



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

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Abstract. Human pressures at the local scale are driving transgressions of a planetary safe operating space, compromising global and regional stability and resilience. Tools are needed to help organizations assess their environmental performance by bridging local pressures to planetary impacts. The Earth System Impact (ESI) metric prototype was developed in 2021 to enable evaluations of an organization's systemic impacts relative to established planetary boundaries translated to the sub-global scale. This metric incorporates key interactions between climate change, land cover change and freshwater flows, distinguishes impacts by region, and accounts for current states of climate, land cover and surface freshwater. Here, we present innovations to the ESI approach to enhance the tool's utility. Simulation data needed for score construction is updated, and the spatial scope is broadened to include dominantly barren land types which were excluded in the prototype. We draw from the latest assessments of safe and just planetary operating spaces to define regional boundaries for land and water. For water, specifically, we account for both upper and lower bounds in flow alteration while the prototype had only recognized the latter. We calculate two sets of metrics: amplification factors, which measure the extent to which impacts are magnified in the Earth system; and location-specific Carbon, Land and Water ESI coefficients which represent the systemic impact of reference pressures in the form of carbon emissions, land cover change and water withdrawal. Overall, amplification factors increased compared to the prototype. The effects of deforestation on the Earth system were doubled to tripled. Most barren land experienced no net amplification except in Australia and Africa (~39% and 65%, respectively) where surface water scarcity is aggravated. The final ESI coefficients were higher in smaller areas (e.g. C3 grass ecosystems in Africa), indicative of the sensitivity of smaller ecosystems to pressures, and in areas where transgressions are coupled with high amplification.



1 Introduction

Human activities are altering Earth system processes, exposing people and ecosystems to increasing risks from cascading hazards, biodiversity collapse and resource constraints. The collective impact of these pressures is assessed by frameworks such as Planetary Boundaries (PBs) and Earth System Safe and Just Boundaries (SJBs), with recent assessments showing increasing deviations from Holocene-like conditions (Gupta et al., 2024; Richardson et al., 2023). The PBs define guardrails for nine key Earth system processes (Richardson et al., 2023) while the Earth Commission's SJBs integrate human well-being with planetary stability, assessing relevant processes across global and sub-global scales (Gupta et al., 2024; Rockström et al., 2023).

The PBs and SJBs have been fundamental in advancing scientific and societal understanding of the state of the Earth system (Bai et al., 2024; Rockström et al., 2024). However, how societal actors should operationalize these boundaries remains unclear. Top-down approaches translate the PBs into equivalent shares at the ecosystem, country or individual levels for target-setting (Dao and Friot, 2025; Ferretto et al., 2022; O'Neill et al., 2018; Serrano et al., 2025). The Earth Commission SJB framework likewise supports cross-scale translation for cities and businesses (Bai et al., 2024), including global annual emissions, natural ecosystems, and surface water withdrawal budgets. Bottom-up approaches (Dao and Friot, 2025) enable individual businesses to set science-based targets (SBT) for greenhouse gas emissions, land, freshwater, and oceans (Bjørn et al., 2022; Kılış et al., 2024; Rockström et al., 2024).

While target-setting is important, so too is the ability to measure impact and track progress towards targets. Research on operationalizing boundaries beyond climate remains limited, particularly in accounting for interconnections between boundaries (Williams et al., 2025). Tools are needed to help public and private actors systemically assess their impacts and performance not just locally, but in relation to wider Earth system stability and resilience. Sustainability-related financial reporting likewise lacks credible standards and metrics for assessing systemic environmental impacts and performance (Berg et al., 2022; Crona et al., 2025, 2026; Crona and Sundström, 2023; Wassénus et al., 2024).

The prototype Earth System Impact (ESI) metric was developed to help companies, investors or other actors assess impacts from three anthropogenic pressures (carbon emissions, land use and water withdrawal) across three Earth system processes (climate change, land system change and freshwater change) (Lade et al, 2021). These pressures are particularly important in that they can disrupt the planet's energy balance and life-support functions and represent key drivers of biodiversity loss. The ESI metric comprises location-specific coefficients that scale with pressure magnitude. These coefficients (1) downscale PBs and SJBs into sub-global boundaries defined by continental biomes; (2) integrate interactions among climate, land and water across sub-global and global scales; and (3) account for local current state, including degradation already incurred. Applying the ESI coefficients to an activity yields a total ESI score and three sub-scores – Carbon ESI, Land ESI and Water ESI – which enable systemic impacts to be evaluated relative to planetary boundaries, while identifying the contribution of each domain to



the overall and regional impact and the need for specific mitigative action. The prototype ESI metric was piloted on the mining industry (Crona et al., 2023).

65 The ESI metric is complementary to other assessment tools. Environmental Impact Assessments (EIAs), for example, can capture interactions and current state, but operate at local scales and are not typically benchmarked against Earth system reference points. Life Cycle Assessments (LCA) assess product or sector-level impacts and are increasingly aligned with PB impact categories (Paulillo and Sanyé-Mengual, 2024; Ryberg et al., 2018), though they do not typically incorporate Earth-system interactions despite proposed model-based approaches (Bjørn et al., 2019). By combining local context, Earth system
 70 boundaries and climate-land-water interactions, the ESI metric therefore addresses a cross-scale assessment gap not hitherto captured by other assessments.

While the ESI metric prototype addressed a cross-scale assessment gap, several key aspects required further development. Both current state and interactions estimates were drawn from now-outdated simulations, and the downscaled boundaries were based on the 2015 PBs. ESI coefficients were not defined for regions with minimal vegetation, limiting its spatial coverage.
 75 Land cover change impacts on climate captured key carbon cycle mechanisms but excluded biogeophysical pathways such as albedo (surface reflectivity).

This paper presents updates to the ESI metric to better capture systemic impacts and enhance its use and applicability. We extend the assessment of current state to 2023 (from 2013 in the prototype) and draw on the latest PBs and SJBs assessments to support the definition of sub-global boundaries. ESI coefficients are extended to minimally or non-vegetated regions that
 80 were excluded from the prototype. For the Water ESI metric, updated boundaries (Porkka et al., 2024; Richardson et al., 2023; Stewart-Koster et al., 2023) recognize both wetter and drier departures from a preindustrial baseline, better capturing water cycle changes. For the Carbon ESI metric, formulations are provided for annual as well as cumulative emissions. In addition, we append guidance on potential use cases, including a method to incorporate the potential albedo effect of land cover change on climate. Combined, these updates promise to enhance both the scientific rigor and applicability for the non-academic
 85 community.

2 Methods

2.1 Constructing the ESI Metric

Four main steps are used to construct the revised ESI metric: (1) estimating interactions strengths, (2) modeling feedback, (3) applying weights determined by current state and, for water, variability, and (4) calculating amplification factors and Carbon,
 90 Land and Water ESI coefficients (Fig. 1). The revised ESI retains the prototype's overall construction and core feedback-modeling framework (Lade et al., 2021), while updating interaction strengths (section 2.1.1 and Supplementary Information, section A), feedback-model inputs (Section 2.1.2), boundaries used for normalization (Section 2.2), and current-state estimates



(Section 2.1.3). New elements include additional weighting of the Water ESI coefficients (Section 2.1.4), coverage of barren land (Section 2.1.1 and Supplementary Information, section A), and an approximation of land-cover albedo effects (Supplementary Information, section B). The final calculation of amplification factors and ESI coefficients follows the prototype method (Section 2.1.5), but with an annual-emissions Carbon ESI option (Section 2.3).

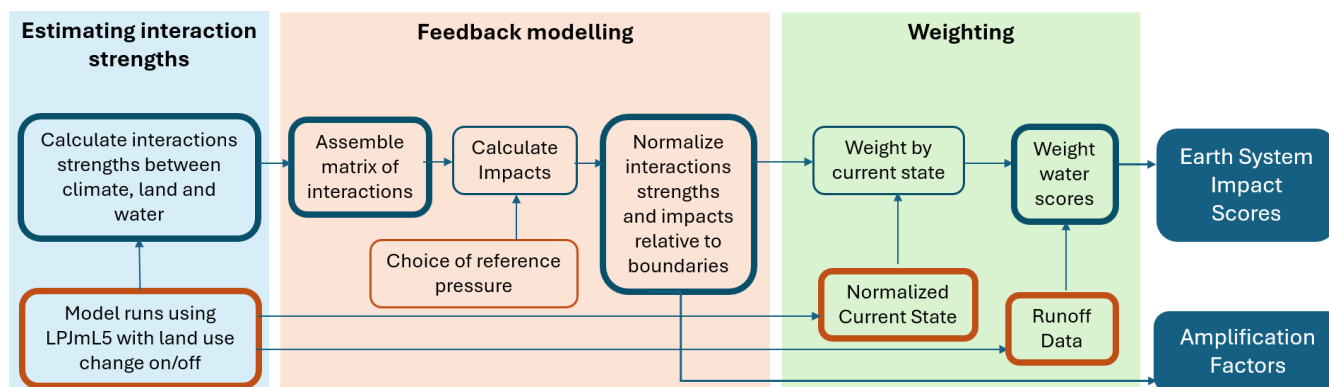


Figure 1. Workflow for constructing the ESI scores and amplification factors (boxes in blue outline are processes and in orange outline, inputs; boxes in bold outline represent processes/inputs that are updated from the ESI prototype). Interaction strengths are estimated and used in feedback modelling to calculate impacts of pressures on climate, land and water. Amplification factors are derived by comparing impacts with and without interactions while ESI scores are produced by weighting impacts by current state and applying additional weighting for water scores. Output from a dynamic global vegetation model, LPJmL, is used for estimating interaction strengths as well as for weighting.

