Earth observation and causal inference in assessing protected area effectiveness

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September 2026

Abstract

Area-based conservation is a fundamental component of global conservation strategies, yet robust causal evidence on the long-term effectiveness of protected areas is still emerging. Alongside traditional field data collection methods, Earth observation offers cost-effective means of generating high-resolution, spatially extensive information, and its broader integration into conservation science is increasingly important. Equally essential are causal inference methods that support rigorous evaluation of conservation effectiveness. We review space- and airborne Earth observation data and causal inference frameworks used to evaluate the impacts of protected areas worldwide. Our review shows that the existing literature mainly uses matching methods for confounder control and avoided deforestation as the primary outcome. This emphasis provides only a partial view of protected areas, not fully capturing their broader ecological roles and social impacts, including effects on ecosystem functioning, biodiversity, and local community livelihoods. We discuss the study findings along with characteristics and limitations of commonly used outcomes and statistical approaches for controlling confounding. We further highlight emerging Earth observation technologies—such as high-resolution sensors, LiDAR, and machine learning approaches applied to remotely sensed data—that can extend assessments beyond traditional land cover metrics. Through practical examples across four thematic areas, we offer a forward-looking synthesis to guide the next generation of conservation impact evaluations and support a more comprehensive understanding of protected area outcomes.

Keywords: conservation; impact evaluation; remote sensing; land use change; forest loss; counterfactual methods

Introduction

Global biodiversity is in decline, driven by habitat loss, climate change, and other anthropogenic pressures[1]. Earth observation (EO) is central, enabling systematic monitoring of ecosystems and conservation interventions, including protected areas (PAs), across space and time. Increasingly, these data underpin conservation impact evaluations that aim to isolate the causal effects of interventions by reconstructing what would have occurred in their absence[2,3]. Advances in satellite and airborne sensing technologies, combined with developments in cloud computing and machine learning—algorithms that learn from data to autonomously make predictions or classifications—have expanded the range and resolution of ecological variables that can be derived from EO data, supporting increasingly detailed assessments of ecosystem structure, functioning, biodiversity, and human pressures[4,5,6]. Despite these advances in EO and the increased interest in evaluating conservation actions[7], including several reviews of PA performance[8,9], systematic assessments of how EO data are used in conservation impact evaluations, including the choice of outcomes and the ways in which data and methodological decisions shape causal estimates, remain rare. The evidence base on PA effectiveness reflects both the analytical methods applied and the spatial, temporal, and thematic limitations of the EO data on which those methods depend: this in mind, we assess the current state of the EO-based evidence on PA effectiveness through an extensive literature review to clarify how data and methodological choices shape what ecological outcomes are captured and what is concluded, and suggest ways forward.

A fundamental issue in PA impact evaluation is that PAs are designated through political and administrative processes, often incorporating ecological aspects but also other land-use considerations. This means they are not established randomly across landscapes but tend to occupy regions with inherently lower human pressure, such as remote or high-elevation areas[10], where conservation outcomes are likely better regardless of protection status[11]; moreover, PA placement cannot be reversed for the purposes of generating experimental controls.

Subsequently, PA effectiveness may be overestimated; robust evaluation methods that account for confounding factors—variables that are associated with both the treatment, in this case PA designation, and the outcome variable(s) of interest—are required to construct reliable counterfactuals (simulated outcomes in the absence of intervention) and credibly attribute causality. Since PA establishment cannot feasibly be randomised[12,13], randomised control trials are not an option. Instead, various quasi-experimental approaches have emerged as viable alternatives, including matching, difference-in-differences (DiD), synthetic control, regression discontinuity, instrumental variables, and interrupted time series (see S3 for details and O'Garra et al.[14] for a comprehensive typology), all of which aim to isolate the causal effects of PAs by addressing non-random placement but operate under different assumptions. Building on the conceptual and empirical foundation for counterfactual analysis in conservation[2,15], a growing body of literature has since applied counterfactual methods to assess PA impacts on forest loss, species declines, human pressures, and other ecological outcomes[16,17,18,19], including meta-analyses synthesising these results[8,20]. The credibility of these causal estimates, in turn, depends on the nature of the outcome variables being measured: here, EO data become central. Satellite and airborne remote sensing provide consistent, scalable, high-resolution data on land cover and land use (LULC), habitat change, and environmental conditions for environmental monitoring and evaluation[21,22,23], including in remote or inaccessible areas where field data collection is impractical. Optical imagery has been extensively used to track LULC change[24] and assess PA effectiveness in mitigating deforestation[15,25,26], while more recent EO developments have further expanded the scope of conservation applications, enabling increasingly detailed monitoring of ecosystem structure, biodiversity patterns, and ecosystem functioning[4,5,6]. Machine learning approaches combined with cloud computing have further enhanced the ability to exploit the spatial, spectral, and temporal complexity of satellite time series, supporting near-real-time disturbance detection and improved monitoring of ecosystem condition[6,27,28].

