

Ecological integrity of avoided deforestation projects

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Reducing deforestation is proposed as a global climate action, yet it remains unclear whether carbon projects based on such interventions also maintain forests' ecological conditions. Here we evaluate 133 projects against matched controls using five ecological-integrity indicators, to show that most projects have mixed, negligible or negative impacts relative to control areas. Results highlight fundamental shortcomings of these climate solutions that limit their ability to safeguard healthy ecosystems and sequester carbon.

Avoided deforestation projects are among the most popular nature-based climate solutions¹. They reduce human activities that cause forest loss and degradation, preventing greenhouse gas (GHG) emissions². These climate benefits can be quantified, verified and transferred as fungible carbon credits to individuals, businesses and governments seeking to meet climate targets^{3,4}. Revenue from the sale of these carbon credits can be channelled into maintaining forest protection, potentially enabling a financially viable means of conservation⁴. However, concerns over credibility and integrity have grown^{1,5}. Several studies suggest that carbon credits claimed by avoided deforestation projects can exceed the verifiable climate benefits⁶.

Governments and businesses are responding by restricting purchases to projects deemed high integrity. While definitions of integrity vary, most tend to focus on environmental integrity—typically referring to the degree to which claimed emission reductions represent genuine climate benefits through demonstrable additionality, permanence and minimal leakage^{1,6}. However, this framing captures only part of the picture. Effective avoided deforestation projects should not only maintain carbon stocks but also safeguard ecological communities, forest structure and complexity, habitat connectivity and ecosystem function^{7,8}. These dimensions of ecological conditions underpin a forest's capacity to support biodiversity, resist disturbance and sustain long-term carbon storage⁹. Here, we adopt the term 'ecological integrity' to distinguish this specific and important aspect of carbon projects from the carbon-centric understanding of integrity.

Specifically, we present a global assessment of the ecological integrity of accredited avoided deforestation projects, compiling data for 196 projects from major voluntary carbon registries based

on publicly available information (Extended Data Table 1). We compare project areas (treatment units) with matched controls in the surrounding areas in the same biome using pixel-level propensity score matching^{2,10}. To account for the unintended displacement of forest loss to adjacent areas (that is, local-scale leakage), we exclude a 10-km zone around each project from sampling of controls². This approach ensures that project and control areas are comparable in key biophysical, socio-economic and pre-intervention land-cover characteristics (Extended Data Table 2), approximating a randomized experimental design². Among the 196 projects, 133 achieved good post-matching balance (standardized mean differences (SMD) <0.25) and were large enough to support pixel-level matching and were retained for analysis.

We evaluate the ecological integrity of each avoided deforestation project relative to control areas using five complementary indicators: biodiversity intactness index (community-level response to human pressures), forest landscape integrity index (measures anthropogenic pressures and degradation intensity), forest fragmentation (quantifies structural fragmentation based on patch configuration), canopy height (vertical structure and forest age) and GHG net flux (indicator of ecosystem function and carbon permanence) (Extended Data Table 3). These indicators capture key dimensions of forest ecosystem health and resilience⁹. We fit linear regression models to estimate treatment effects, scaling them by the maximum observed value in each matched sample and sign-standardizing so positive values consistently represent better ecological outcomes.

Among the 133 well-matched projects, we have sufficient data to make direct comparisons between avoided deforestation project areas and unprotected forests for 116 globally distributed projects

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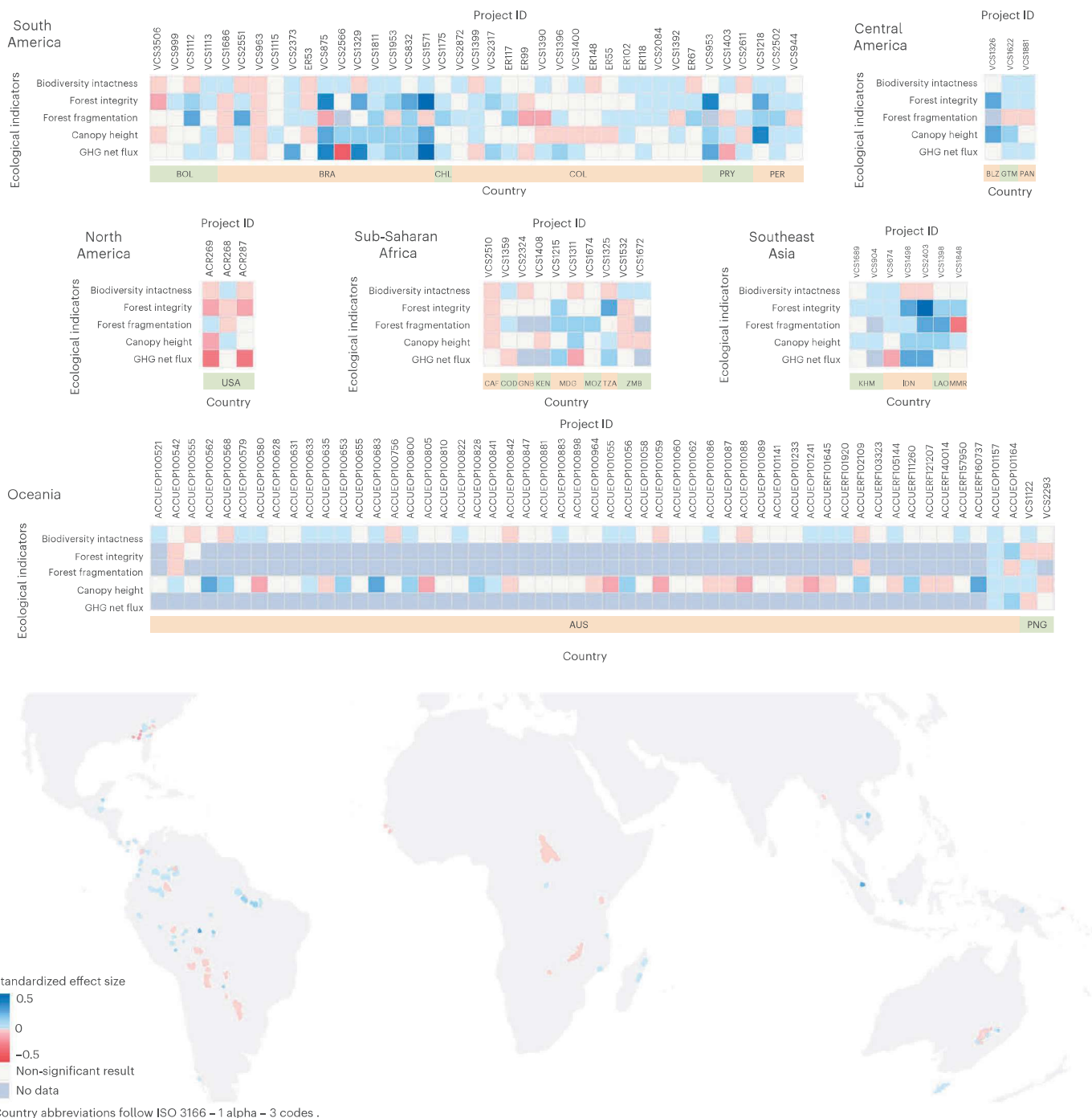