2.1.1 Estimating Interaction Strengths

“Interaction” refers to the one-way causal relationship between two Earth-system components (Flores and Staal, 2022; Lade et al., 2021). Interaction strength is the magnitude of linear change in one variable driven by a change in another (Lade et al., 2021). These strengths quantify feedback among climate, land and water, thereby capturing critical systemic impacts. We updated the same four interaction strengths used in the prototype: the effect of land cover change on runoff ($LCC \rightarrow RO$), land cover change on climate ($LCC \rightarrow CC$), climate change on land cover ($CC \rightarrow LCC$), and climate change on runoff ($CC \rightarrow RO$).

In the prototype, interaction strengths were quantified using simulations performed by the Lund-Potsdam-Jena model with managed land (LPJmL), version 4, driven by Climate Research Unit gridded time series (CRU TS) monthly climate data until 2013 (Harris et al., 2014). LPJmL is a process-based dynamic global vegetation model (DGVM) that simulates potential natural vegetation and managed land (e.g., croplands, pastures and bioenergy plantations) within a coupled framework of carbon, water and energy fluxes (Schaphoff et al., 2018a, b). Vegetation is represented by plant functional types (PFTs) in which establishment and competition, phenology, photosynthesis, respiration, carbon allocation and mortality shape grid-cell carbon stocks and fluxes (Schaphoff et al., 2018a). Managed land is simulated using crop functional types (CFTs) and prescribed land-use fractions. Crop growth and yields reflect the same coupled carbon-water limitations with added management routines.

Hydrology is computed with a daily water balance including interception, soil evaporation, transpiration, percolation and runoff, with optional modules for irrigation and water withdrawals, reservoirs and river discharge (Schaphoff et al., 2018a).

120 We recalculated the four interaction strengths between *LUC*, *CC* and *RO* using LPJmL v5.7.9 simulations (Wirth et al., 2024), which extend LPJmL4 by, among other developments, introducing an explicit terrestrial nitrogen cycle that constrains plant productivity and modifies CO₂ fertilization responses. We forced LPJmL with monthly observation-based CRU TS gridded climate data over global land at 0.5° resolution for 1901-2023 (Harris et al., 2020, 2024). Atmospheric CO₂ concentrations were prescribed from ISMIP3b historical atmospheric composition input data (Büchner and Reyer, 2022), based on historical
 125 concentrations (Lan et al., 2023; Meinshausen et al., 2011) and SSP concentration pathways for the scenarios (Meinshausen et al., 2020).

We ran two transient experiments: (1) a *NoLU* simulation, with potential natural vegetation and no human land use, and (2) a *WithLU* simulation, with managed land enabled, with other settings held constant to isolate land-use effects on carbon-water dynamics. Irrigation was disabled in the *WithLU* scenario to avoid artificially enhancing local runoff. Because the ESI metric
 130 is intended for applications beyond agriculture, and anthropogenic land use in LPJmL is represented by crops only, irrigation was excluded to avoid introducing agriculture-specific effects on runoff. For each historical simulation, we extracted the following variables:

- Foliar projective cover (FPC), representing annual fractional vegetated cover of natural plant functional types (PFTs) per grid cell, used with cell area to determine vegetation cover (km²).
- 135 ▪ Vegetation carbon storage density recorded annually (g m⁻²).
- Total runoff density, recorded monthly but aggregated to annual flows (mm yr⁻¹).
- Albedo, reported monthly and averaged annually (fraction of reflected sunlight)

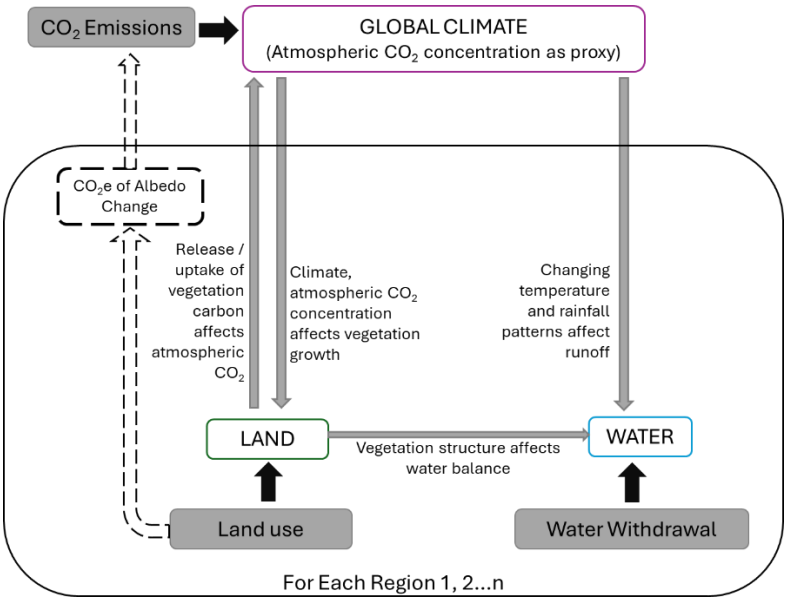
While the prototype used *surface* runoff from LPJmL4, this version used *total* runoff to capture both surface and subsurface components of rapid lateral flow to streams. In both historical experiments, river routing was switched on to let runoff be
 140 carried to downstream discharge and used as a proxy for freshwater flows. Stream flow alteration is the control variable for SJBs (Section 2.2), and land cover change affects stream flow via direct impacts on total runoff. Land cover change can also affect groundwater discharge to streams, and hence streamflow discharge, but over longer time scales stretching to billions of years (hence deep groundwater contributing less than 0.1% to global streamflow (Ferguson et al., 2023)).

Consistent with Lade et al. (2021), CC-driven interaction strengths were derived by regressing runoff (for *CC* → *RO*) or natural
 145 land cover area (for *CC* → *LCC*) against atmospheric CO₂ concentration over time using output from the *NoLU* simulations. Deriving the *LCC*-driven interactions involved comparing the last 30 years of the *WithLU* and *NoLU* simulations: *LCC* → *RO* was computed as the difference in runoff volume between the last 30 years of the simulations divided by the difference in natural land cover area also between the last 30 years. Likewise, *LCC* → *CC* was computed as the difference in total vegetation carbon between the ends of the simulations divided by the difference in natural land cover area between the ends of the



150 simulations (soil carbon is excluded because the longer time scales of soil carbon dynamics contradict equilibrium assumptions in the feedback modeling (Section 2.1.2)). Minor calculation adjustments from the prototype are in the Supplementary Information, section A.

The $LCC \rightarrow CC$ interaction was limited to the vegetation carbon pathway and omits the albedo effect on climate. Albedo affects radiative climate forcing, so land cover change causing surface brightening (darkening) has a cooling (warming) effect (Hasler et al., 2024). Although LPJmL5.7.9 produced albedo values based on land cover, it cannot estimate the climate response to changing albedo without coupling to an atmospheric model. To estimate the potential albedo impact, we propose a separate approach incorporating albedo by comparing it to the carbon pressure (described in the Supplementary Information, section B). Figure 2 summarizes the interactions integrated in the ESI.



160 **Figure 2. Interactions integrated in the ESI. Interactions between regional land cover change, regional runoff and global climate determine overall impact from pressures in the form of carbon emissions, land use and water withdrawals. While the impact of changing surface albedo on climate is not yet incorporated in the interaction strength for the Land->Climate pathway, this can be incorporated into the analysis by calculating the equivalent CO₂ emissions of the albedo change.**

Interaction strengths were aggregated according to vegetation types within each continent (excluding Antarctica and treating Oceania separately). A minimum threshold of a total count of 10 grid cells was applied to define large-scale continent-biome combinations; those below the threshold were excluded (e.g. boreal forests in South America, tropical forests in Europe). While the prototype considered five major vegetation types – tropical, temperate, and boreal forests, and cool climate C3 and warm climate C4 grasses – the updated ESI metric adds sparsely-vegetated and predominantly barren, such as deserts, rocky terrain and ice-covered areas (see Supplementary Information, section A). This extends ESI interaction and impact estimates to regions excluded from the prototype. Maps of early and current dominant vegetation cover, which are used to define regions,

are shown in Fig. 3, with additional maps of current potential natural vegetation in Supplementary Information, section C. Fig. 3b maps FPC, which is indicative of the area covered by the dominant vegetation type. Lower FPC fractions indicate more mixed cells. The choice of clustering by continent and dominant vegetation types is supported by a comparative multivariate cluster analysis (Supplementary Information, section D), following the approach of Zoller et al., (2026) comparing average within-cluster sum-of-squares of 33 established Earth partitions covering climatic and biogeographic classification criteria.