To provide systematic understanding of how EO data and causal methods have been combined for assessing PA effectiveness, we did a systematic review of conservation impact evaluations that apply counterfactuals and use an EO-based outcome (see SI1 and SI2). Specifically, we focused on studies that use satellite or airborne remote sensing–based outcome variable to assess the causal impact of PAs. We excluded studies relying on other forms of remote sensing, such as passive acoustic monitoring, camera traps, or mobile phone data and studies using methods outside of causal inference. These criteria led to the inclusion of 189 scientific articles comprising of 275 studies: here, "study" is defined as *a line of investigation based on an outcome variable* which means that one scientific article may contain several studies. The requirement of EO-based outcome(s) combined with causal inference eliminated all papers published before 2008 (the first eligible paper[15] was published then), but the study period may and often does extend further back in time than 2008. By synthesising this body of work, we aim to:

1. Examine how EO data and causal inference methods have been combined to evaluate PA effectiveness worldwide
2. Identify methodological and thematic trends in the current evidence base
3. Discuss future directions for advancing the integration of EO technologies into conservation impact evaluations.

Trends in the current evidence base

Description of the reviewed studies

Studies evaluating PA effectiveness span the globe (Figure 1), and have increased rapidly over the last two decades (Figure 2a); the year 2000 is the most common study-period start year in papers published throughout the 2010s and 2020s, marking a watershed in both study volume and outcome diversification (Figure 3). The median number of studies per country is 22; the 90th percentile is 35, covering 21 countries. Latin America and Southeastern Asia are the most studied regions; top 10 countries in descending order are China, Brazil, Indonesia, Thailand, Peru, México, Tanzania, Costa Rica, Colombia, and Ecuador. These countries also have high shares of targeted studies (regional, national, subnational, or site level), along with for example Madagascar, Spain, and South Africa. The overlap with the tropical forest biome is strong: 69 % of studies published between 2008 and 2024 assessed solely forest PAs. Conversely, underrepresented regions, such as Northern and Western Africa, and Central and Western Asia, largely overlap with deserts, shrublands, grasslands, and savannas, indicating a knowledge gap on PA performance beyond forest biomes; non-forest ecosystems appear alongside forest ecosystems in 27 % of the studies and alone in only 3 %. Some countries in the underrepresented regions do lack complete or reliable PA data: this is the case for e.g., Libya and Syria. Coverage across IUCN categories is relatively broad; the most common between-category comparison is strict (IUCN categories I–II) versus non-strict protection (IUCN categories III–VI), and some studies compare PAs against certain unprotected governance regimes like logging or mining concessions (e.g.[16,29]). Governance-type analyses covering e.g., state-governed, Indigenous, and community-managed PAs, tend to be national in scope, with global analyses being rare (but see Sze et al.[30]). One notable underrepresentation is private protected areas, whose effectiveness remains little studied (but see e.g.[31,32]).

