America, with 21% and 23% standard deviations, respectfully, and the temperate forest of Africa, with 20%. More variation was found across grasslands and barren
500 lands, particularly where the interaction strengths were small.

There was relatively more variability across the $CC \rightarrow RO$ and $CC \rightarrow LCC$ interactions. The $CC \rightarrow RO$ and $CC \rightarrow LCC$ relationships are modelled through a chain of processes in LPJmL (Schaphoff et al., 2018; Wirth et al., 2024), there being other intermediary or concurrent factors affecting vegetation cover and runoff. For example, the area occupied by a certain vegetation
505 type is determined through its foliar projective cover, which is affected by establishment rates and by productivity and allocation processes rather than directly by temperature and precipitation. Likewise, the runoff is influenced not by precipitation alone, but also by vegetation and soil characteristics. In addition, the climate models represent a spread of precipitation projections (as shown in Ahn et al., 2023; Du et al., 2022; Lange and Büchner, 2021; Li et al., 2022; Mehran et al., 2014). The choice of CRU-driven LPJmL output presented the advantage of deriving interaction strengths based on
510 assembled from observed data in most parts of the world (refer to supplemental maps in Section C for CRU coverage).

Both across the different climate models and across scenarios, the interaction strengths (and hence, the amplification factors and impact metrics) were found to be sensitive to the variances in vegetation distributions. Smaller ecosystems such as C3 grasslands in Africa, C4 grasslands in Europe and barren land in Europe occupy relatively few grid cells at the resolution of
515 LPJmL and can meet the minimum threshold of 10 grid cells in some simulations but fall below in other. Interaction strengths could not reliably be defined in scenarios that did not produce enough grid cells of a certain region, or scenarios that resulted in the loss of that region over time.



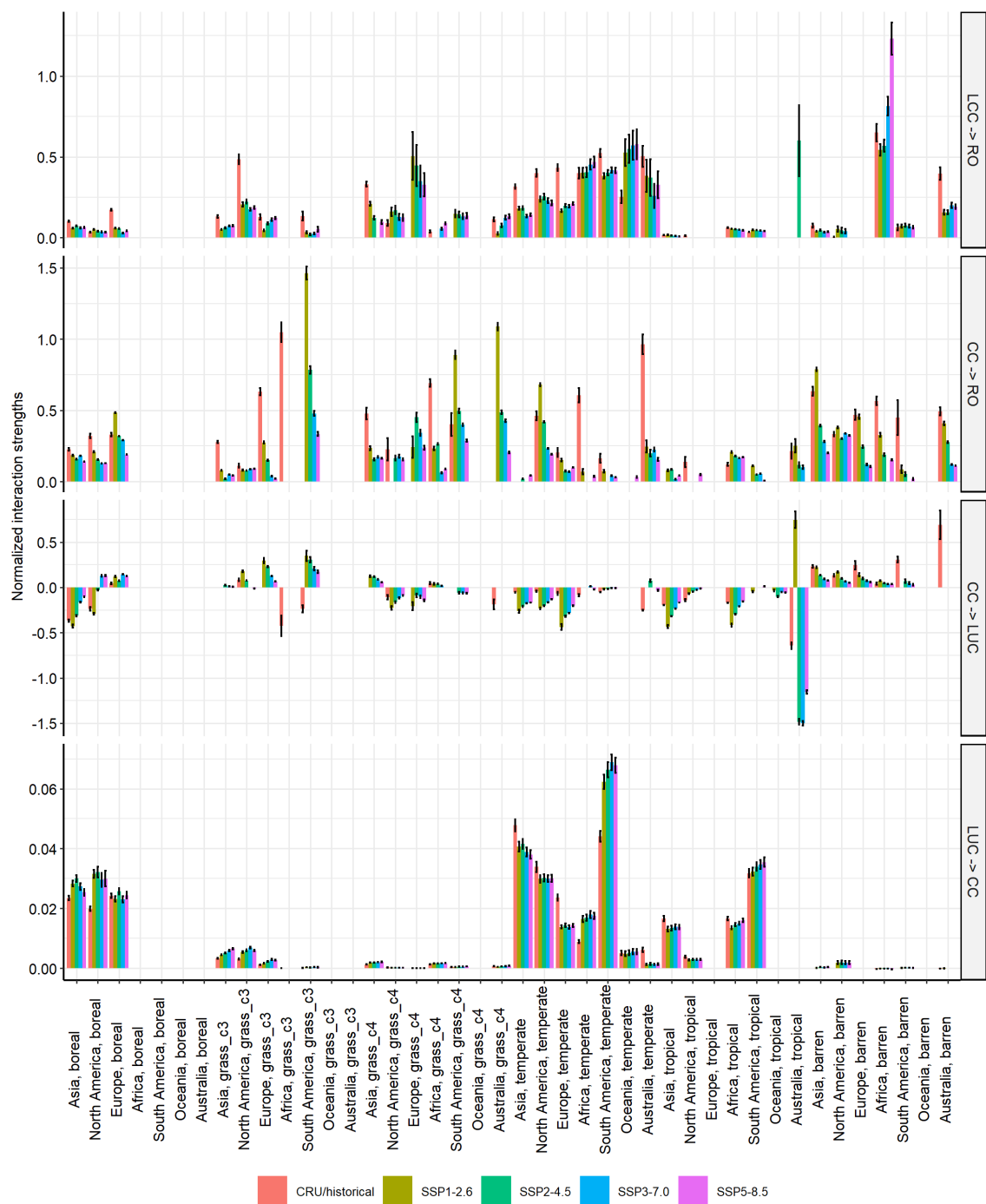
520 **Figure S17. Comparison of metrics across historical and SSP scenarios for pressure on climate: (top) Amplification factor and (b) Carbon ESI-C metric for 0.1 MtC carbon emissions. Climate drivers for future scenarios were taken from the MPI-ESM1-2-LR model.**