Fig. 1 | Ecological integrity of avoided deforestation projects relative to unprotected matched areas nearby. Unprotected projects are compared with unprotected matched controls. **Top**, Project-level standardized effect sizes for each ecological-integrity indicator, with columns representing individual projects grouped by country and region. Effect sizes were estimated using linear regression models; statistical significance was assessed using two-sided tests ($P < 0.05$). Positive values (blue) indicate higher biodiversity intactness, greater forest landscape integrity, lower fragmentation, taller canopy height and lower GHG emissions in project areas relative to controls; negative values (red) indicate

the opposite. Colour intensity reflects effect magnitude. White indicates no significant difference ($P \geq 0.05$), and grey indicates indicators not evaluated due to insufficient data or failed model diagnostics. Country abbreviations follow ISO 3166-1 alpha-3 codes. No adjustments were made for multiple comparisons. **Bottom**, Global distribution of avoided deforestation projects, coloured by the mean standardized effect size across ecological-integrity indicators. Effect sizes are averaged across all indicators with available data for each project. Blue indicates higher ecological integrity in project areas relative to matched controls, whereas red indicates lower ecological integrity.

(Fig. 1). Three projects show significantly positive effects across all five ecological-integrity indicators, and another six exhibit similar positive effects for all indicators with available data (Fig. 1). Together, these nine projects (8%) maintain higher levels of ecological integrity than surrounding unprotected areas—suggesting reduced human activities and fragmentation, maintenance of tall and structurally

complex forests, greater species intactness and higher carbon retention within project areas⁹. Such outcomes are often linked to approaches that emphasize community engagement, local participation and livelihood-improvement programmes, as exemplified by the Oddar Meanchey REDD+ project (VCS904) in Cambodia¹¹. More broadly, success also depends on governance conditions, including