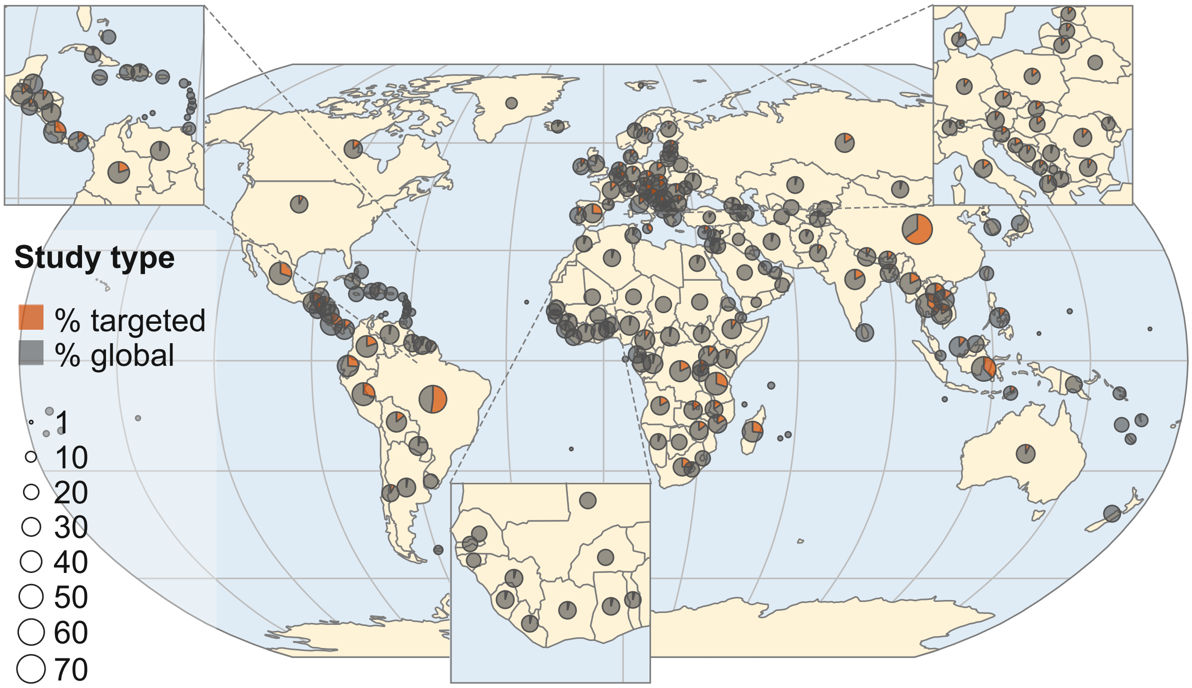
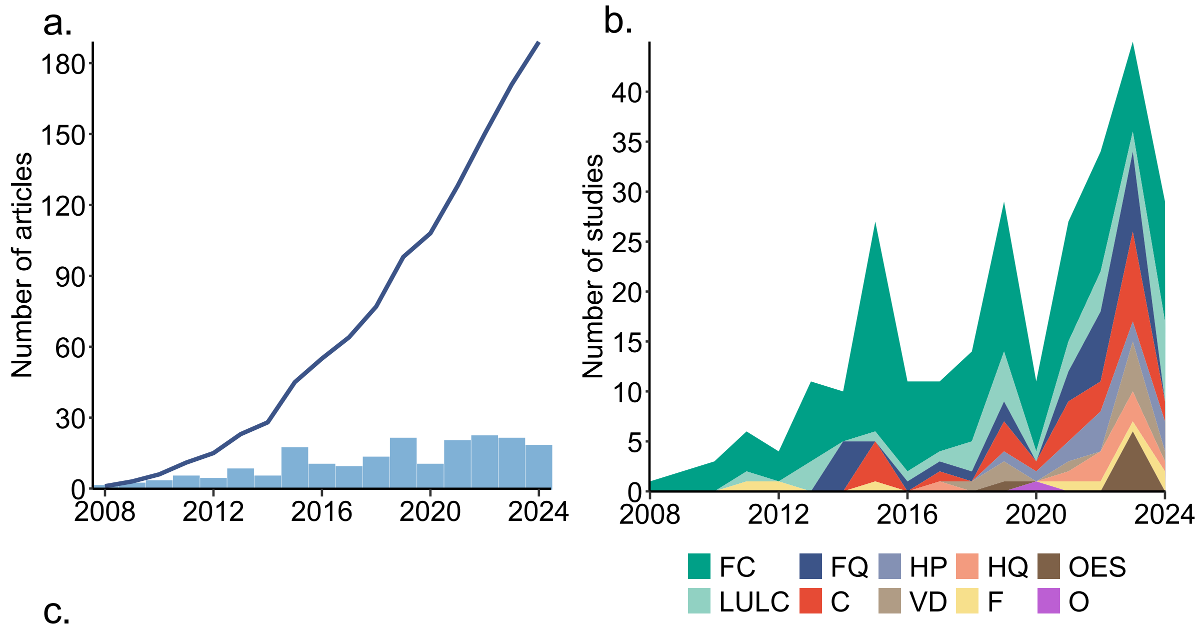


Figure 1. A global map of the share of studies based on the study scope (grey = global; orange = regional, national, or sub-national). The size of the circles corresponds to the number of studies. World base map made with Natural Earth.