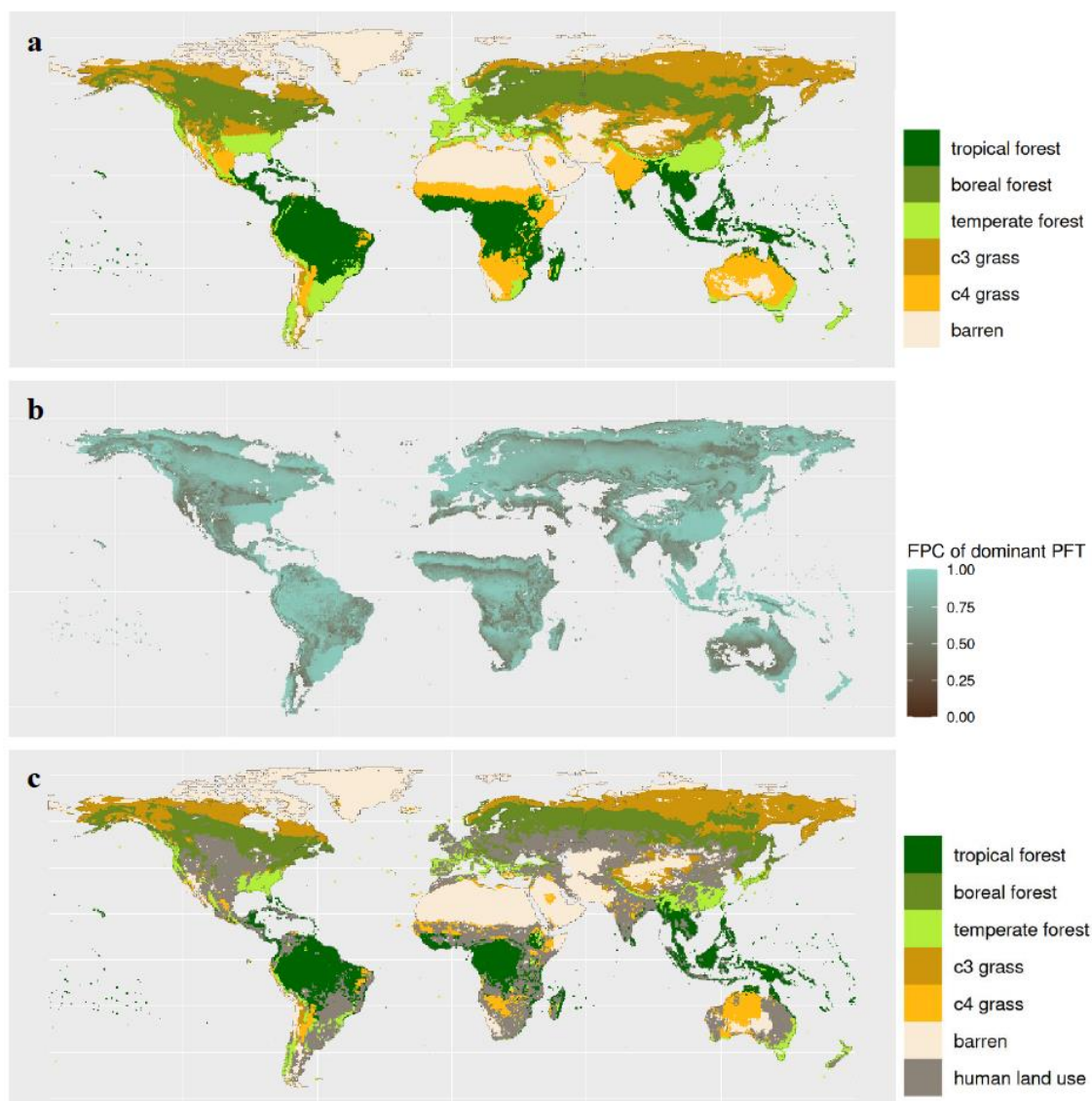


Figure 3. Early and recent vegetation cover used as the basis for defining regions within continents. (a) Early 20th century vegetation dominant in each cell, assuming no human land use change, based on the first 30 years of the *NoLU* simulation using LPJmL. This was used as the preindustrial estimate. (b) Foliar projective cover (FPC), expressed as a fraction, of the dominant vegetation type in each cell in the vegetation cover map in (a). (c) Recent vegetation cover map with human land use based on the last 30 years of with *WithLU* simulation.



2.1.2 Modeling Feedback

The interaction strengths were assembled into a matrix used to determine the overall Earth-system impact of land, water and climate pressures through feedback modelling (Eq. 1):

$$\Delta x = (I - B)^{-1} \Delta d \quad (1)$$

where Δx represents the change in Earth system state;
 Δd the pressure magnitudes;
 B the matrix of biophysically-mediated interaction strengths;
 I the identity matrix.

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The model calculated net changes in atmospheric CO₂ concentrations, natural land cover, and runoff given the direct impacts of the pressures and the magnitude and direction of interaction strengths. Only interaction strengths meeting the statistical significance threshold $p < 0.01$ were included in B . B , Δx and Δd , and the derivation of Eq. (1) follow the prototype (recapped in Eqs S1 to S3). Pressures magnitudes (Δd) were fixed at the following values which we refer to as “reference pressures”: 0.1 MtC emissions (0.367 MtCO₂ emissions), 5 km² natural land cover change, and 10⁶ m³/year surface water withdrawal. These arbitrary pressures were selected to yield comparable outcomes, but the resulting ESI coefficient can be scaled linearly to other magnitudes to generate location-specific ESI scores (see Section 3.4).

The impacts on each Earth system component in each region were then normalized (Eq. 2), expressing impacts according to how much each component is pushed towards its boundary given the reference pressure and interactions, thereby integrating changes across Earth system components with different units of measure. Impacts were then tallied per region with equal weight given to *CC*, *LCC* and *RO*.

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$$\text{Normalized impact } \Delta x^N = \frac{\Delta x}{x^B - x^0} \quad (2)$$

where Δx represents the total impact on the Earth system component X , given interactions;
 the superscripts 0 and B refer to values under pre-industrial conditions and at their boundaries, respectively (a global boundary for climate, and sub-global boundaries for land and water). The first 30 years of the *NoLU simulation* (Fig. 3a) were averaged as a proxy for a preindustrial baseline.

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The interaction strengths in matrix B were used unnormalized for the feedback modeling, then normalized to facilitate comparison (Eq. 3):

$$\text{Normalized interaction strength for } X \rightarrow Y = \frac{\Delta Y}{\Delta X} \frac{x^B - x^0}{y^B - y^0} \quad (3)$$



210 where $\Delta Y/\Delta X$ represents unnormalized interaction strengths (the change in Y per change in X , (Section 2.1.1));
 0 and B superscripts refer to values as above.

A value of one indicates that changing X from its preindustrial value to its boundary drives Y by the corresponding distance from its preindustrial value to its boundary. A value greater than 1 indicates Y is pushed beyond its boundary, while values below one indicates a proportionally smaller response (see Section 2.2. for more information on boundary estimation).

215 Reference pressures for land and water were similarly normalized to compare magnitudes relative to the natural land cover and available runoff volume in each region (Eq. 4, Supplementary Information, section A):

$$\text{Normalized reference pressure } \Delta d^N = \frac{\Delta d}{X^B - X^0} \quad (4)$$

2.1.3 Weighting by Current State

Current states for land, water, and climate were determined as follows: climate state was 2023 global atmospheric CO₂
 220 concentration (420ppm); land state was regional vegetation cover in the last LPJmL simulation year (2023); water state was mean regional runoff over 2014-2023 in the *WithLU* simulation calculated over the corresponding region determined from the *NoLU* simulation to capture runoff changes in areas originally occupied by natural vegetation or barren land.

Current states were then normalized relative to their boundaries (Eq. 5):

$$\text{Normalized current state of } X = \frac{X - X^0}{X^B - X^0} \quad (5)$$

225 where X is the unnormalized state variable;
 0 and B superscripts refer to values as above.

Positive values indicate movement away from the preindustrial baseline and towards or beyond the boundary; negative values indicate deviation away from the boundary (e.g. forest expansion instead of loss). For runoff, both lower and upper bounds
 230 were introduced (Section 2.2), so any change represents movement towards a boundary. A value of one indicates the state is at its corresponding land, water, or climate boundary; values greater than one indicate transgressions.

The normalized current state of each region was then applied as a weighting factor to the impacts calculated via feedback modelling, so that the ESI metric incorporates existing degradation in the region.



2.1.4 Additional Weighting of Water ESI Coefficients

235 Additional weighting was applied to the Water ESI coefficients because the reference pressure – water withdrawal – reduces runoff and therefore pushes the water state towards the lower boundary. After the current-state weighting (Section 2.1.3), the resulting Water ESI coefficients represent the impact of the reference water pressure, accounting for how much runoff in the area has already deviated from the preindustrial baseline; however, this deviation could be in either the wet or dry direction. Inter-annual and intra-annual variability were therefore added as weighting factors to better reflect drying impacts, since
 240 vegetation productivity depends on short- and long-term water variability (Smith and Boers, 2023). Intra-annual variability suits ecosystems with limited seasonal buffering capacity, while inter-annual variability suits ecosystems that tolerate seasonal variation but are sensitive to year-to-year fluctuations.

The final Water ESI weight was based on the larger of inter- vs. intra-annual variability, ranging from 0 to 1. These estimates used the last 10 years of simulated runoff data to determine current state. For each region, we calculated each region's fraction
 245 of dry years (by comparing annual runoff density to the preindustrial baseline) and dry months (by comparing monthly averages over the 10 years). The larger of these two fractions was applied to weight the water ESI. A weight of one means all years or all 12 months averaged over the last 10 years were drier than the preindustrial baseline. A weight of less than one means only that fraction of the last ten years, or the twelve months averaged over the last 10 years, were drier than the preindustrial baseline. In some regions, all years or months were wetter than the baseline, giving a weight of 0 (more details in
 250 Supplementary Information, section A) indicating minimal water availability impact from withdrawal pressure.

2.1.5 Assembling the Amplification Factors and Earth System Impact Coefficients

Amplification factors quantify how pressure in one Earth system component interacts with and magnifies (or dampens) other components (Lade et al., 2021). Derived during feedback modeling, the magnitudes of amplification factors are independent of pressure magnitude. Amplification factors were calculated by comparing overall changes in variables with vs. without
 255 interactions (Eq. 6) for carbon emissions and land cover change only, since $RO \rightarrow LCC$, CC interactions remain unquantified:

$$\text{Amplification factor} = \frac{|\Delta x^N|}{|\Delta d^N|} \quad (6)$$

where the vector norm $|\Delta x^N|$ sums normalized impacts on state variables, so impacts on climate, land, and water are weighted equally. An amplification factor of 1 means changes in a variable's state are a direct result of the pressures with no amplification via interactions, while a factor greater than 1 denotes amplification. An amplification factor of less than 1 denotes dampening
 260 (e.g. climate change mitigated by vegetation expansion that sequesters carbon).