525 **Table S5. Values of metrics across historical and SSP scenarios for pressure on climate: Amplification factor and Carbon ESI metric for 0.1 MtC carbon emissions. Climate drivers for future scenarios were taken from the MPI-ESM1-2-LR model.**

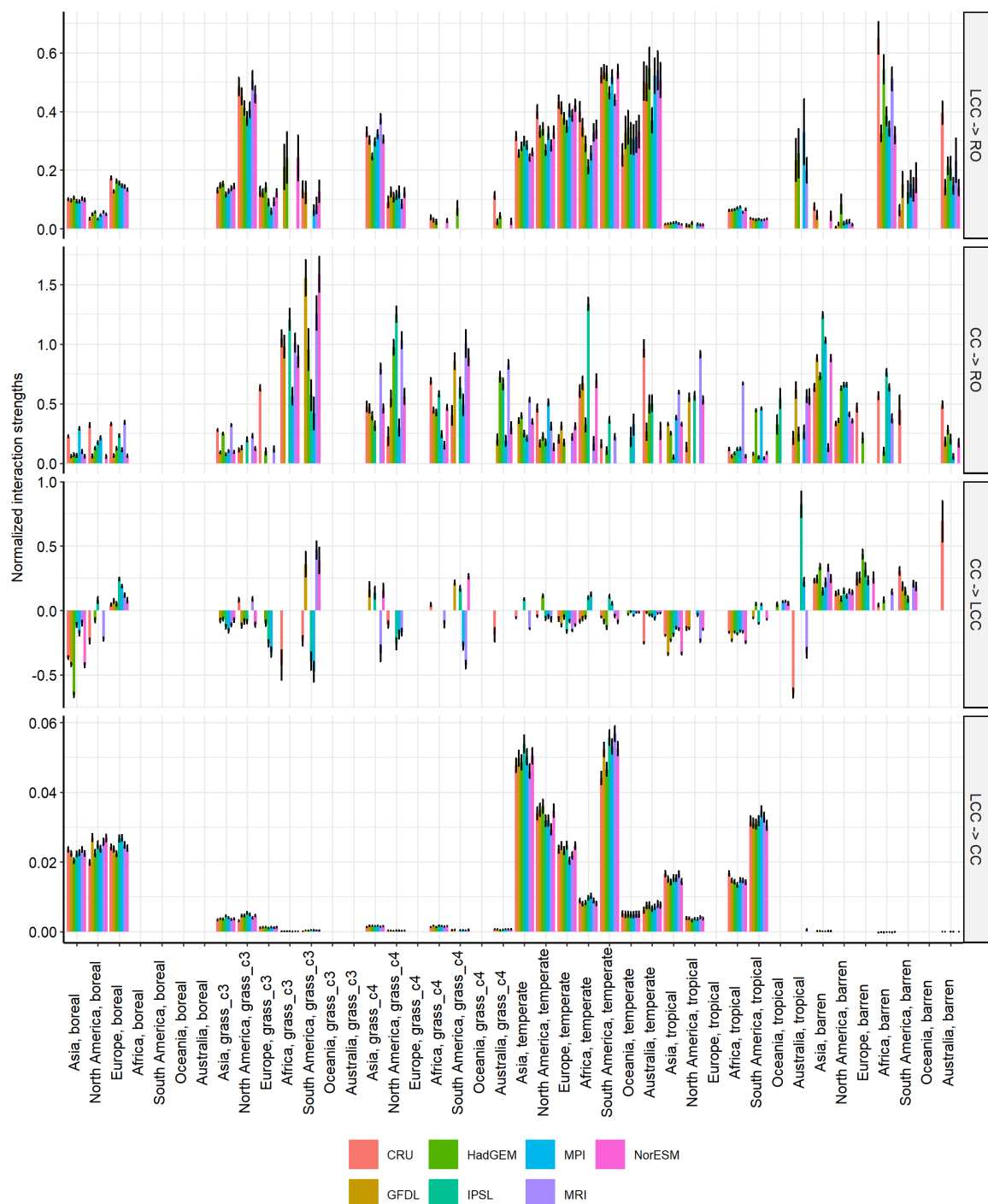
SSP	Amplification factor for carbon emissions	Carbon ESI-C for 0.1 MtC carbon emissions
CRU	1.26	3.96E-07
SSP1-2.6	1.22	3.61E-07
SSP2-4.5	1.11	3.53E-07
SSP3-7.0	1.06	3.51E-07
SSP5-8.5	1.05	3.49E-07