When inspecting what measures for PA outcomes have been used, the dependence on forest data is apparent across the 10 identified outcome-variable categories (Figure 2b). LULC-based proxies of PA effectiveness account for almost two thirds (63 %) of the studies, with avoided deforestation alone used in over half (51 %); dominance is most pronounced in study periods spanning the pre- and early 2000s (Figure 3), likely reflecting the limited data availability, though it persists in more recent work, too. Almost one fifth (19 %) of the studies rely on a single dataset, the Global Forest Change (GFC)[33], applied at global[30], national[34,35], and subnational[36,37] studies despite known limitations: for instance, it has been criticised for not distinguishing natural tropical forests from plantations and other areas with forest regrowth[38] and potentially flagging short-term degradation as deforestation[30]. Moreover, forest canopy cover thresholds vary across ecosystems, potentially affecting cross-study comparability[39,40,41].

Non-LULC outcome use has grown steadily (Figure 2b): forest quality accounts for 10 % of studies; carbon, habitat quality, and other ecosystem services collectively for 16 % (10 %, 3 %, and 3 % respectively); human pressure for 5 %, typically via compound indices of nighttime lights, population density, and land use intensity[17,42,43,44,45]; vegetation dynamics for 4 %; fire proxies for 3 %; and one study (0.5 %) used biodiversity intactness[46]. Carbon and vegetation dynamics are often studied using MODIS products, as is fire, while DMSP and VIIRS nighttime lights occur in human pressure studies. Despite this growing diversification, geographic and thematic gaps remain (Figure 2c): non-carbon ecosystem services have only been studied as an outcome in China; fire has featured in only one global study[47] and is absent from Europe, Australia, New Zealand, and Northern America, where incorporating fire dynamics under accelerating climate change could yield important insights; and vegetation dynamics, such as long-term greening and browning trends, have similarly not been studied globally or in Oceania or Northern America, where they could provide essential knowledge on the ecosystems' response to climate and land use pressures. These patterns likely reflect where causal signals are clearest and policy demand strongest. Multi-source and multi-outcome study designs have become increasingly common in the late 2010s and 2020s, highlighting the emergence of more comprehensive approaches.



c.

	Outcome variable									
	FC	LULC	FQ	C	HP	VD	HQ	F	OES	O
Global	12	7	5	4	6	0	0	1	0	0
Africa	11	8	4	2	0	2	0	2	0	1
Asia[1]	48	2	9	13	7	8	8	2	7	0
Oceania[2]	1	1	0	0	0	0	0	0	0	0
Europe[3]	4	13	0	4	0	1	0	0	0	0
Latin America[4]	64	7	6	7	0	1	0	3	0	0
Northern America	0	1	4	0	0	0	1	0	0	0

Figure 2. Panel A: The number of reviewed articles (cumulative and annual) across the review period. Panel B: The number of studies per outcome variable category across the review period. FC = forest cover, LULC = other land use and land cover, FQ = forest quality, C = carbon, HP = human pressure, VD = vegetation dynamics, HQ = habitat quality, F = fire, OES = other ecosystem services, O = other. Panel C: The number of studies as a cross-tabulation of outcome variable category and geographical region (regions adapted from UN M49). For outcome variable abbreviations, see b. Here, global studies have not been calculated into the regional figures but are shown as "stand-alone"; The total sum of the studies is >275 because some of them span across region borders.

Methodologically, the evidence base of PA effectiveness relies overwhelmingly on statistical matching, underpinning 80 % of the studies—or 86.5 % when including matching combined with other methods. Roughly half (51 %) of all studies opt specifically for propensity score matching, with within-category variation remaining subtle (e.g., matching types, distance metrics, replacement/not). Other approaches include BACI (4 % of the studies) and DiD (1 % of the studies), probabilistic inference (e.g., odds ratio within a causal Bayesian model) (1.5 %), synthetic control (1.5 %), regression discontinuity (1 %), and instrumental variables (0.5 % or one study), with other designs, e.g., weighting schemes[48,49] and stratified matching with random sampling[50], accounting for 4 % of the studies. Some studies combine methods, such as matching followed by synthetic control[51], or covariate balancing[52].