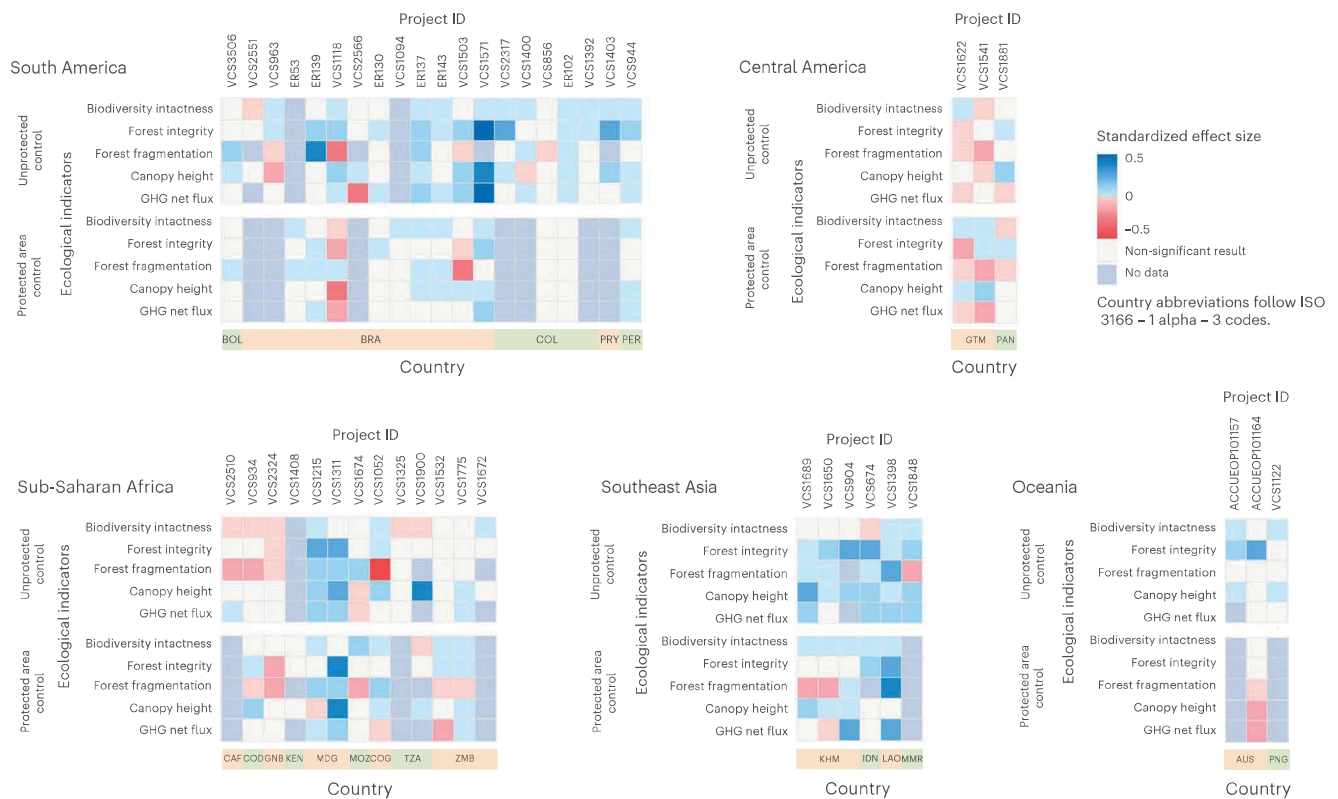


Fig. 2 | Protected projects are compared with both unprotected controls and protected-area controls. Each project (column) is evaluated against two matched counterfactuals: unprotected controls and protected-area controls. Project-level standardized effect sizes are shown for each ecological-integrity indicator, with columns representing individual projects grouped by country and region. Effect sizes were estimated using linear regression models; statistical significance was assessed using two-sided tests ($P < 0.05$). Positive values (blue)

indicate higher biodiversity intactness, greater forest landscape integrity, lower fragmentation, taller canopy height and lower GHG emissions in project areas relative to controls; negative values (red) indicate the opposite. Colour intensity reflects effect magnitude. White indicates no significant difference ($P \geq 0.05$), and grey indicates indicators not evaluated due to insufficient data or failed model diagnostics. Country abbreviations follow ISO 3166-1 alpha-3 codes. No adjustments were made for multiple comparisons.

secure land tenure, effective regulatory frameworks and socio-political contexts shaped by population pressures and conflict.

Importantly, some of these successful projects are located in regions with high deforestation pressure, such as the Jari Pará project (VCS1811) in the Brazilian Amazon¹². Positive outcomes here potentially reflect both the degraded conditions (low ecological integrity) of the surrounding matched control areas, and the effective reduction of human activities within project boundaries^{2,12}. These cases demonstrate clear additional ecological benefits².

However, we also find that it is more common for projects to provide only limited ecological gains. For instance, 29 projects (25%) show significantly positive effects for at least one ecological-integrity indicator, with all remaining indicators showing no significant differences (Fig. 1). This can be attributed to the carbon-centric design of most accounting frameworks, which prioritizes carbon storage over maintenance of ecological integrity¹³. These carbon gains are best captured through aboveground biomass or tree cover, rather than ecological attributes that underpin long-term ecosystem resilience¹⁴. In such cases, the maintenance of any indicators of ecological integrity can be considered an additional co-benefit. Demonstrating these ecological co-benefits (as in Fig. 1) could support claims of biodiversity benefits and potentially justify price premiums for projects that deliver them¹⁵.

Caution is warranted when interpreting ecological benefits inferred through counterfactuals. For instance, 13 projects (11%) in New South Wales, Australia, show no significant differences in any ecological-integrity indicators assessed (Fig. 1). These projects occur in areas with low agricultural productivity and limited human activity, so the absence of significant effects probably reflects low baseline

deforestation risk rather than a project's inability to maintain ecological conditions^{16,17}. While additionality is central to issuing credible carbon credits, it may be less emphasized in conservation efforts^{18,19}.

We also note that indicator choice matters, as limited data coverage constrains evaluation; for instance, many Australian projects only have data for biodiversity intactness and canopy height. Ecological responses to these interventions can also be time-lagged, requiring temporally explicit analyses⁵. It is also likely that unobserved factors—such as degree of enforcement, land tenure and governance, and land-use opportunity costs—mask ecological impacts. Hence, we further assess the robustness of our estimates to potential unobserved confounding using sensitivity analyses, benchmarking against the strongest observed covariate included in each linear model, which represents residual imbalance after matching²⁰ (Extended Data Table 4).

Notably, our analysis also identifies projects associated with negative ecological outcomes. Nine projects perform significantly worse across all ecological-integrity indicators for which data are available, and another ten perform worse on at least one indicator (Fig. 1). These 19 projects (16%) appear to have poorer ecological conditions than the surrounding unprotected forests. One potential explanation is that developers sometimes site projects in forests that are already degraded to maximize the appearance of additionality, thereby locking in a lower baseline of ecological integrity that may remain below that of less-disturbed neighbours even if deforestation is reduced¹⁷. Another possibility is that weak land tenure, inadequate regulatory frameworks and limited enforcement allow encroachment into project areas, undermining ecological integrity²¹. More broadly, carbon finance can sometimes exacerbate existing social tensions, reinforcing the need

for strong safeguards²². For example, the Purus Project (VCS963) in Brazil faced unresolved land tenure issues and lacked formal regulatory mechanisms to manage disputes, undermining enforcement capacity and community support despite achieving Climate, Community and Biodiversity certification²³. These challenges contributed to continued deforestation and conflict, limiting ecological gains despite carbon finance inflows.

The remaining 46 projects (40%) show a mix of positive, negative and non-significant responses across the five ecological-integrity indicators. These heterogeneous outcomes highlight that avoided deforestation interventions do not consistently maintain ecological integrity. Variation probably reflects local context, project design and implementation differences²⁴, combined with the lack of explicit incentives or technical guidelines for safeguarding biodiversity and ecological conditions^{13,25}. This aligns with our observation that ecological integrity across most projects is largely uncorrelated to socio-economic variables, except for subnational corruption and human development indices (Extended Data Figs. 1 and 2). These two factors suggest that avoided deforestation projects have a greater relative impact on preserving ecological conditions in areas facing higher governance risks.