530 **Figure S18. Comparison of metrics across historical (1901-2023) and SSP (1901-2099) scenarios for pressure on land and water: (top) Amplification factor for vegetation cover change; (middle) Land ESI metrics for 5km² vegetation cover change; and (bottom) Water ESI metrics for 10⁶ m³/year water withdrawal. Climate drivers for future scenarios were taken from the MPI-ESM1-2-LR model.**



535 **Figure S19. Comparison of interaction strengths estimated from historical (1901-2023) and future SSP (1901-2099) scenarios. CRU**
refers to the historical re-analysis data set. The climate drivers for the future scenarios were taken from MPI-ESM1-2-LR climate
model.



540 **Figure S20. Comparison of interaction strengths estimated by driving LPJmL with climate from different climate models (NorESM1-M_r1i1p1, MRI-ESM1_r1i1p1, HadGEM2-ES_r1i1p1, IPSL-CM5A-LR_r1i1p1, and GFDL-ESM2M_r1i1p1, MPI-ESM-LR_r1i1p1) from 1901 to 2023. CRU refers to the historical re-analysis data set.**

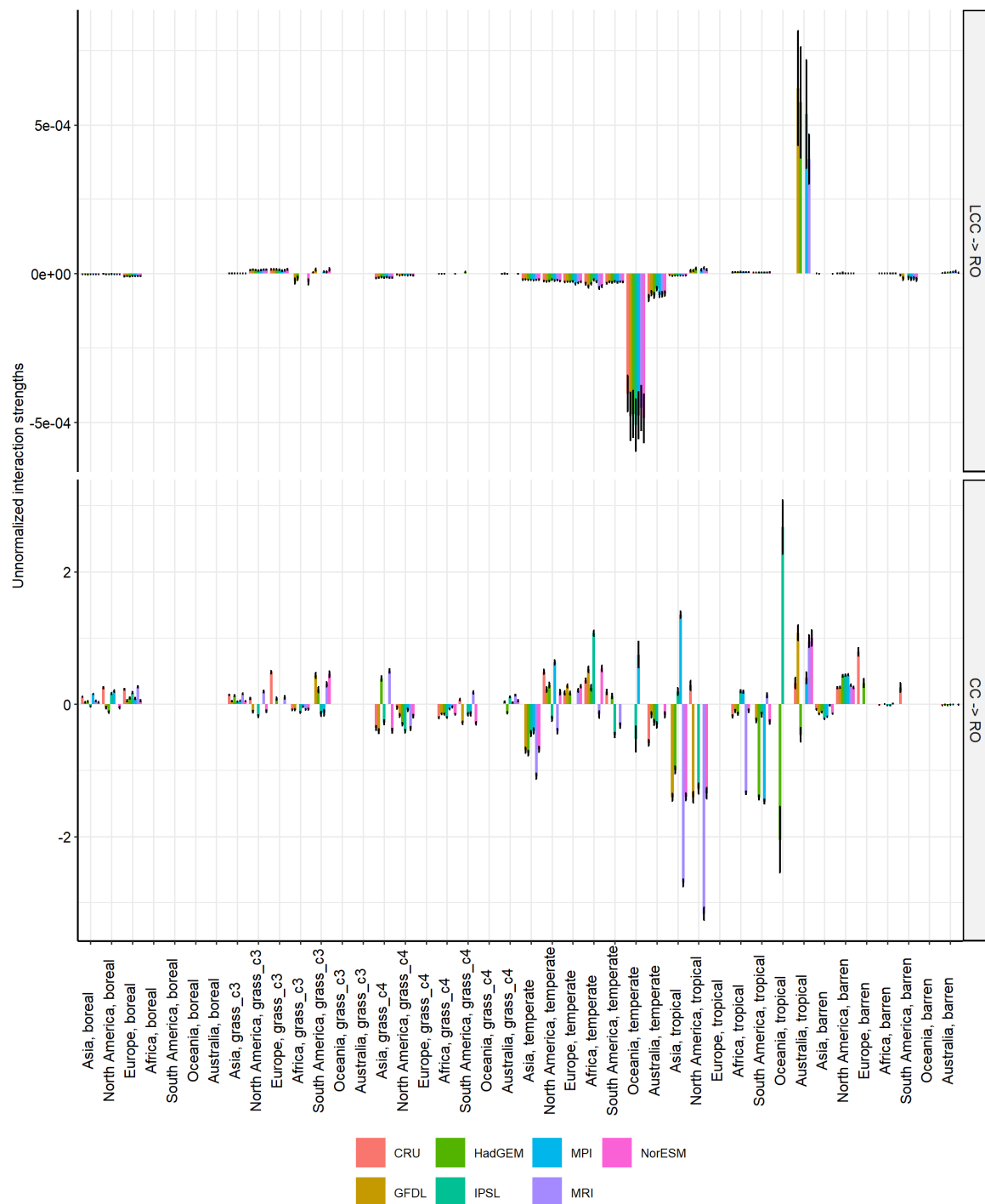


Figure S21. Unnormalized interaction strengths involving runoff estimated by driving LPJmL with climate from different climate models (NorESM1-M_r1ilp1, MRI-ESM1_r1ilp1, HadGEM2-ES_r1ilp1, IPSL-CM5A-LR_r1ilp1, and GFDL-ESM2M_r1ilp1, MPI-ESM-LR_r1ilp1) from 1901 to 2023. CRU refers to the historical re-analysis data set. Negative values indicate that as LUC or CC increases, RO decreases (and vice versa).

G. Application of ESI Metric

The Carbon, Land, Water and ESI scores for the reference pressures can be used as coefficients to calculate the impacts and overall ESI scores of different perturbations. For any given asset (e.g. factory or other facility, farm, mining site, community, etc.), the Land ESI coefficients (Fig. 7 in the main text) represent estimates of the impact of every 5 km² of natural land cover change in the region, while the Water ESI coefficients represent impacts per 10⁶ m³/year of water withdrawal. The Carbon ESI-C coefficient represents the impact of every 0.1 MtC of cumulative carbon emissions, while the Carbon ESI-A coefficient assesses impact for every 1 ktC emissions/year. These coefficients can be applied in different use contexts to calculate the overall ESI scores to support different types of decision-making.

Below we discuss two hypothetical cases to illustrate two distinct applications of the ESI: planning of a new facility (and hence, measuring lifetime impact) and evaluation of the performance of existing assets for annual tracking. (All coefficients discussed are in units of 10⁻⁸, in accordance with Fig.7). Table S6 summarizes the data needed for these two basic use cases of the ESI. Note that the first case on measuring overall impact does not only apply to facilities that are in the design stage but can also apply to existing facilities evaluating different options for investing in long-term sustainability interventions.