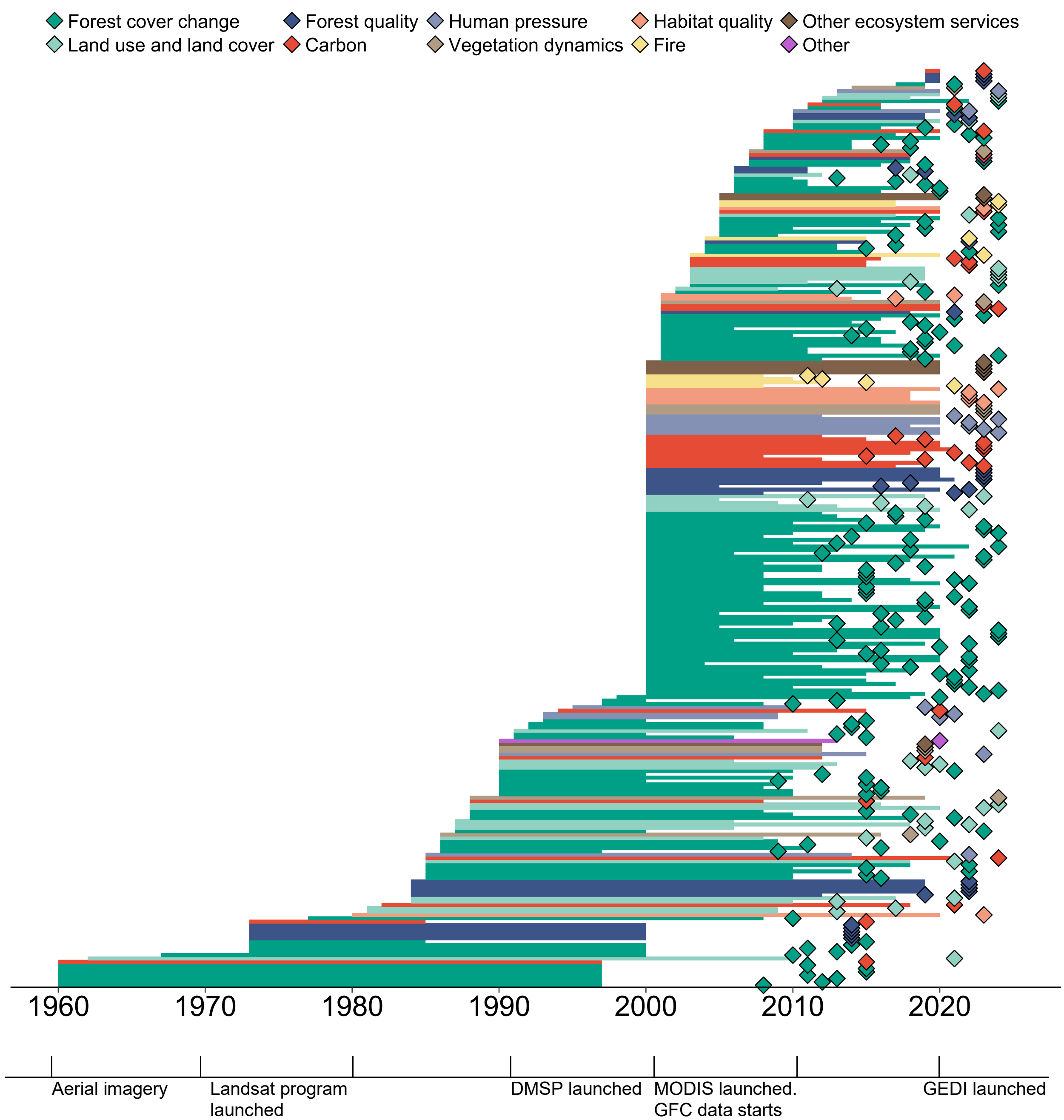


Figure 3. Timescales and publication years of the studies included in the review (n = 274; one study dropped from the plot data due to it being a simulation extending to 2050). Each horizontal bar represents the period covered by one study. The diamonds represent the publishing year of each study. The colours in both the bars and diamonds represent the outcome type. The "timeline" at the bottom highlights some remote sensing data sources and products that emerged in the review; the list is non-comprehensive.