From the amplification factors, removing normalization by the size of the pressure and introducing weighting factors yield the final ESI metric (Eq. 7):



$$ESI = |\Delta x^N \cdot u(x^{now}) \cdot w| \quad (7)$$

where Δx^N was determined from the feedback modelling step;

265 $u(x^{now})$ refers to the weighting by current state x^{now} ;

w represents the weighting of only the water ESI scores.

The u function bounds the current state between 0 to 1: a value of 1 is assigned if the climate state, or, in each region, the land or water state, is already at or beyond its boundary; otherwise, the weight equals the normalized current state. Current states below zero (i.e., improved relative to preindustrial conditions) are rounded up to 0. Defined in this way (and prior to the additional weighting of the Water ESI coefficients), the ESI metric is such that a value of 1 would mean that the climate state variable, or the land state variables across all areas, or the water state variables across all areas, have moved from their boundaries (the lower boundary in the case of water) to twice the boundaries (Lade et al., 2021).

This result is a set of coefficients: a single value for Carbon ESI, and sub-global values for the Land and Water ESIs across different regions. These coefficients indicate the Earth system impacts of carbon emissions, land use change and water withdrawal at the reference pressures, accounting for climate-land-water interactions and regional context. Unlike amplification factors, ESI scores are sensitive to reference pressure magnitude but scale linearly for pressures of other magnitudes. The ESI coefficients can thus be used to determine the scores of an organization's context-specific pressures.

2.2 Determining Boundaries

In both the prototype and this update, a global boundary for climate change of 350ppm atmospheric CO₂ (Steffen et al., 2015; Richardson et al., 2023, and Rockström et al., 2023) was retained, consistent with the SJB of 1°C warming under long-term equilibrium assumptions. Downscaled sub-global boundaries for land and water were determined for each continent-dominant PFT combination. The downscaled land and water boundaries were updated here using current PB and SJB research.

For sub-global land boundaries, the prototype downscaled PBs proposed by Steffen et al (2015): 85% of preindustrial area for tropical and boreal forests, and 50% for temperate forests. As no PBs were proposed for grasslands, the prototype adopted 50%, recognizing grasslands' ecological significance and their threat from agricultural expansion. Preindustrial land cover estimates were calculated from the first 30 years of the *NoLU* simulations, when human land use was minimal. In this update, we maintained the 85% boundaries for the tropical and boreal forests but a more stringent boundary of 60% of preindustrial area remaining for other ecosystem types, including barren ecosystems. This uses the upper end of the SJB range of 50-60% natural vegetation area, set based on the natural ecosystem intactness needed for large-scale climate and hydrological regulation and species extinction prevention (Gupta et al., 2024). Applying the same boundary to barren ecosystems recognizes their biodiversity and ecosystem functions (for example: Pausata et al., 2020). Another SJB for local ecosystem functional integrity is defined as 20–25% of every km² being natural or semi-natural vegetation (Gupta et al., 2024; Rockström et al., 2023).



LPJmL's 0.5° resolution is too coarse to reliably assess kilometer-scale land area, so integrating impacts on functional integrity remains a future area of research.

- 295 The prototype defined only minimum annual regional surface water flow (Steffen et al., 2015), whereas updated freshwater PBs (Porkka et al., 2024) and SJBs (Gupta et al., 2024; Stewart-Koster et al., 2023) recognize both wetter and drier streamflow deviations as potentially adverse. The blue water PB uses percentage of global land area experiencing local streamflow deviations beyond the 5th and 95th percentiles of a preindustrial baseline as the lower and upper bounds, while the SJB sets a $\pm 20\%$ alteration of monthly surface water flows relative to the prevailing natural flow regime (Stewart-Koster et al., 2023).
- 300 The SJB can also be downscaled and related to asset-level water withdrawals, as well as defined from shorter simulations.

- We adapted the SJB $\pm 20\%$ flow alteration to determine upper and lower sub-global boundaries for surface runoff density, with two modifications: (1) flows were aggregated annually, accommodating water withdrawal data often reported annually by assets rather than monthly; and (2) aggregation occurred over regions defined by continent and dominant PFTs, rather than catchment scale, to correspond with the scale of ESI interaction strengths and impacts measurement. Like land boundaries, the
- 305 first 30 years of *NoLU* simulation defined the pre-industrial baseline. The lower runoff boundary in each region was set at a 20% decrease, and the upper runoff boundary to a 20% increase relative to the preindustrial mean. The 20% threshold produced a tighter flow envelope than the PB 5th – 95 percentile thresholds in all regions except South American tropical forests, where the difference was small (Supplementary Information, section E). However, these boundaries applied to changes in surface freshwater flows only, excluding groundwater flows for which the SJB is defined relative to rates of replenishment.
- 310 The boundary used to normalize current runoff states in each region depended on the direction of deviation: areas drier (wetter) than baseline were normalized against the lower (upper) boundary. Since the reference pressure was water withdrawal, which always decreases available surface freshwater, pressure was normalized using the lower boundary across all regions. Climate and land use change effects on runoff can move in either direction, so net impact was calculated using unnormalized interaction strengths (Section 2.1.2) and then normalized using either the lower or upper boundary, per its direction of change.

315 2.3 An Alternative Metric for Carbon

- The PB expressed as atmospheric CO₂ concentration is a stock-based indicator (Wolfram et al., 2026) and requires that the associated CO₂ emissions be cumulative emissions from the activity or facility evaluated. The Carbon ESI coefficient from Eq. 5 (Section 2.1.5) applies to cumulative emissions. For an asset, this means the stock of total emissions over a substantial period, ideally asset lifetime from construction to operation and decommissioning. This requires data on project lifetime and
- 320 annual emissions. While emissions can be measured, lifetime may not be accurately known or may not be decision-useful (e.g., in the case of firms using the ESI scores to evaluate annual performance).



To flexibly cater to different use cases, the updated ESI approach provides an alternative for when only data on annual emission rates are available. If estimating years of operation is infeasible (e.g. from statistics or secondary literature), users can apply the Carbon ESI coefficient for annual emission rates, calculated by apportioning responsibility for the historical increase (and transgression) in atmospheric CO₂ concentration, adapted from Lade et al. (2019), and scaling the Carbon ESI coefficient proportionately (Eq.9; see Supplementary Information, section A for calculation details). This metric approximates the asset's potential long-term impact if it continued emitting at the specified annual rate using an annual reference pressure of 1 KtC/year.

Unlike the water weighting factor (Section 2.1.4), this alternative scaling was not integrated into the coefficient; instead, both approaches for Carbon ESI are provided so users can choose the most relevant application for their purpose. We designate “Carbon ESI-C” for the cumulative emissions coefficient, and “Carbon ESI-A” for the annual emission rate coefficient.

$$\text{Carbon ESI-A} = \frac{CC_{ref_{new}}}{CC_{ref_{original}}} * \text{Carbon ESI-C} \quad (8)$$

Where $CC_{ref_{new}}$ refers to the atmospheric CO₂ concentration apportioned to the annual reference pressure, 1 KtC/year
 $CC_{ref_{original}}$ refers to the atmospheric CO₂ concentration associated with the original reference pressure of 1 MtC

3 Results

In this section, we present the re-calculated interactions strengths and assessments of current states (as of 2023) and the updated amplification factors and ESI coefficients. Outcomes of an uncertainty analysis of the interaction strengths, amplification factors and the ESI metrics are summarized in the Supplementary Information, section F.

3.1 Interaction Strengths

The normalized interaction strengths (Eq 3), represent the fraction by which Y is driven to its boundary by X moving to its boundary. The interaction analysis for $LCC \rightarrow CC$ indicated that the loss of natural vegetation cover predominantly results in increased atmospheric CO₂ concentrations driving climate change (Fig. 4). The effect was stronger over forests compared to grasslands and barren land which store minimal vegetation carbon. Average $LCC \rightarrow CC$ normalized interaction strengths (regions with significant interactions only) were 0.035, 0.024 and 0.017 for boreal, temperate and tropical forests, respectively.

In the prototype, the highest $LCC \rightarrow CC$ normalized interaction strengths were found over South American and Asian tropical forests, whereas in this update, the highest were over temperate Asia and North America. The strongest effect within each forest type was in Asian temperate, South American tropical, and European boreal forests. The higher normalized interaction strengths over temperate forests (40% higher than tropical forests, averaged over regions with significant interactions) reflect the lower land boundary for temperate forests (0.6 vs. 0.85 for boreal and tropical forests) rather than differences in stored



350 carbon (only 3% higher averaging across temperate regions): the reference pressure of 5 km² deforestation, when normalized, represents a smaller step towards the land boundary in temperate forests, allowing more deforestation – and correspondingly more carbon release – before the boundary is reached. However, comparing tropical forest interaction strengths between this update and the prototype, LPJmL5.7.9 simulated less carbon loss in per unit area of land cover change compared to LPJmL4, which lacks the dynamic nitrogen limitations.

355 The $CC \rightarrow LCC$ interactions showed that worsening climate change, represented by increased atmospheric CO₂ concentrations, encouraged vegetation expansion in forests and grasslands (negative interaction strengths in Fig. 4), consistent with observed global vegetation greening driven by CO₂ fertilisation (Piao et al., 2019). Encroachment of other vegetation contributed to the loss of barren ecosystems in the *NoLU* simulation. However, the simulations did not capture potential moisture-stress-driven greening reversal (Chen et al., 2024; Kashyap and Kuttippurath, 2026); or warming-driven forest dieback (e.g., Buermann et al., 2014; Melnikova et al., 2025; Nath et al., 2024), so these interactions likely underestimate the potential adverse effects of
 360 climate on vegetation.