Among the 133 avoided deforestation projects analysed, we also find that 43 projects are located adjacent to formally designated protected areas, creating spatially proximate project–protected area pairs that allow a comparison of ecological-integrity outcomes (Extended Data Fig. 3). We find that, on average, protected areas maintain better ecological conditions than avoided deforestation projects. Among these 43 projects, 9 projects show significantly negative effects for at least one indicator (with all others non-significant), 1 performs worse across all indicators assessed, and 21 show mixed outcomes (Extended Data Fig. 3). Nonetheless, some projects match the performance of nearby protected areas. For example, the Luangwa Community Forests Project (VCS1775) in Zambia maintains ecological conditions comparable to neighbouring protected areas (Extended Data Fig. 3). In total, 12 projects achieve such results, showing either no statistical differences or positive effects across all indicators. These cases demonstrate that well-designed projects can complement protected areas and deliver conservation outcomes of comparable quality.

Our results also indicate that 48 projects overlap with formal protected areas. Of these, 46 intersect partially, while 2 lie entirely within protected areas (VCS934 in the Democratic Republic of Congo and VCS1900 in Tanzania). Although additionality requirements should generally preclude such overlaps¹⁶, formal protected status does not necessarily ensure effective protection. Some protected areas experience ongoing deforestation due to weak enforcement or limited resources, often described as ‘paper parks’^{26,27}. In these contexts, avoided deforestation projects may enhance protection by providing additional finance, monitoring and community engagement. Consistent with this interpretation, we find that combining legal protection with carbon market resources appears to deliver clear ecological benefits (Fig. 2), particularly in regions with lower gross domestic product and more remote areas (Extended Data Figs. 1 and 2). This alignment could represent the importance of complementarity across public or legal frameworks and private investment to strengthen conservation outcomes²⁸. Most projects in South America, South-Eastern Asia and Oceania perform as well as, or better than, surrounding controls across multiple ecological-integrity indicators (Fig. 2). These projects can provide a model for scaling up area-based conservation globally, supporting policy goals such as the Convention on Biological Diversity’s ‘30 by 30’ target to protect 30% of the planet by 2030²⁹.

Overall, our global analysis shows that, while avoided deforestation projects can maintain ecological integrity under specific conditions, their performance is inconsistent overall. This variability reflects an inherent inability of current carbon standards to provide broader

ecological outcomes. Ecological integrity remains an overlooked dimension, yet it is essential to preserving resilient and healthy forests, ensuring that climate and other benefits are retained in the long term.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41558-026-02657-2>.

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Methods

We extracted the spatial boundaries of 196 avoided deforestation projects from five major carbon registries: Verra, EcoRegistry, the Australian Carbon Credit Unit Scheme, the American Carbon Registry and the Climate Action Reserve (Extended Data Table 1). These project data were obtained and screened following existing procedure³⁰, in which project classifications, public documentation and Project Design Documents were reviewed to identify avoided deforestation projects using standardized keywords (for example, 'REDD+' and 'forest conservation'). The resulting dataset spans tropical and subtropical regions of South America, Central America, North America, Sub-Saharan Africa, Southeast Asia and Oceania (Australia and Papua New Guinea) and includes a range of project sizes, start dates and registry statuses. Project locations probably reflect real-world siting decisions influenced by biophysical suitability (for example, forest cover and carbon stocks), accessibility, governance context and institutional feasibility, rather than random assignment. All spatial analyses were conducted using the WGS 84 datum and implemented in R version 4.3.1.

Analyses proceeded in two stages. First, we constructed matched samples of treatment and control units to assess project-level effects. Treatment units were defined as raster cells (1, 2, 4, 8 or 16 km resolution, scaled to project extent) within project boundaries. Control units were drawn from surrounding buffers within the same biome, following the Ecoregions 2017 classification, with a 10-km exclusion zone to account for local leakage effects. Matching employed 1:1 nearest-neighbour propensity score matching without replacement, using Mahalanobis distance and a 0.25-standard-deviation caliper, implemented with the R package MatchIt³¹.

Eight covariates captured key biophysical and socio-economic conditions that are known to influence ecological dynamics, deforestation risk and project siting, while being available as globally harmonized datasets at fine (1 km) resolution: pre-intervention aboveground biomass carbon, mean annual precipitation, elevation, slope, human footprint, gross domestic product, population density and travel-time accessibility³² (Extended Data Table 2). These variables were harmonized by resampling to the project-specific raster resolution. To ensure that covariates were non-redundant, we excluded those with high multicollinearity (variance inflation factor >10) or low project-level variation (coefficient of variation <15%)³³. Matching quality was assessed using standardized mean differences (SMD), retaining only projects with SMD <0.25. Projects with <30 matched pairs were also excluded to ensure statistical robustness.

Second, we quantified ecological integrity using five complementary indicators: biodiversity intactness index, forest landscape integrity index, forest fragmentation index, canopy height and forest GHG net flux (Extended Data Table 3). Each project was evaluated across four comparison groups based on overlap with formally protected areas (as defined by the World Database on Protected Areas³⁴). Protected area data were preprocessed following standard cleaning protocols³⁵. Matched control units overlapping protected areas served as positive controls, while unprotected controls represented the counterfactual baseline.

Linear models were fitted independently for each project and ecological-integrity indicator, with treatment status as the sole predictor and matched pair identifiers used to control for pairwise structure, thereby estimating the average treatment effect on the treated (ATT)—the mean difference in ecological integrity between treatment and control. To facilitate cross-indicator and cross-project comparisons, model coefficients were standardized by dividing by the maximum observed value within the matched sample and sign-standardized such that positive values consistently reflect better ecological conditions in treatment areas relative to controls.

We conducted correlation analyses to examine associations between ecological-integrity effect sizes and project characteristics, socio-economic conditions and governance indicators^{36,37}. To assess

robustness to potential unobserved confounding, we used the R package `sensemakr` (version 0.1.6)²⁰.