Findings across outcomes and methods

We also assessed how findings on PA effectiveness behave with different outcome variables and comparisons. Pooling all studies together, most find net-positive PA outcomes relative to the counterfactual, but heterogeneity and small or insignificant impacts are common, with failures reported occasionally: e.g., Ghoddousi et al.[53] found Caucasian PAs "largely ineffective" in preventing rangeland degradation. Conversion and pressure increases were also observed inside PA boundaries. Importantly, we find that findings vary by outcome category: studies relying on forest cover change as the outcome variable mostly report that PAs reduce deforestation, but effectiveness is conditional on e.g., governance[16], pressure[54], accessibility[55], and PA category[26], with heterogeneity across space[31,54] and time[54,56]. Globally, Yang et al.[31] estimate that ~71 % of PAs prevent some forest loss, albeit only 30 % of total loss is avoided, with inter-country variation, greater effectiveness in high-risk regions, stricter PAs outperforming multi-use ones, and private and public PAs performing similarly. At national scales, e.g., Cambodia's PAs significantly reduced deforestation though the effect decreased over time[56], while in the Peruvian Amazon, state PAs, conservation concessions, and Indigenous territories all outperformed the unprotected landscape in reducing deforestation and forest degradation rates, though not consistently so against logging or mining concessions[16]. Spillover effects are reported in several cases, including deforestation leakage across a sample of 120 PAs in Africa, Asia, and the Americas[57], both positive and negative spatially heterogeneous spillover on the Qinghai-Tibetan plateau[58], and positive protection spillovers in Cambodia[56]. Broader LULC outcomes show that PAs are at least moderately effective in reducing land conversion or development, albeit with variation: globally, PAs were found to face habitat loss from built-up land expansion, agriculture, and deforestation, and while they reduced habitat loss by 33 % compared to unprotected areas, their effectiveness against nearby human pressures was mixed and spatially variable[59]; in the Spanish context, active management drove greater effectiveness within the multiple-use PAs examined, while spatially, coastal PAs showed the weakest resistance to land development[60].

In the non-LULC categories, fire outcomes generally show that PAs consistently reduce fire frequency or likelihood: e.g., Nelson & Chomitz[47] found that tropical PAs—including mixed-use and indigenous lands—significantly reduced forest fires, with the strongest effects in high-pressure, less remote regions; mixed-use PAs were generally at least as effective as strict PAs. Carbon outcomes generally show positive impacts on carbon sequestration, storage, and emissions reduction—e.g., 0.39 % improvement capacity in global carbon sequestration by establishing PAs; but interestingly, some studies (e.g., Ferraro et al.[61]) find that carbon storage is spatially decoupled from avoided-deforestation impacts. Carbon findings are often subject to institutional quality and governance type like findings in the Chinese context indicate: lower-level nature reserves failed to secure carbon sequestration due to weak enforcement and extractive pressures, while national and provincial reserves with stricter oversight succeeded[43]. Forest quality, depending on the type of proxy, often yields findings of partial success: positive impacts on biomass and forest structure on a global level[62] and e.g., in Tanzania[63] were reported. However, PAs seem to reduce degradation less reliably and with weaker significance than they reduce outright deforestation, and particularly forest fragmentation seems to be an issue e.g., in the PAs of Bangladesh[37] and Indonesia[64], and for instance, Peruvian PAs have a significant effect on deforestation but not on disturbance, with strict PAs seeming to even increase disturbance[65]. PAs harbour generally higher biomass attributable primarily to avoided deforestation, but roughly one fifth of PAs have higher aboveground carbon despite no counterfactual forest cover loss—suggesting optically invisible degradation in unprotected areas—and key differences in drivers of deforestation versus degradation have been identified elsewhere[16]. Habitat quality and non-carbon ecosystem services show mostly positive, environment-dependent outcomes, such as higher-elevation PAs performing better due to lower pressures[42,66]; however, all but one of these studies are from China. Vegetation dynamics generally indicate protection-driven greening—e.g., African PAs showed higher within-boundary growth than unprotected areas[67]—but Caucasus PAs were largely ineffective, with higher vegetation loss inside PAs in most analysed countries[53]. Human pressure studies show the most intra-category variation: some find that PAs have mitigation effects while not limiting local economic development[68] while others indicate that PAs either do not reduce overall pressure[17] or simply slow its increase as found for transboundary PAs in Eastern Asia[45].