In the case of the $CC \rightarrow RO$ and $LCC \rightarrow RO$ interaction strengths, a consequence of introducing both lower and upper boundaries for water meant normalization captured change in both directions (decreased and increased runoff), producing positive values throughout. In contrast, the prototype ESI metric incorporated only a lower bound, so an LCC or CC pressure
 365 that increased runoff would instead register as a negative interaction strength – denoting a mitigating or dampening effect on Earth system impacts. This RO-related dampening effect is absent from the updated ESI metric.

The normalized $CC \rightarrow RO$ and $LCC \rightarrow RO$ interaction strengths were more mixed, despite all registering as positive (since both wet and dry deviations from the baseline move towards either the minimum or maximum boundary). Figure 4 marks the areas in which worsening climate change resulted in drier conditions. While there was much variability in the magnitude of
 370 $CC \rightarrow RO$ interactions across regions, the effect of climate change is mostly wetter conditions.

The loss of natural land cover also led to variable impacts on runoff across regions. It increased runoff (associated with decreased interception and transpiration) in boreal and temperate forests, Asian tropical forests, and C4 grasslands. This is consistent with the coupling of evapotranspiration and runoff: given the same precipitation, more canopy interception and evapotranspiration from vegetation lowers soil moisture and runoff, so vegetation loss increases runoff (Piao et al., 2019; Yang
 375 et al., 2023). In contrast, runoff decreased in some barren lands, C3 grasslands and other tropical forests. In barren lands and grasslands, this could be attributed to transpiration from the crops introduced by LPJmL5.7.9, aligned with previous reviews of agricultural expansion in barren land (Yang et al., 2023). In the tropical forests of the Americas and Africa, the loss of tree cover increased soil evaporation (via decreased canopy cover and increased soil exposure) and hence decreased runoff. Increased transpiration and decreased runoff were also observed upon conversion of some tropical forest areas in Africa, South
 380 America and Australia to crops, though the main driver is less apparent. A possible explanation is the reduced interception and



consequent water availability for transpiration by the remaining mixed forest-crop vegetation. However, the impact of mixed versus dominantly forest cover on hydrological dynamics in these regions needs further investigation. In comparison, the prototype (Lade et al., 2021) showed stronger negative normalised $LCC \rightarrow RO$ interactions – vegetation loss increasing runoff – partly driven by irrigation applied where natural land cover was converted to crops.

385 For a more refined picture, we provide interaction strengths at a grid-cell resolution (Fig. S11), since spatial patterns can become apparent on scales below that of the chosen aggregation (Zoller et al., 2026). Aggregation by continent and dominant plant functional type clearly outperformed the majority of similarly-sized aggregations (Fig. S13), as did the corresponding univariate cluster analysis of land-use change effects on carbon storage and water runoff (Fig. S12 A-B). However, not all four interaction types follow the same spatial pattern: our clustering analysis suggested that climate change effects on water runoff
390 are better represented by climatic than by vegetation-based Earth divisions (Fig. S12 C).

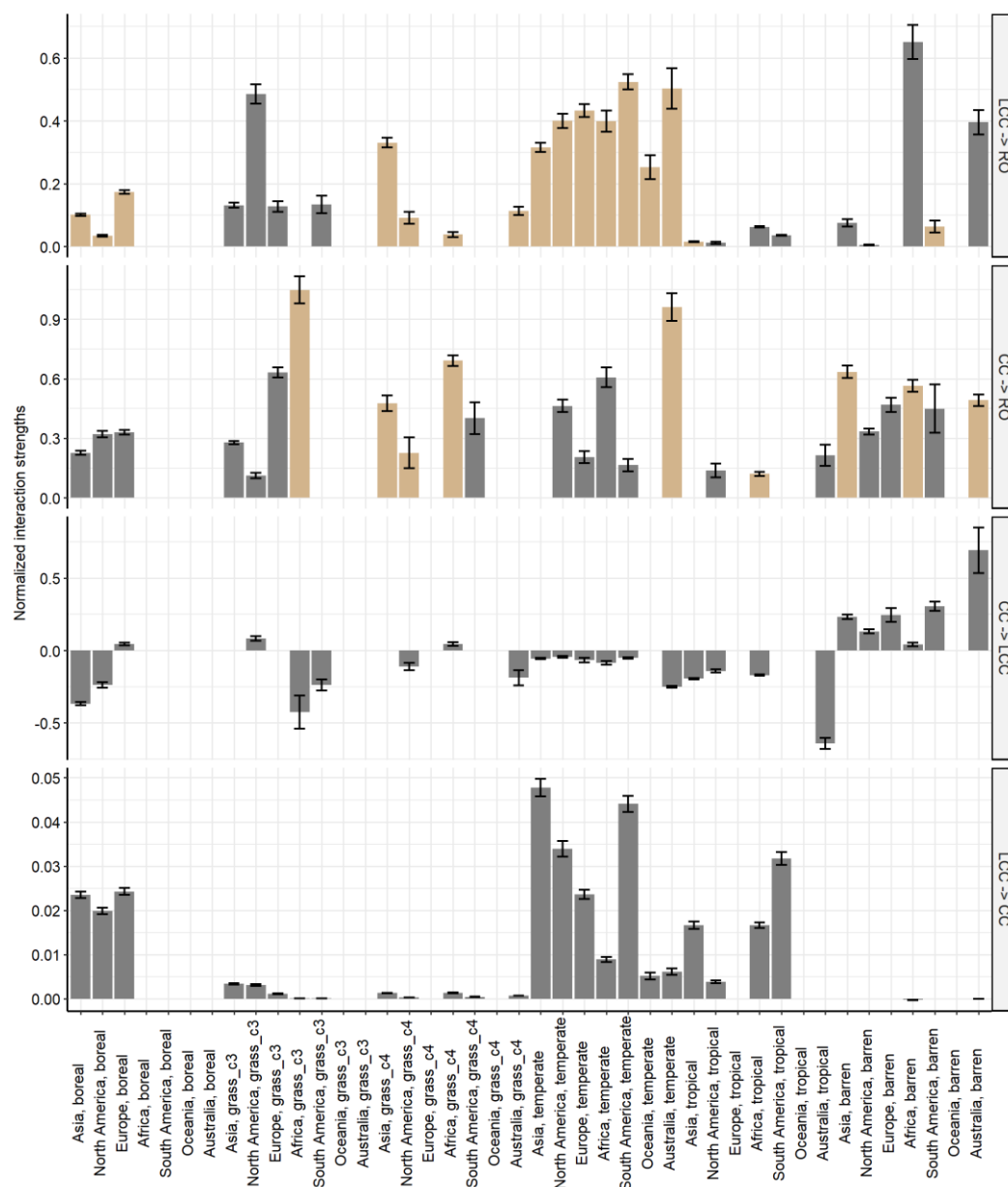


Figure 4. Normalized interaction strengths for the effects of (a) land cover change on total water runoff (LCC → RO), (b) climate change on total water runoff (CC → RO), (c) climate change on land cover change (CC → LCC), and (d) land cover change on climate change (LCC → CC, using results from LPJmL5.7.9 from 1901–2023). A normalized interaction strength of 1 means that if one Earth system component changes from its pre-industrial value to its boundary, it drives the other Earth system component to change by the difference between its pre-industrial value and its boundary. Positive interaction strengths indicate that an increase in impacts on one Earth system component (such as increased climate change or natural land cover loss) causes an increase in impacts on another Earth system component. Negative interaction strengths indicate that an increase in impacts on one Earth system component causes a decrease in impact on another. Since impacts on RO will always have positive interaction strengths, LCC → RO and CC → RO bars in tan color indicates changes in opposite directions (e.g. loss/gain of natural vegetation cover results in more/less runoff). Error bars indicate one standard error, calculated from variation over grid cells, for the LCC→CC,RO interactions, and the standard error of the linear regression for the CC→LCC,RO interactions.



3.2 Current States

Current state estimates for climate, land and water (Fig. 5) reflected transgressions of their respective boundaries across multiple regions. At 420ppm in 2023, the normalized current state for climate was already twice the distance from the preindustrial baseline (280ppm) to the 350ppm boundary.

Natural land cover had also transgressed its boundaries notably in the boreal and tropical forests and the African and North American warm grasslands. In the 2021 prototype (simulations to 2013), the highest transgressions were in tropical North America and Africa, and boreal Europe. The updated LPJmL5.7.9 outputs (to 2023) showed the same trend, but more severe. These land cover transgressions coincided with conversions to human land use (Fig. 3c).

Regions of forest transgression identified using the LPJmL output agree with those of Sakschewski et al. (2025), who assessed land use system change to 2022. Both Fig. 5 and Sakschewski et al. (2025) show boreal and temperate forests in Europe, Asia, and the Americas, and tropical forests in Africa, Asia and the Americas are beyond their boundaries, although the estimated extent of transgression differs. Sakschewski et al. (2025), estimate 70% and 57% boreal forest cover remaining in Eurasia and the Americas, respectively; given our lower boundary of 85%, a normalized current state of 1 (2) corresponds to 15% (30%) of forest cover lost. Our estimates of remaining boreal forest cover for Europe, Asia and North America (including Central America) are approximately 50%, 35% and 67%, indicating a potential overestimate of boreal forest loss in Eurasia but a slight underestimate in the Americas. Similarly, Sakschewski et al. (2025) place tropical forest cover in the Americas at approximately 84%, having only recently breached the boundary; our simulations reflected more severe degradation, with North American tropical forest cover at only 34% (consistent with human land use patterns in Fig. 3c) and South American at 66%. However, these differences in the magnitude of transgression did not affect the final Land ESI scores, given the weighting approach described in Section 2.1.3 – any transgression (normalized current state >1) was given a weight of 1.

The only forest to have expanded slightly compared to its preindustrial baseline was the tropical forest in Australia, with a current state value of -0.42 value in Fig. 5 (the negative sign indicates a change away from the boundary). This implies a 6.5% increase (Eq. 5: $6.5\% = 0.42 \times (100\% - 85\%)$), a more realistic than the 140% increase in Lade et al. (2021). Rainforest expansion in Australia has indeed been documented, associated with reduced fire and other disturbances and increased atmospheric CO₂ and other resources (Baker et al., 2020).