Data availability

The datasets used to support the findings of this study are available for download by request from their respective providers. The spatial boundaries of avoided deforestation projects were obtained from publicly accessible carbon registry platforms as listed in Extended Data Table 1 and are available via Zenodo at <https://doi.org/10.5281/zenodo.19726735> (ref. 38). Protected area boundaries were sourced from the World Database on Protected Areas (WDPA, <https://www.protectedplanet.net>). Covariates used in propensity score matching were obtained from publicly accessible global datasets, as listed in Extended Data Table 2. All ecological-integrity indicators—biodiversity intactness index, forest landscape integrity index, forest fragmentation index, canopy height and forest GHG net flux—were obtained from publicly available datasets as listed in Extended Data Table 3. We make all processed data (in the form of SMD values from propensity score matching) freely available. Similarly, processed project-level results generated in this study, including treatment effect estimates for each ecological-integrity indicator across projects and comparison groups, are provided. Project-level sensitivity analysis results for unobserved confounding are available via Zenodo at <https://doi.org/10.5281/zenodo.19726735> (ref. 38) (Extended Data Table 4). Source data are provided with this paper.

Code availability

Codes used in this Brief Communication are available via Zenodo at <https://doi.org/10.5281/zenodo.19726735> (ref. 38).

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Author contributions

Y.Z., T.C., Z.C., C.T.P.-B. and K.O. conceived the study. K.O. conducted spatial and statistical analyses and interpreted results. Y.Z. contributed initial discussions and modelling insights. K.O. and Y.Z. wrote the initial draft of the manuscript. All authors contributed subsequent discussions and improvements to the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Extended data is available for this paper at <https://doi.org/10.1038/s41558-026-02657-2>.

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Extended Data Table 1 | Voluntary carbon project registries used for project data extraction

Project Registry	Data Source
Australian Carbon Credit Unit Scheme	Australian Carbon Credit Unit (ACCU) Scheme. ACCU project and contract register. https://cer.gov.au/markets/reports-and-data/accu-project-and-contract-register (2025).
American Carbon Registry	American Carbon Registry (ACR). Projects. https://acr2.apx.com/myModule/rpt/myrpt.asp?r=111 .
Climate Action Reserve	Climate Action Reserve (CAR). Public Registry. https://thereserve2.apx.com/myModule/rpt/myrpt.asp?r=111 .
EcoRegistry	EcoRegistry. Projects List. https://www.ecoregistry.io/projects-list/cercarbono-co2 .
Verra	Verra. Verified Carbon Standard. https://registry.verra.org/app/search/VCS/All%20Projects .

Extended Data Table 2 | Environmental and socio-economic variables used as covariates in propensity score matching

Covariate	Year(s) Covered	Data Source
Pre-intervention above- and belowground biomass carbon	2000	Gibbs, H. K. & Ruesch, A. <i>New IPCC Tier-1 Global Biomass Carbon Map for the Year 2000</i> . https://www.osti.gov/biblio/1463800 (2008) doi:10.15485/1463800.
Mean annual precipitation	1970–2000	Fick, S. E. & Hijmans, R. J. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. <i>Int. J. Climatol.</i> 37 , 4302–4315 (2017).
Elevation	1970–2000	Fick, S. E. & Hijmans, R. J. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. <i>Int. J. Climatol.</i> 37 , 4302–4315 (2017).
Slope	1970–2000	Derived from WorldClim elevation data.
Human footprint	2020	Mu, H. <i>et al.</i> A global record of annual terrestrial Human Footprint dataset from 2000 to 2018. <i>Sci. Data</i> 9 , 176 (2022).
Gross Domestic Product	1992–2019	Chen, J. <i>et al.</i> Global 1 km × 1 km gridded revised real gross domestic product and electricity consumption during 1992–2019 based on calibrated nighttime light data. <i>Sci. Data</i> 9 , 202 (2022).
Population density (GHS-POP-E2020-GLOBE-R2023A)	2020	Pesaresi, M. <i>et al.</i> Advances on the Global Human Settlement Layer by joint assessment of Earth Observation and population survey data. <i>Int. J. Digit. Earth</i> 17 , 2390454 (2024).
Travel-time accessibility to urban centers	2015	Weiss, D. J. <i>et al.</i> A global map of travel time to cities to assess inequalities in accessibility in 2015. <i>Nature</i> 553 , 333–336 (2018).