Table S6. Data needed for potential ESI applications

	Long-term Planning	Annual Performance Tracking
Carbon ESI score	Cumulative emissions	Annual emission rate
Land ESI score	Geolocation data Average land area occupied (Any area of land that does not revert to potential natural vegetation, regardless of whether it is actively used, will still be considered as part of the asset’s footprint.)	Geolocation data Land area occupied during the year
Water ESI score	Geolocation data Average annual water withdrawal	Geolocation data Total water withdrawal over the year

Planning a new facility

In this example, a mining facility in Africa is being planned. It will occupy 25 km² of land and will have an estimated average annual water withdrawal of 3*10⁶ m³/year (based on assets reviewed in Crona et al. (2023)). Its annual CO₂ emissions are estimated at 0.20 MtCO₂ per year, equivalent to 0.054 MtC per year. The facility’s planned lifetime before decommissioning

570 is projected to be 30 years, which results in cumulative carbon emissions of 1.62 MtC. Developers are considering two potential sites – Site A located in a warm climate grassland (C4 grass) and Site B in predominantly barren land. Site A and Site B yield similar Carbon ESI and Land ESI scores. However, the two sites differ considerably in their Water ESI scores (Table S7). Barren land ecosystems in Africa are highly water-stressed, hence, the Water ESI score in Site B is much higher than Site A.

575 **Table S7. ESI score calculations (in units of 10⁻⁸) for Site A and Site B. The parameters for the asset at each site are the same. Differences in score are due to differences in regional context.**

		Data available	Applicable Coefficient (refer to Fig. 7 or Tables S9-10)	Score
Site A in Africa: warm climate grassland (C4 grass)	Carbon ESI score calculations	0.054 MtC/year for 30 years: 1.62 MtC cumulative emissions	39.6 for every 0.1MtC of cumulative emissions (ESI-C is used in this case.)	641.5
	Land ESI score calculations	25 km ² average land use over 30 years	4.9 for every 5km ²	24.5
	Water ESI score calculations	3*10 ⁶ m ³ /year average annual water use over 30 years	4.4 for every 10 ⁶ m ³ /year	13.2
	Total ESI Score for Site A			679.2
Site B in Africa: Barren land	Carbon ESI score calculations	0.054 MtC/year for 30 years: 1.62 MtC cumulative emissions	39.6 for every 0.1MtC of cumulative emissions	641.5
	Land ESI score calculations	25 km ² average land use over 30 years	4.2 for every 5km ²	21.0
	Water ESI score calculations	3*10 ⁶ m ³ /year average annual water use over 30 years	258.8 for every 10 ⁶ m ³ /year	776.4
	Total ESI Score for Site B			1438.9

In this application, Site B has a higher overall ESI score than site A, indicating greater systemic impacts on the planet, driven mostly by the carbon and water pressures. Comparing the amplification factors for the two sites offers additional information. The amplification factor for natural land cover loss is 1.09 in C4 grasslands and 1.65 in barren Africa (Fig. 6). A major driver of this amplification is the relatively high normalized $LCC \rightarrow RO$ interaction strength in barren Africa (Fig. 4) which indicates proportionately greater decreases in runoff (compared to C4 grasslands in Africa) due to land cover change. This decrease in runoff can likewise affect surface water availability. Proponents can then plan to develop the site with the lower impact score, or, if Site B is preferable for other reasons, to redesign the facility to lower water use. In this way, the ESI can be useful as a decision support tool for planning, to evaluate different options for project development and make strategic decisions, for example, on location, technology research and business model to be prioritized. More broadly, where siting in high-impact areas such as this is unavoidable, this example illustrates the value of pairing ESI tracking with concrete mitigation measures to offset and monitor impact over an asset's operating life.

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Evaluating the performance of existing assets

A second potential application is using the ESI to evaluate the sustainability performance of existing assets. Consider an existing facility in South America, in an area which would have been tropical forest had it not been developed for human use. The Water ESI coefficient in this region is two orders of magnitude smaller compared to the Carbon and Land ESI coefficients which means that the latter contribute more to Earth system impacts.

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This facility withdraws water at the rate of 17×10^6 m³/year and occupies 47 km² of land. Since this is an existing facility, the application of the Land ESI coefficient in this case represents the impact of this appropriation of land and the current resultant prevention of tropical forest regrowth as well as the opportunity cost of all the associated ecosystem services. However, there is no or limited data historical data and age of the facility. There is also limited information on its remaining lifetime, and operations managers are primarily interested in tracking any improvements in their impact over time. Given this, the ESI-A is used to estimate the Carbon ESI, based on current annual carbon emission is estimated at 0.21 MtCO₂ per year, equal to 0.058 MtC per year. This results in a total ESI score of 1528 (Table S8).