However, this expansion was potentially overestimated due to LPJmL's resolution limitations, which did not capture small-scale changes, and its lack of representation of built-up infrastructure. This is a general caveat of LPJmL simulations: human land use was introduced primarily through large-scale agriculture, so the 0.5° grid cell resolution did not capture small-scale farming. Separately, the absence of an urbanization module meant cities/towns, road networks and other infrastructure went uncaptured. Thus, natural land cover loss may be underestimated.



Transgressions of upper runoff boundaries occurred in the temperate forests of North America and Africa (Fig. 5), while transgressions of the lower boundaries occurred over cool grasslands (C3 grasses) in Africa and barren Asia and Australia. Australia, in general, has experienced drying across PFTs (additional maps in Supplementary Information, section C). Porkka et al. (2024) mapped broader areas of dry streamflow deviations, including the tropical and temperate forests of Asia which were found to be wetter than the baseline.

A key caveat, however, is that LPJmL5.7.9's land-use implementation did not capture societal water demand or withdrawal beyond crops (e.g. industrial and domestic use). Surface water withdrawal was therefore likely underestimated and current states may be drier in more populous regions, such as in Asia.

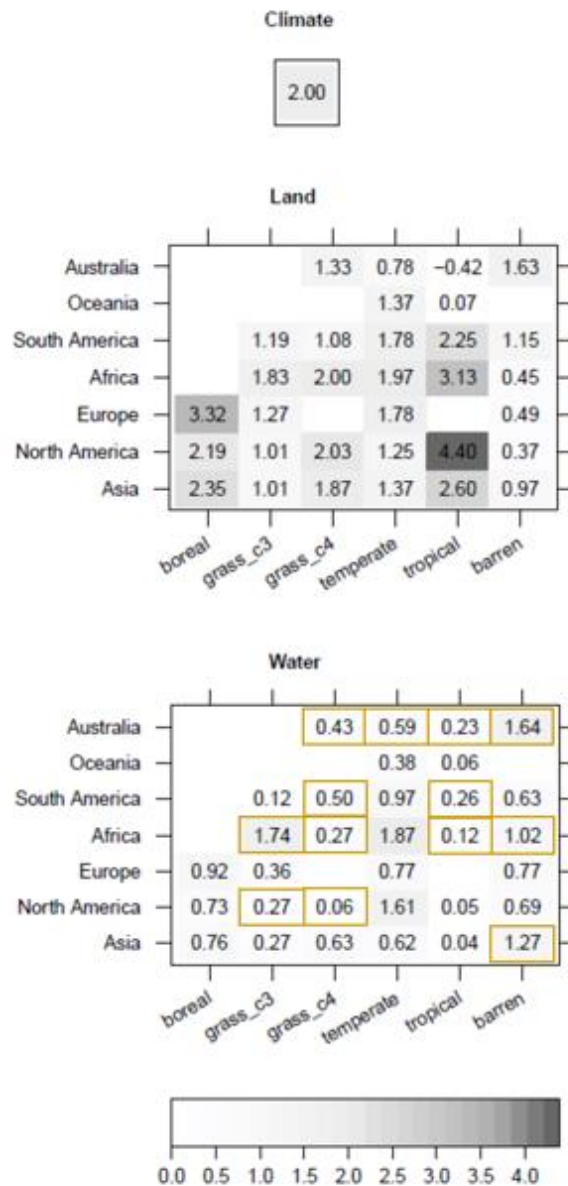


Figure 5. Estimates of current state variables for global climate, regional land and water. Values greater than 1 indicate a transgression of boundaries. Positive values less than 1 indicate movement towards the boundary relative to preindustrial conditions while negative values indicate movement away from the boundary. The current states for runoff are differentiated the tan outlines which indicate drier conditions compared to the preindustrial baseline. No outlines indicate wetter condition. Empty cells mean that these regions did not exist or were not large enough to meet the minimum number of grid cells.

445



3.3 Updated Amplification Factors

All the amplification factors were estimated to be greater than or equal to one (Fig. 6), which indicates that the net effect of feedback mechanisms was to magnify rather than dampen impacts. In the ESI prototype two mechanisms could mitigate the impacts of pressures: (1) natural vegetation expansion under warmer conditions, which sequestered carbon; and (2) increased runoff from vegetation loss, which added to available surface freshwater supply. In this updated, natural land cover expansion under warming still compensates for climate emissions in some areas, as indicated by the negative $CC \rightarrow LCC$ interaction strengths (Fig. 4). However, unlike in the prototype, increased surface water availability is no longer considered solely a benefit, since both lower and upper boundaries are applied to flow alterations: mitigative impacts on land persist, but the amplification factors now also reflect potential adverse impacts of both wet and dry runoff deviations. This explains the increased carbon emissions amplification factor, now 1.26 compared to the prototype's 0.61.

The highest amplification of adverse impacts across the Earth system (doubling to tripling of impacts) was found for loss of forest cover in the temperate (the Americas, Asia and Europe), tropical (South America) and boreal (Europe and Asia) regions, underscoring the central importance of forests to the Earth system (e.g., Ellison et al., 2024; Snyder et al., 2004; West et al., 2011). Among the forest types, the temperate forests of South America, Asia, North America and Europe exhibited the highest amplifications, compared to the prototype, where the highest was over tropical forests of South America (2.50) and Asia (2.07). This difference is explained by higher $LCC \rightarrow CC$ and $LCC \rightarrow RO$ interaction strengths: as seen in Fig. 4, the loss of temperate forests increases runoff substantially.

Most barren land types exhibit no substantial amplification of land cover loss, except in Africa and Australia (65% and 39% respectively). Conversion of barren land to human land use via dryland farming in these regions increased transpiration (by crops) and reduced runoff, aggravating water scarcity in these already arid areas (Wang et al., 2023).

No amplification factors were generated in Fig. 6 for water withdrawal, since the scope of the interaction analysis did not include relationships where runoff changes were the driving variable (i.e., $RO \rightarrow LCC$ or CC). Amplification factors for water use across all regions are therefore equal to one.

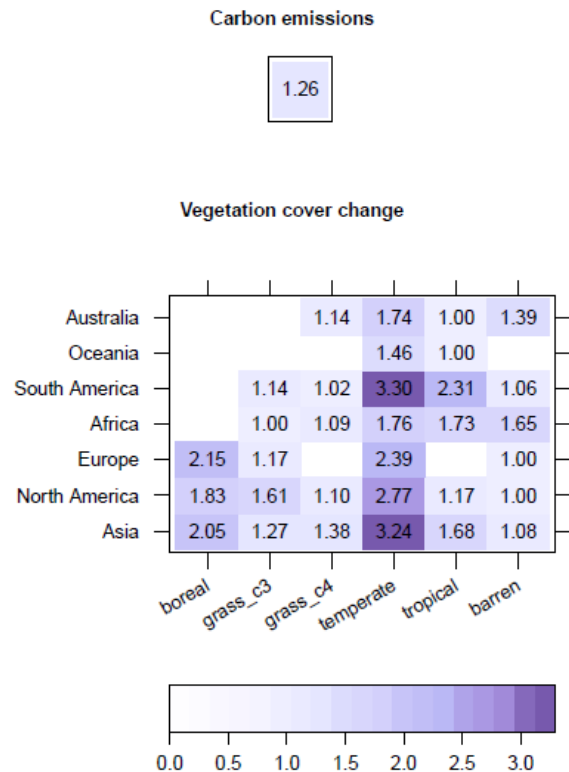


Figure 6. Amplification Factors reflecting the extent to which impacts in carbon emissions and natural land cover change are magnified in the Earth system. Given the interactions modelled ($CC \rightarrow RO$, $CC \rightarrow LCC$, $LCC \rightarrow RO$ and $LCC \rightarrow CC$), an amplification factor greater than 1 means net amplification; equal to 1, no net amplification; and less than 1, mitigation of the carbon or land pressure. No amplification factors were estimated for water withdrawal since the feedback model did not include interactions driven by changes in runoff.

3.4 Updated ESI Coefficients

The integration of interaction strengths, current states and sensitivity to reference pressures determined the ESI coefficients, presented in Fig. 7. These values (all in magnitude 10^{-8}) represent the impacts of the reference pressures (0.1 MtC emissions, 5km² land cover change, and 10⁶ m³ annual water withdrawal) and can be scaled to different pressure magnitudes (see Supplementary Information sections G,H). Scores closer to 0 represent lower Earth system impacts.

Areas where the impacts of natural land cover loss were most amplified were not always the areas with the highest Land ESI coefficients. Unlike the amplification factors, the ESI metrics are sensitive to the magnitude of natural land cover loss caused by the pressure. The normalized reference pressures (Eq. 4, Figs. A1 and A2) indicate pressure size relative to the region's maximum perturbation, determined by its area (a small region allows fewer square kilometers of natural cover loss than a large one). Weighting by current state also made the coefficients sensitive to existing degradation or deviation from the preindustrial



baseline Consequently, the highest Land ESI coefficients were found in African C3 grassland, temperate forests in Oceania and tropical forests in North America, all relatively small regions with current states that have transgressed their boundaries.

490 However, a small area and high normalized reference pressure did not necessarily translate into a high Land ESI coefficient, as seen in tropical forests in Oceania and Australia, which had the highest values of normalized reference pressures for land but not the highest Land ESI coefficients across regions. In Oceania's tropical forests, no significant interaction strengths were detected in the LPJmL output. In tropical Australia, the weighting by current state (a negative number indicative of expansion relative to the preindustrial baseline) brings the impact to 0 (Section 2.1.3 and Eq. 7).