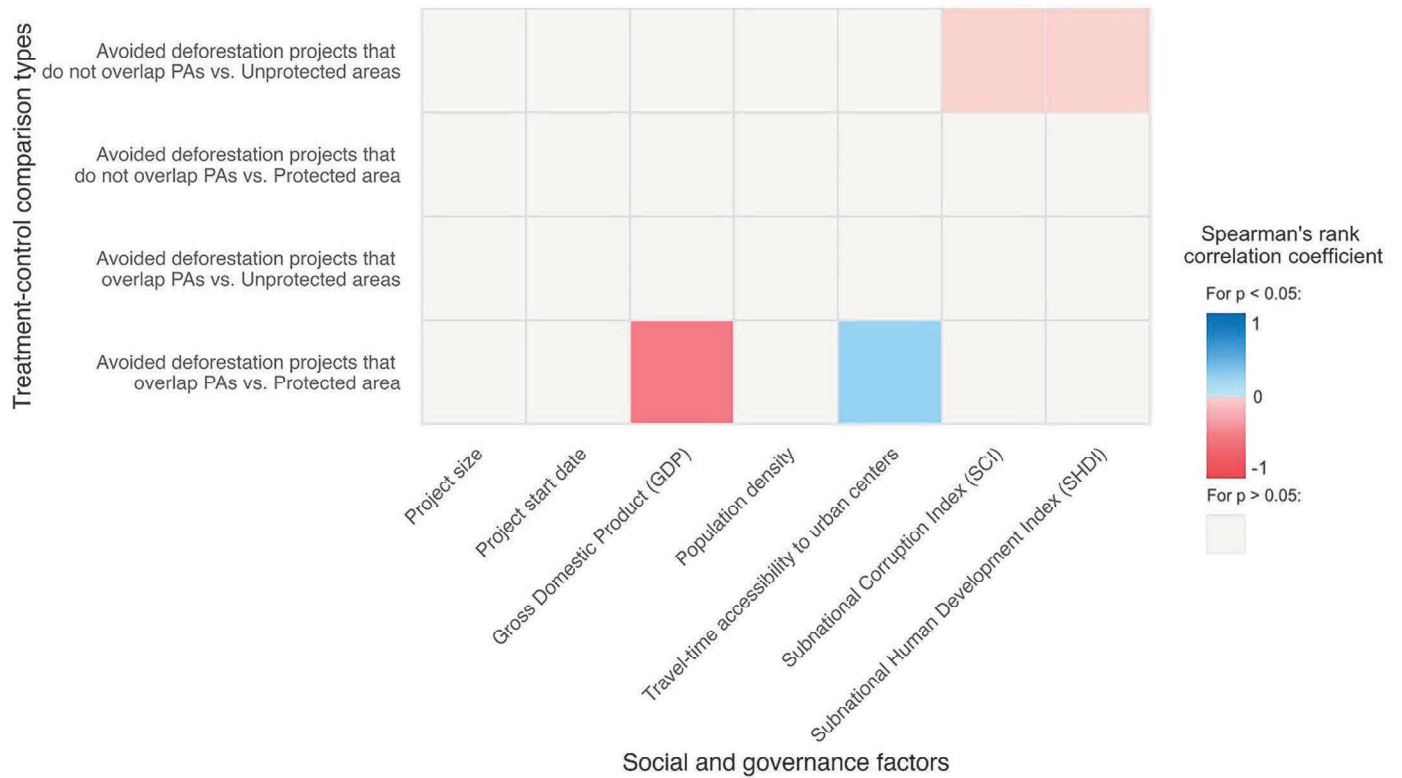
Extended Data Table 3 | Variables representing indicators of ecological integrity

Indicator	Definition	Year(s) Covered	Data Source
Biodiversity Intactness Index	The average abundance of originally present terrestrial species (vertebrates, invertebrates, plants, and fungi) relative to their expected abundance in an undisturbed, intact ecosystem. BI is generated using the PREDICTS (Projecting Responses of Ecological Diversity in Changing Terrestrial Systems) global biodiversity database and hierarchical mixed-effects models that relate species abundance to land use, land-use intensity, and human pressures.	2015	Derived global raster distributed by UNEP-WCMC / UNDP GeoHub (2022), based on Newbold et al. Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. <i>Sci.</i> 353 , 6296 (2016).
Forest Landscape Integrity Index	A globally consistent index quantifying the degree of human modification in forests, integrating observed human pressures, inferred diffuse disturbances, and changes in forest connectivity.	2019	Grantham, H. S. et al. Anthropogenic modification of forests means only 40% of remaining forests have high ecosystem integrity. <i>Nat. Commun.</i> 11 , 5978 (2020).
Forest Fragmentation Index	Quantifies the degree of fragmentation of forest patches, focusing on edge density, patch density, and mean patch size, which collectively describe fragmentation, isolation, and the spatial continuity of forest cover.	2020	Ma, J., Li, J., Wu, W. & Liu, J. Global forest fragmentation change from 2000 to 2020. <i>Nat. Commun.</i> 14 , 3752 (2023).
Canopy Height	Mean forest canopy height in meters, derived from the integration of GEDI LiDAR and Landsat satellite data.	2019–2021	Potapov, P. et al. Mapping global forest canopy height through integration of GEDI and Landsat data. <i>Remote Sens. Environ.</i> 253 , 112165 (2021).
Greenhouse Gas (GHG) Net Flux	Net carbon flux (emissions and removals) in forest ecosystems, representing the balance of forest-related GHGs based on satellite and inventory data.	2001–2020	Harris, N. L. et al. Global maps of twenty-first century forest carbon fluxes. <i>Nat. Clim. Change</i> 11 , 234–240 (2021).

Extended Data Table 4 | Summary of sensitivity analysis statistics for unobserved confounding across comparison-indicator pairs