605

Table S8. ESI score calculations (in units of 10⁻⁸) for a hypothetical facility in the tropical forest of South America focusing on the land and carbon pressures

	Data available	Applicable Coefficient (refer to Fig. 7 or Tables S9-10)	Score
Carbon ESI score calculations	Annual emission rate: 0.21 MtCO ₂ /year, equal to 0.058 MtC /year	22.9 for every 1ktC/year annual emissions rate (ESI-A is used in this case.)	1328.2
Land ESI score calculations	47 km ² current land use	19.8 for every 5km ²	186.1
Water ESI score calculations	17*10 ⁶ m ³ /year	0.3 for every 10 ⁶ m ³ /year	5.1
Total ESI Score			1519.4

610 An additional issue is that the tropical forest has been converted into predominantly concrete land cover, which represents substantial albedo change from an approximate value of 0.15 (tropical forest) to a more reflective 0.25 (concrete) (refer albedo values in the SI). We can estimate the CO₂ equivalent of the albedo change using the land footprint of the asset and the GWP_A of albedo in Section B (divided by the time horizon of 100 years to yield an annual estimate:

615
$$\text{CO}_2\text{e of albedo change} = 0.0259 \frac{\text{kgCO}_2}{(\text{m}^2)(0.01 \text{ reduction in albedo})(\text{year})} * \frac{\text{old-new albedo}}{0.01} * \text{area} = (0.0259) * \frac{(0.15-0.25)}{0.01} * (47*10^6)$$
$$\text{CO}_2\text{e of albedo change} = -1.21*10^7 \text{ kgCO}_2/\text{year} = -0.012 \text{ MtCO}_2/\text{year or } -0.003 \text{ MtC/year} \quad (\text{S9})$$

The negative sign of the albedo contribution indicates an equivalent carbon sequestration rather than emissions, due to the increased surface reflectivity which has a slightly cooling effect on temperature. However, compared to direct emissions of 0.058 MtC/year, the albedo contribution is an order of magnitude smaller. Furthermore, an equivalent carbon sequestration, if the original forest cover had remained, would have reduced the carbon pressure to 0.055 and the Carbon ESI to 1265 from 1334. The removal of vegetation and the continued prevention of vegetation growth can therefore be thought of as a lost opportunity for carbon sequestration, built into the operations of the asset simply from the land use. To act on this, the facility could consider re-greening strategies as one potential solution.

625 Operations managers could track resulting annual ESI performance related to year-to-year changes in emissions resulting from using the annual coefficient (ESI-A) for carbon emission rates and comparing ESI scores over time. In this case, the ESI should be interpreted as the potential impact of the asset on the Earth system should it continue to perform over the long term as it did

in that year. Note that given this interpretation the ESI scores generated annually should not be summed up to generate a
630 cumulative score. Users should also avoid switching between Carbon ESI-C and Carbon ESI-A within the same use case, as
scores would not be directly comparable.

Future Exploration of Use Cases

Beyond these illustrative cases, different configurations can be explored employing either or both a retrospective lens and a
635 prospective lens. The ESI framework could be tested at other entity scales, for example, aggregating pressures across a multi-
location company portfolio, or across a city or community (for public sector use), and could potentially be integrated into the
workflow of complementary tools such as life cycle assessments and environmental impact assessments.

H. Tables of ESI Coefficients

640 **Table S9. Carbon ESI coefficients for cumulative emissions data vs. annual emissions rate data, scaled for different units of C and CO₂.**

	Carbon ESI Coefficient (for use with 0.1 Mt C)	Carbon ESI Coefficient (for use with t C)	Carbon ESI Coefficient (for use with t CO₂)
For Cumulative Emissions	3.96E-07	3.96E-12	1.08E-12
	Carbon ESI Coefficient (for use with 1 kt C yr⁻¹)	Carbon ESI Coefficient (for use with t C)	Carbon ESI Coefficient (for use with t CO₂)
For Annual Emission Rate	2.29E-07	2.29E-10	6.24E-11

645 **Table S10. Land and Water ESI coefficients, scaled for different units of land cover change and water withdrawal. (NA entries indicate that scores were not defined for that region due to region size being below the threshold of 10 grid cells.)**