495 Across the boreal and temperate forests of Europe, North America and Asia, and temperate South America, the Land ESI coefficients are more attributable to interaction strengths and current states (Figs. 4 and 5). In Australia, the highest Land ESI coefficient is in temperate forests (78.1×10^{-8}), driven by the amplifying interaction strengths combined with relatively large reference pressure.

500 The Water ESI coefficients, absent interactions and amplifications, are sensitive mainly to the magnitude of water withdrawal relative to baseline annual runoff, and to current state. The highest were in relatively small areas that had already transgressed their regional lower runoff boundaries: African C3 grassland (a coefficient of 3252.2×10^{-8}), barren land in Africa (258.8×10^{-8}) and barren land in Australia (635.7×10^{-8}). The next highest (100.0×10^{-8}) was C4 grasslands in South America, also a relatively small area, with current runoff estimated about halfway to its boundary from preindustrial levels.

505 Considering both the Land and Water ESI coefficients, tropical forest areas in Australia, Oceania and South America, ranked lowest among the PFTs in each continent. This is not unsurprising: tropical forest Water ESI metrics indicate these are the areas where water withdrawals would cause the least water stress, given typically higher precipitation and moisture in tropical forests than other biomes (Flores and Staal, 2022). It would be misleading, however, to suggest that tropical forests are preferable locations for human pressures in these regions: the Water ESI coefficient for Australian tropical forests (19.9×10^{-8}) was the highest of all tropical forest Water ESI coefficients and still relatively high compared to other vegetation types elsewhere; the Land ESI coefficient for Oceania tropical forest (a score of 55.1×10^{-8}) is also still relatively high compared to 510 other Land ESI coefficients; and tropical forests in South America have an amplification factor of 2.31, indicating the likelihood of magnified Earth system impacts.

515 In Africa and Asia, there are trade-offs to consider when evaluating the Land and Water ESI coefficients: in these continents, the lowest ranking vegetation type for the Land ESI is not the same as for the Water ESI. For example, the Water ESI coefficients for temperate and tropical forests in Asia are 0, but these areas have the highest Land ESI coefficients in the continent. Shifting pressures to C3 grasslands would substantially lower the Land ESI contribution at the cost of slightly increasing the Water ESI contribution. In Africa, pressures in barren lands would contribute the least to the Land ESI but



highly to the Water ESI, whereas the reverse would occur if we considered temperate forests. These examples illustrate that shifting location can trade one form of impact for another.

The global Carbon ESI coefficient of 39.6×10^{-8} increased from the prototype's 28×10^{-8} , due to factors such as the more severe boundary transgression in 2023 vs. 2013, and the recognition of hazards from increased runoff, represented by the upper runoff bound. The Carbon ESI coefficient in Fig. 7 assumes cumulative carbon emissions data is available and is designated as Carbon ESI-C. The scaled option for annual emissions data, Carbon ESI-A, is presented in Table 1, along with CO₂ equivalents. The Carbon ESI-A value (22.9 per 1 KtC/year) is approximately 57.5 times larger than the Carbon ESI-C (scaled to the same pressure), implying an assumed 57.5-year asset lifetime where no operational data is available. This may overestimate impacts for short-lived assets but underestimation them for long-term / permanent assets such lands used traditionally for farming and some old mining operations.

Because the climate boundary is a stock-based indicator, the Carbon ESI-A coefficient was estimated essentially by converting the pressure to an equivalent stock, to facilitate comparison. Other studies instead convert the climate boundary into annual flows: Wolfram et al. (2026) estimate annual emissions of 4–17 GtCO₂ would be consistent with limiting warming to 1.5°C. Earlier work by Fang et al. (2015) set the range higher, at 18–25 Gt CO₂e yearly, but for a target of 2°C, well beyond the SJB.

The Wolfram et al. range reflects the sensitivity of the flow-based boundary to the remaining carbon budget, carbon removal assumptions, and the time frame over which the budget is spent: the lower end (4 GtCO₂/year) uses a 100-year timeframe, and the higher end (17 GtCO₂/year), a 2020-2050 timeframe. Applying a scaling approach similar to that in section 2.4 to these flow-based boundaries yields a Carbon ESI-A coefficient range of 26 (for 17 GtCO₂) to 109 (for 4 GtCO₂) $\times 10^{-8}$ – more stringent than the paper's stock-based value of 22.9×10^{-8} (Table 1). However, a key difference is that the flow-based boundaries were derived relative to the present-day remaining budget, while the ESI approach compares the pressure to the difference between the boundary and the preindustrial estimate (as seen in Eq. 4), incorporating present-day conditions instead through the current state weighting. This time-dependency in converting between stock and flow equivalents of the climate boundary has yet to be fully explored within the ESI framework.

Table 1. Carbon ESI ($\times 10^{-8}$) coefficient depending on use case and available data

	Carbon ESI Coefficient
Carbon ESI-C for 0.1MtC (0.367 MtCO ₂)	39.6
Carbon ESI-A for 1 KtC/year (3.67 KtCO ₂ /year)	22.9

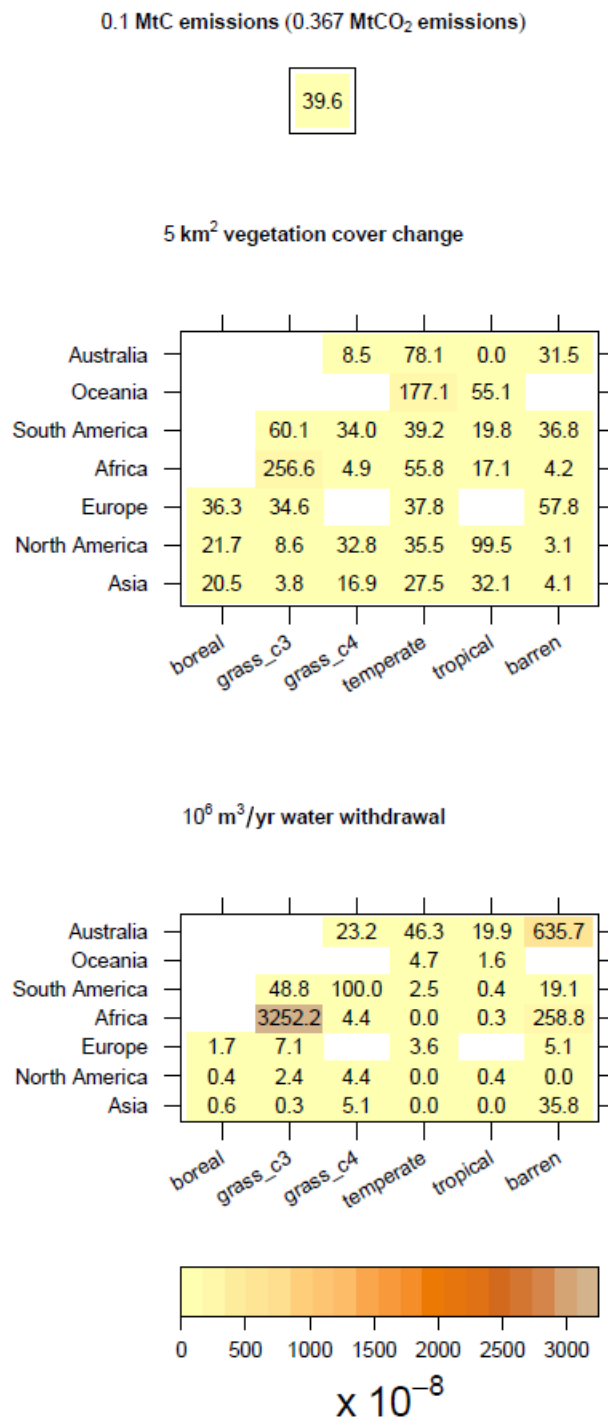


Figure 7. Final ESI coefficients for the reference pressure of 0.1 MtC (0.367 Mt CO₂) emissions, 5km² of natural land cover change, and 10⁶ m³/year of surface freshwater withdrawal. While the use of normalized units yields small values, these do not represent non-negligible impacts. Values rounded to 0 are affected by the Water ESI weighting, as can be seen in Table S1.

545



To diagnose uncertainties in the final ESI metrics (Supplementary Information, section F), amplification factors and interaction strengths, the MPI (Max Planck Institute) MPI-ESM1-2-LR model was also used to drive LPJmL 5.7.9 simulations from 1901-2099 for different scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP 5-8.5). Interaction strengths were also derived from LPJmL5.7.9 simulations (1901-2023) driven by six additional climate models. The Carbon ESI-C coefficients were comparable across scenarios (5.4% relative standard deviation), as were the Land and Water ESI coefficients: they reflected the same trends in terms of which regions had the highest coefficients, supporting the ESI metric's use for ranking business assets. The exception was the Water ESI coefficient for C3 grasslands in Africa, which was highest in the CRU-driven outputs but undefined in other scenarios, since the region did not meet the minimum threshold of 10 grid cells.

Guidance on how to apply the ESI coefficients to generate ESI scores can be found in Supplementary Information, section G, which provides two hypothetical cases demonstrating how the ESI coefficients can distinguish regional impacts, and when Carbon ESI-A coefficient might be used in place of Carbon ESI-C.

4 Discussion and Recommendations

In this update to the ESI metric, we preserve the prototype's systemic, cross-scale assessment approach, while anchoring it in the latest science and broadening the spatio-temporal scope. This section discusses the wider implications of amplification factors and ESI scores, clarifies the emerging paradox of small ecosystems and the embedded assumption on the value of ecosystems, and identifies avenues for future work.