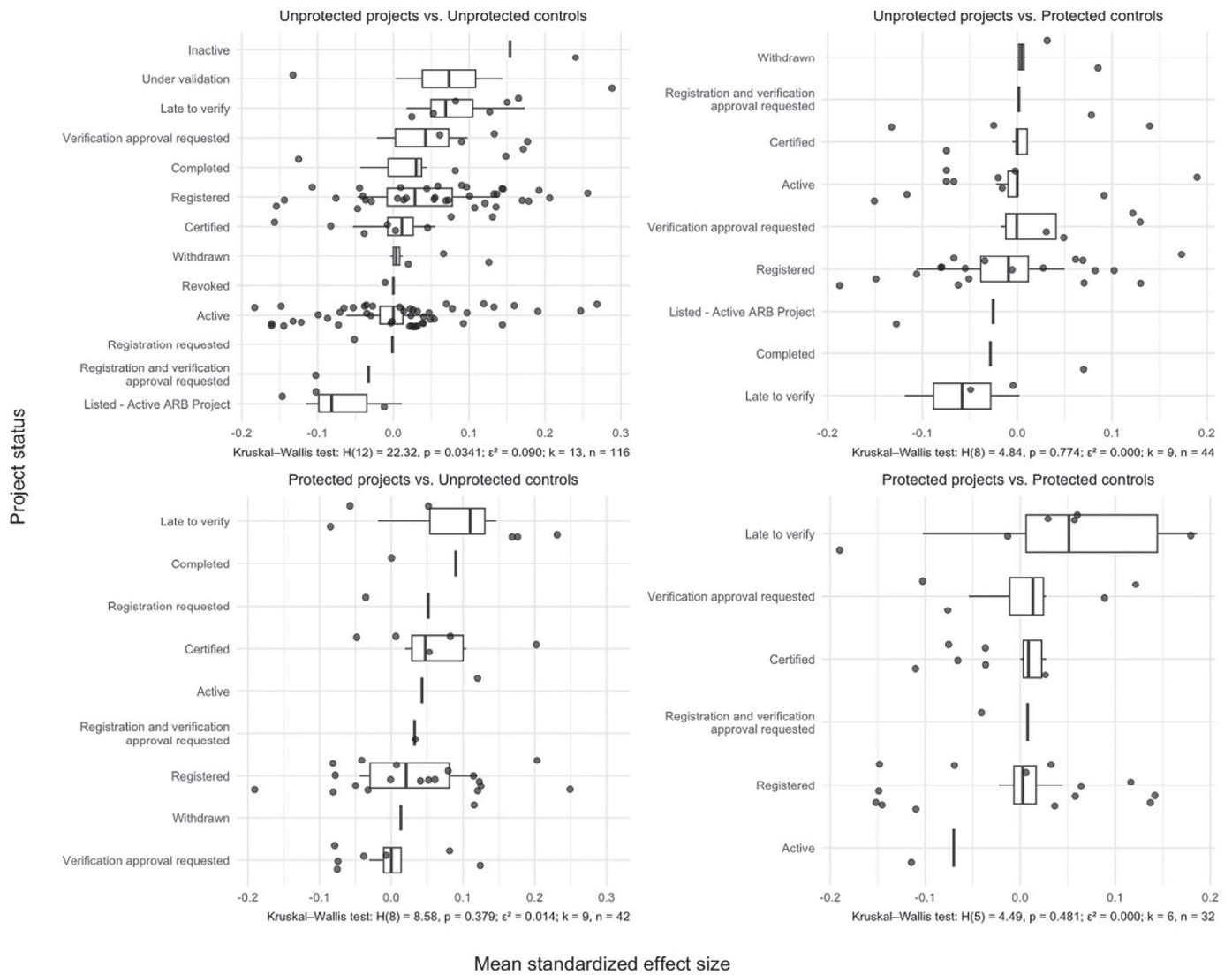
Comparison	Indicator	N	Median partial R ² (IQR) (%)	Median RV _{q=1} (IQR) (%)	Median RV _{q=1,α} (IQR) (%)
Unprotected projects vs. unprotected controls	Biodiversity Intactness	114	4.2 (0.9–12.0)	18.7 (9.1–30.7)	6.0 (0.0–20.0)
	Forest Integrity	73	4.2 (1.9–14.6)	18.9 (12.9–33.7)	7.8 (0.0–18.0)
	Forest Fragmentation	59	11.5 (2.5–35.6)	30.1 (14.2–51.7)	21.2 (2.0–46.5)
	Canopy Height	116	3.8 (0.7–9.8)	18.0 (8.0–28.0)	5.1 (0.0–17.1)
	GHG Net Flux	62	4.6 (1.5–14.2)	19.5 (11.7–33.2)	7.8 (0.0–24.5)
Unprotected projects vs. protected controls	Biodiversity Intactness	40	6.0 (1.9–24.3)	22.3 (12.9–42.9)	5.0 (0.0–33.6)
	Forest Integrity	36	1.8 (0.6–7.8)	12.6 (7.2–25.0)	0.6 (0.0–11.0)
	Forest Fragmentation	30	6.2 (1.1–26.1)	22.6 (9.6–44.3)	7.2 (0.0–30.1)
	Canopy Height	40	2.6 (1.0–6.8)	15.1 (9.2–23.6)	0.0 (0.0–7.5)
	GHG Net Flux	35	0.8 (0.2–4.7)	8.7 (4.0–19.8)	0.0 (0.0–1.3)
Protected projects vs. unprotected controls	Biodiversity Intactness	41	7.5 (1.1–17.9)	27.4 (9.8–37.0)	7.0 (0.0–26.0)
	Forest Integrity	41	6.3 (1.3–14.2)	22.8 (11.0–33.2)	6.4 (0.0–20.9)
	Forest Fragmentation	35	15.1 (1.9–42.0)	34.2 (12.8–56.3)	18.2 (0.0–44.9)
	Canopy Height	42	7.9 (3.8–22.0)	25.3 (17.9–40.8)	13.9 (0.0–28.8)
	GHG Net Flux	36	5.0 (1.2–8.0)	20.3 (10.3–25.4)	1.8 (0.0–12.4)
Protected projects vs. protected controls	Biodiversity Intactness	30	7.5 (1.0–24.5)	24.6 (9.8–43.0)	13.9 (0.0–30.3)
	Forest Integrity	31	3.3 (0.6–5.6)	16.7 (7.4–21.6)	0.0 (0.0–8.8)
	Forest Fragmentation	27	11.9 (5.0–29.3)	30.7 (20.5–46.9)	16.3 (5.9–36.2)
	Canopy Height	30	3.9 (1.6–11.2)	18.2 (11.7–29.8)	7.0 (0.0–20.0)
	GHG Net Flux	29	2.5 (0.4–11.8)	14.9 (6.4–30.5)	1.3 (0.0–11.3)

Full project results are available via Zenodo at <https://doi.org/10.5281/zenodo.19726735>.