Findings by causal inference method broadly mirror the overall sample, given that matching underpins almost 90 % of the studies: matching-based studies show a net-positive-but-heterogeneous signal. There is some indication that matching combined with DiD might produce more cautious effect sizes (e.g.[69,70]). BACI designs show clearer positive narratives, with less emphasis on counterfactual rigor, but notably, all except one article (five studies) share a lead author and study context. Probabilistic and simulation methods seem to highlight uncertainty and model dependence more explicitly[71,72]. Consistent with Caruana et al.[73], pre-treatment data are rarely used, the assumptions underlying causal claims are rarely reported, method selection is seldom justified, and robustness checks or sensitivity tests are done in only a minority of the studies, potentially resulting in reduced confidence in the effectiveness findings.

Integrating EO with counterfactual methods: Potential and limitations

The preceding results show an evidence base with methodological concentration and strong thematical focus: matching dominates causal inference, and forest cover change dominates outcome measurement. These patterns reflect real constraints in data availability and methodological compatibility. For policy frameworks like 30x30 relying on this literature to justify expanded protection, this is a meaningful caveat: the evidence base supports a relatively narrow and conditional claim on PA effectiveness, i.e., that PAs in forest ecosystems generally avoid deforestation when compared to a matching-based counterfactual. These findings could potentially overlook subtler degradation and unresolved confounding, and give little interest to entire ecosystems. At the same time, a small but growing set of studies has begun to explore alternative approaches to conservation impact evaluation beyond traditional land cover metrics, demonstrating what becomes possible when emerging EO capabilities are integrated with counterfactual frameworks: as shown in the results section, these metrics include e.g., forest structure, vegetation condition, and human pressure.

What emerging EO approaches offer

A significant recent development is the availability of three-dimensional structural metrics capable of detecting ecological change invisible to conventional optical sensors. E.g., spaceborne LiDAR (an approach using laser light to derive three-dimensional maps and models) from the GEDI mission has been leveraged to assess forest structural attributes inside and outside protected areas. Liang et al.[63] presented a new methodology to derive forest structural information and aboveground biomass density from GEDI observations and applied it to Tanzanian PAs, finding them to be effective in maintaining forest carbon stocks and multiple forest structure metrics (maximum canopy height, canopy cover measured by the vertical projection of canopy material, and plant area index). Building on and expanding on this approach, Duncanson et al.[62] implemented a global counterfactual framework using matched 1-km pixels inside and outside PAs, integrating GEDI-derived canopy height and aboveground biomass products to evaluate carbon outcomes across biomes and countries worldwide, and reporting generally higher biomass within PAs with biome- and region-specific variation. Crucially, they also looked at forest cover and found that higher PA aboveground carbon is largely attributable to avoided emissions from deforestation, but in roughly one fifth of PAs, GEDI detected higher aboveground carbon despite no counterfactual forest cover loss—suggesting optically invisible degradation in unprotected areas. This finding emphasises the need for alternative data sources to detect subtle changes in forest structure, and the value in employing several outcome variables in one case.

A parallel development involves indicators that capture different ecosystem attributes such as landscape configuration and vegetation productivity, along with indicators representing human pressure. The first temporally intercomparable human footprint maps were created by Venter et al.[74]; Geldmann et al.[75] produced a methodologically consistent map of change in human pressure (Temporal Human Pressure Index (THPI): a combination of stable nighttime lights, population density, and cropland cover) in 2014 and applied it to produce estimates of PA effectiveness, revealing that PAs have not reduced the overall pressure globally[17]. Compared to the generally positive signal[7,76], this demonstrates that individual study conclusions may be shaped by the outcome variable selection. Later, similar approaches have been increasingly used: for example, Wu et al.[42] evaluated changes in human pressure in parallel with habitat quality in Northeastern China's nature reserves using a combination of anthropogenic pressure, fractional vegetation cover, net primary production, and vegetation aggregation index, reporting improvements linked to declining human disturbance. Vegetation greening and browning trends looked at by e.g., Ghoddousi et al.[53] can provide additional insights into ecosystem degradation within and outside PAs. Alongside more traditional outcomes such as avoided deforestation, the metrics discussed here can provide a more comprehensive view on ecosystem health and resilience, functionality, connectedness, and the trends in human pressure driving change and PA effectiveness, and they represent a methodological direction the field is beginning to move toward.