Dominant PFT	Continent	Land ESI coefficients for 5 km² land cover change	Land ESI coefficients for 1 km² land cover change	Water ESI coefficients for 10⁶ m³ yr⁻¹ water withdrawal	Water ESI coefficients for 10³ m³ yr⁻¹ water withdrawal
boreal	Asia	2.05022E-07	4.10043E-08	5.66664E-09	5.66664E-12
grass_c3	Asia	3.75765E-08	7.51529E-09	3.35592E-09	3.35592E-12
grass_c4	Asia	1.69491E-07	3.38981E-08	5.13662E-08	5.13662E-11
temperate	Asia	2.74809E-07	5.49618E-08	0.00000E+00	0.00000E+00
tropical	Asia	3.21103E-07	6.42206E-08	4.87102E-10	4.87102E-13
barren	Asia	4.08856E-08	8.17712E-09	3.58275E-07	3.58275E-10
boreal	North America	2.16741E-07	4.33481E-08	4.07604E-09	4.07604E-12
grass_c3	North America	8.64397E-08	1.72879E-08	2.44632E-08	2.44632E-11
grass_c4	North America	3.27916E-07	6.55832E-08	4.41434E-08	4.41434E-11
temperate	North America	3.55156E-07	7.10311E-08	0.00000E+00	0.00000E+00

Dominant PFT	Continent	Land ESI coefficients for 5 km² land cover change	Land ESI coefficients for 1 km² land cover change	Water ESI coefficients for 10⁶ m³ yr⁻¹ water withdrawal	Water ESI coefficients for 10³ m³ yr⁻¹ water withdrawal
tropical	North America	9.94567E-07	1.98913E-07	3.74656E-09	3.74656E-12
barren	North America	3.13232E-08	6.26464E-09	0.00000E+00	0.00000E+00
boreal	Europe	3.63113E-07	7.26226E-08	1.67379E-08	1.67379E-11
grass_c3	Europe	3.45819E-07	6.91639E-08	7.09482E-08	7.09482E-11
grass_c4	Europe	NA	NA	NA	NA
temperate	Europe	3.77843E-07	7.55687E-08	3.58657E-08	3.58657E-11
tropical	Europe	NA	NA	NA	NA
barren	Europe	5.77652E-07	1.15530E-07	5.11241E-08	5.11241E-11
boreal	Africa	NA	NA	NA	NA
grass_c3	Africa	2.56603E-06	5.13206E-07	3.25220E-05	3.25220E-08
grass_c4	Africa	4.91656E-08	9.83312E-09	4.41622E-08	4.41622E-11
temperate	Africa	5.57592E-07	1.11518E-07	0.00000E+00	0.00000E+00
tropical	Africa	1.70631E-07	3.41262E-08	2.65171E-09	2.65171E-12
barren	Africa	4.22234E-08	8.44468E-09	2.58813E-06	2.58813E-09
boreal	South America	NA	NA	NA	NA
grass_c3	South America	6.00719E-07	1.20144E-07	4.87774E-07	4.87774E-10
grass_c4	South America	3.39624E-07	6.79247E-08	1.00028E-06	1.00028E-09
temperate	South America	3.91726E-07	7.83452E-08	2.49801E-08	2.49801E-11
tropical	South America	1.97966E-07	3.95933E-08	3.54795E-09	3.54795E-12
barren	South America	3.68454E-07	7.36908E-08	1.91457E-07	1.91457E-10
boreal	Oceania	NA	NA	NA	NA

Dominant PFT	Continent	Land ESI coefficients for 5 km² land cover change	Land ESI coefficients for 1 km² land cover change	Water ESI coefficients for 10⁶ m³ yr⁻¹ water withdrawal	Water ESI coefficients for 10³ m³ yr⁻¹ water withdrawal
grass_c3	Oceania	NA	NA	NA	NA
grass_c4	Oceania	NA	NA	NA	NA
temperate	Oceania	1.77147E-06	3.54294E-07	4.65488E-08	4.65488E-11
tropical	Oceania	5.51416E-07	1.10283E-07	1.57139E-08	1.57139E-11
barren	Oceania	NA	NA	NA	NA
boreal	Australia	NA	NA	NA	NA
grass_c3	Australia	NA	NA	NA	NA
grass_c4	Australia	8.46360E-08	1.69272E-08	2.31998E-07	2.31998E-10
temperate	Australia	7.80536E-07	1.56107E-07	4.63394E-07	4.63394E-10
tropical	Australia	0.00000E+00	0.00000E+00	1.98536E-07	1.98536E-10
barren	Australia	3.15374E-07	6.30748E-08	6.35676E-06	6.35676E-09

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