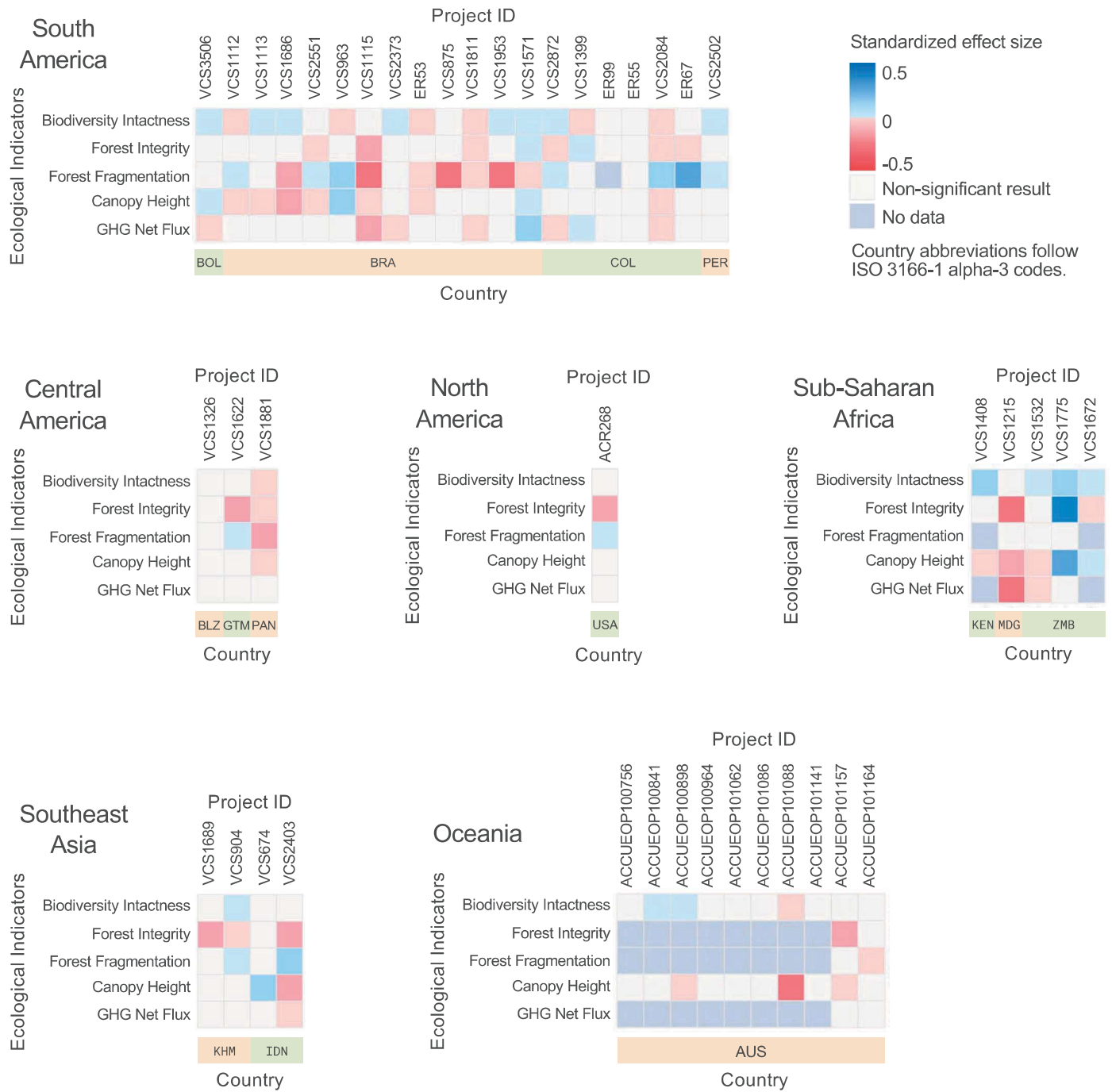
Extended Data Fig. 1 | Associations between ecological integrity outcomes and project, socio-economic and governance characteristics. Heatmap showing Spearman's rank correlation coefficients between mean standardized ecological-integrity effect sizes and project characteristics, project-level socio-economic factors and subnational governance factors across the four treatment-control comparison types. Factors include project size, project start date, gross domestic product (GDP), population density, travel-time accessibility to urban centres, the Subnational Corruption Index (SCI), and the Subnational Human Development Index (SHDI). Colored cells indicate statistically significant correlations ($p < 0.05$), while non-significant associations are shown in white.

Overall, correlations are weak and largely non-significant, with a small number of context-specific associations, including negative correlations with SCI (lower SCI values indicate higher corruption) and SHDI for avoided deforestation projects that do not overlap protected areas relative to unprotected areas, and associations with GDP and travel-time accessibility for avoided deforestation projects that overlap protected areas relative to protected areas. Data sources: SCI and SHDI were obtained from the Subnational Corruption Database³⁶ and the Subnational Human Development Database³⁷. All other variables are described in Extended Data Table 2.



Extended Data Fig. 2 | Associations between ecological integrity outcomes and project status. Distribution of mean standardized ecological-integrity effect sizes by project status for each treatment–control comparison. Differences across status categories were assessed using Kruskal–Wallis tests (two-sided), with test statistics and sample sizes reported beneath each panel. Boxes show the interquartile range (25th–75th percentiles), the centre line shows the median,

whiskers extend to the most extreme values within $1.5 \times$ the interquartile range, and points represent individual projects. For unprotected projects relative to unprotected controls, we find a significant overall association between project status and ecological integrity outcomes. However, post-hoc Dunn’s tests indicate that pairwise differences are not statistically significant after adjustment for multiple comparisons.



Extended Data Fig. 3 | Ecological integrity of avoided deforestation projects relative to protected-area controls. Project-level standardized effect sizes are shown for each ecological-integrity indicator, with columns representing individual projects grouped by country and region. Effect sizes were estimated using linear regression models; statistical significance was assessed using two-sided tests ($p < 0.05$). Positive values (blue) indicate higher biodiversity intactness, greater forest landscape integrity, lower fragmentation, taller

canopy height, and lower greenhouse gas (GHG) emissions in project areas relative to controls; negative values (red) indicate the opposite. Color intensity reflects effect magnitude. White indicates no significant difference ($p \geq 0.05$), and grey indicates indicators not evaluated due to insufficient data or failed model diagnostics. Country abbreviations follow ISO 3166-1 alpha-3 codes. No adjustments were made for multiple comparisons.