4.1 Implications of Amplification Factors and ESI Scores

Together, the updated amplification factors and ESI coefficients provide complementary insights into cross-scale interactions and impacts. Amplification factors highlight the regions with strong interactions, where perturbations are likely to cause ripple effects. The magnifying effect derives from interaction strengths and is independent of current state, so pressures in regions with high amplification factors can affect other Earth system components, even where the region itself is still relatively far from transgressing its boundaries. The global carbon amplification factor, for example, indicates how much the impacts of carbon emissions are magnified overall, considering interactions and amplifying or dampening effects across all regions.

Higher amplification factors over temperate forests (e.g. temperate vs. tropical South America) do not indicate greater ecological importance than tropical or boreal forests. Steffen et al. (2015) prescribed more stringent boundaries the latter precisely because of their outsized potential impact on the Earth system. Indeed, the amplification factors for boreal and tropical forests are likely underestimates. For boreal regions, long-term permafrost thaw and soil carbon dynamics (Schuur et al., 2022; Treat et al., 2024) are not yet captured in the $LCC \rightarrow CC$ interaction, which is limited to vegetation carbon. For tropical forests, local to regional moisture recycling and transboundary moisture flows (Flores and Staal, 2022; Keys et al.,



2019) are not incorporated into the interaction and feedback analysis. Estimating these teleconnections would require a coupled land-atmosphere model and is outside the scope of this update.

In contrast, the ESI score of a given pressure incorporates sensitivity to local conditions such as state of resource degradation vs. availability, indicating the extent to which the Earth system is pushed towards its boundaries by that reference pressure.

580 Cool C3 grasslands in Africa, for example, show no significant amplification from land cover perturbations, but score highly on the Land ESI, because their small area means local pressures more easily transgress the downscaled boundary. Conversely, tropical forest loss in South America shows relatively large amplification, but its Land ESI coefficient is lower than for the smaller, more sensitive tropical forests of North America.

4.2 Small Ecosystems, Clustering and Interaction Strengths

585 As the previous examples illustrate, smaller ecosystems do not necessarily amplify anthropogenic pressures but are more sensitive to them, yielding higher ESI coefficients than larger, intact tracts of land. Whether these small ecosystems “exist” at all is itself sensitive to vegetation establishment and distribution: given the minimum grid cell threshold defined in Section 2.1.1, and as seen in the uncertainty analysis (Supplementary Information, section F), small ecosystems can disappear entirely under changing climatic conditions. This creates a paradox: the more an ecosystem shrinks the higher it ranks on the ESI

590 metrics, yet the more difficult it becomes to define statistically significant interaction strengths for it. Avoiding this trade-off will require higher resolution models complemented by Earth observations.

Measuring interaction strengths over space is also shaped by the clustering scheme itself: aggregating by continent and dominant PFT increases accessibility and facilitates communication, but always at the cost of information (Zoller et al., 2026). An alternative for small clusters is work at grid-cell resolution instead (Supplementary Information, section D). In the North

595 American boreal forest, for example, interaction strength is significant and uniform over most of the cluster, but a distinct zone of no measurable effect emerges south of the transition to C3 grassland (Fig. S14 A-B) – a mismatch that is especially pronounced for the effect of climate change on surface water runoff (Fig. S14 C-D). In the South American and the Asian tropical forests, similarly, distinct patches of strongly positive and negative interaction strength cancel each other out in the cluster average. Maps of spatially resolved interaction strengths (Fig. S11) let users assess a cluster’s heterogeneity directly

600 and refine their own decisions accordingly.

4.3 Recognizing the Inherent Value of Ecosystems

The ESI approach recognizes the inherent value of ecosystems: boundaries are set for barren land and grasslands even though Steffen et al. (2015) prescribed no minimum areas for these regions. Loss of barren land relative to its preindustrial baseline is treated as an Earth system impact whether driven by encroachment from other ecosystems (Fig. 1(a) vs Fig. S5(a)) or by

605 conversion to human land use (Fig. 1(a) vs 1(c)). While normalized interactions show that vegetation loss in barren land has



little climate, given its minimal vegetation carbon, these areas can still be sensitive to the impacts of vegetation loss and climate change on runoff ($CC \rightarrow RO$ and $LCC \rightarrow RO$ in Fig. 3; barren Australia and Africa in Fig. 5). Accordingly, the ESI coefficients of barren land regions (Fig. 6) are comparable to other ecosystems – for example, in Europe, barren lands have the highest Land ESI coefficient, and in Australia, the highest Water ESI coefficient.

610 These outcomes should not be taken as a recommendation to locate assets in, say, temperate forests over barren land in Europe, or tropical forest over barren land in Australia. Rather, they reflect the ESI's treatment of ecosystems for their own sake and how complementary assessments (e.g. on biodiversity and ecosystem services and on socio-cultural aspects) embodying different value judgements when evaluating trade-offs between potential asset locations.

4.4 Future Research Pathways

615 This update to the ESI approach highlights several avenues for further research to improve its utility as a decision-making tool, particularly expanding its scope to incorporate other interactions, pressures, and their corresponding boundaries.

This albedo pathway of the $LCC \rightarrow CC$ interaction is relatively well-established in literature but absent from the estimated interaction strength. While the albedo effect can be estimated through calculating equivalent carbon pressures, future improvements should explore embedding the albedo effect in the ESI coefficients (e.g., potentially using radiative kernel techniques (Hasler et al., 2024)).

625 Other interactions to prioritize would include LCC impacts on soil moisture and groundwater flux, and, following the tropical forests recycling gap noted above (Section 4.1), incorporating deforestation's effects on long-term moisture recycling and transboundary flows. Carbon-related interactions should also define distinct interaction pathways for CO_2 vs. non- CO_2 greenhouse gases and albedo, given the carbon fertilization effects specific to the former, and $LCC \rightarrow CC$ analysis could explore a more comprehensive treatment of ecosystem carbon stocks.

Additional pressures to be prioritized could include groundwater extraction, which affects progress towards the freshwater boundary, and nitrogen and phosphorus application, which affects progress towards the biogeochemical flows boundary – both particularly relevant for agricultural assets and for domestic water use and sewage generation.

630 Future updates should also test interaction strengths with other drivers of natural land conversion, such as urbanization: the Land ESI aims to be agnostic as to what land area is converted into, but LPJmL simulates vegetation loss only via agricultural expansion. Although irrigation was excluded from the *WithLU* simulations, to preclude artificially inflating runoff, crop introduction still affects the water cycle – for example higher crop transpiration reduces runoff, whereas conversion to non-permeable built-up land would likely have the opposite effect. A range of *WithLU* simulations representing diverse land uses



635 would help test how water-related interactions depend specifically on land use; since LPJmL cannot currently do this, an ensemble of different DGVMs would be needed.

640 A DGVM ensemble would also benefit the ESI approach by bracketing variability in interactions for more robust estimates, and by addressing the small ecosystem issue: ensemble outputs could help diagnose the stability of PFT clusters and identify where ESI reliability is sensitive to variability in vegetation distribution. Combined with a range of future scenarios and different time periods, an ensemble could also help diagnose how interaction strengths might vary over time, potentially enabling a more dynamic ESI framework.

645 In its updated form, the ESI metric advances its prototype's cross-scale, science-based approach for comparing location-specific asset impacts beyond carbon emissions, and can support businesses, investors, and the public sector in evaluating current assets and planning future developments. Its unique value for setting site-specific environmental performance targets lies precisely in ensuring alignment with sub-global boundaries. Breaking down an ESI score into its Carbon ESI, Land ESI and Water ESI components allows decision-makers to weigh all dimensions jointly and develop appropriate optimization strategies. Combined with complimentary assessments of local socio-ecological context, the ESI coefficients can support a shift towards a "business within planetary boundaries" paradigm (Crona et al., 2024). Continued maintenance and improvement of the ESI metric will be crucial to mainstream its use, and to keep it calibrated to the latest understanding of Earth system processes underpinning planetary stability and resilience.

650



Supplementary Information, Code and Data Availability

The appendices and other documents, code and data are available as supplementary information. The final R scripts and simulation outputs from LPJmL5.7.9 will be deposited in Zenodo and a link will be provided upon acceptance for publication.

655 All supplementary information will be deposited at the same Zenodo link. [A draft preview of the Zenodo site is available here.](#)

Author Contributions

All authors contributed valuable inputs and feedback on the conceptualization and design of the ESI and its applications. CKGG led the content development and writing of the manuscript, while SJL, BC, GP, HZ, DM, LWE, JCR, IF, NC, TF, AA reviewed and edited. IF and NC implemented model simulations, and SJL and IF wrote the initial scripts for analysis. CKGG
660 further revised these scripts and led the analysis with inputs from team members. HZ contributed supplementary analysis. SJL, IF, CKGG, HZ contributed visualizations or scripts to produce visualizations. Funding acquisition was led by SJL, BC, IF, TF, LWE, JCR. SJL and BC oversaw project administration, while SJL, BC and TF supervised researchers of the project.

Competing Interest

Editorship CI! The authors have the following competing interests: At least one of the (co-)authors is a member of the editorial
665 board of Earth System Dynamics.

Acknowledgements

Hereby we acknowledge provision and support for computing by National Academic Infrastructure for Supercomputing in Sweden' (NAISS) projects 2025/6-131 and 2025/5-193.

We also acknowledge the Global Carbon Project, which is responsible for the Global Carbon Budget, and we thank the Fossil
670 Emissions working group for producing and making available their model output.

Financial Support

CKGG and SJL are supported by the Australian Government through the Australian Research Council (CKGG: Discovery Project DP230101280; SJL: Future Fellowship FT200100381). GP, IF, LWE, JCR and NC are supported by the Swedish Research Council Formas (grant 2023-00310). L.W.-E. also receives funding from Formas grants 2022-02089, 2023-00321,
675 2024-01655), the IKEA foundation, and Horizon Europe (101081661). BC, GP and JCR were also supported by the Mistra Program on Finance to Revive Biodiversity FinBio (DIA 2020/10).



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