What currently limits integration

Although causal inference methods are widely recognised as essential for evaluating conservation intervention effectiveness, our review still shows their application is often constrained by EO data availability and characteristics; recent work on causal inference with satellite data highlights challenges such as measurement error—e.g., from missing radiometric calibrations or atmospheric corrections—and systematic prediction biases e.g., in poverty mapping[77,78]. Many methods—such as DiD, synthetic control, and interrupted time series—require both pre- and post-intervention data. This poses a significant challenge for evaluating PA effectiveness, as some of the most commonly used EO datasets only provide consistent coverage from the early 2000s onward, with certain datasets like GEDI becoming available even more recently. Consequently, the difficulty of integrating these methods with EO data to evaluate PAs established decades, or even a century ago, remains difficult due to a lack of pre-intervention data (see S3).

This explains one of the most prominent patterns in our results: matching is the dominant quasi-experimental method used to assess PA effectiveness, underpinning almost 90 % of the studies. Unlike for example DiD and synthetic control, matching does not require pre-intervention data on outcomes, making it usable for most of global PAs. Matching is sensitive to unobserved confounders[79], and specifically, propensity score matching has been critiqued for performing poorly in certain settings due to its built-in feature to approximate a completely randomised experiment which may increase imbalance, inefficiency, model dependence, and bias[80]. However, when done, sensitivity tests show that results are robust to unobservables (e.g.[81,82]); the issue lies in the rarity of such testing in the literature. Matching remains valuable for producing provisional estimates, but they should be examined further before making causal claims.

Where the field is heading

However, as EO data availability continues to expand and time series lengthen, methods like DiD and synthetic control will become increasingly viable for evaluating newer PAs, enabling direct methodological comparisons and potentially validating findings from earlier matching-based analyses. Applying multiple methods with different underlying assumptions to the same data would substantially increase robustness; agreement on treatment effect estimates across different methods would increase confidence in the findings and leveraging the strengths of each method while addressing their individual limitations. At the same time, the integration of structural, multi-source, and multi-dimensional outcome variables into counterfactual frameworks offers a path toward an evidence base that reflects the full range of what protection can and should achieve.

Future research directions

Based on our review, we argue that there are four avenues where a stronger integration of the most recent advances in air- and spaceborne remote sensing technologies could be beneficial for advancing a more comprehensive range of causal analyses of PA effectiveness. In each, data limitations may have so far prevented remotely sensed PA assessments along these dimensions.

i. Animal species responses

Animal population trend data outside PAs, essential for counterfactual study designs, are scarce. Although studies have documented declines within PAs[83,84], the lack of comparable data from unprotected areas hinders evaluation of PA performance in mitigating biodiversity loss (but see[85,86]). Traditional monitoring of large wildlife, particularly in Africa, has relied heavily on crewed aerial surveys[87,88]. Recent applications of deep learning to satellite imagery are reshaping wildlife monitoring by enabling scalable and transferable survey methods: they allow total counts, herding pattern assessments, and even detection of previously undocumented large mammal migrations[89].

These approaches automate animal detection from submeter-resolution satellite imagery, processing input through successive layers that extract basic visual features (texture, colour, edges), then complex patterns (shapes, body parts, animal-like groupings), and finally full objects and semantic categories (individual animals, herds, and distinctions from similar non-animal features).Submeter imagery has been globally available since IKONOS (1999–2014), commercial successors including GeoEye 1 (launched 2008), WorldView 2 (2009), and WorldView 3 (2014). Applications to date include detection of livestock[90], African elephants[91], and migratory ungulates[89]. Duporge et al.[91] showed deep learning can detect and count elephants with accuracy comparable to human observers, even outside the training region. The cost of imagery and the need for large, annotated datasets remain challenges, though emerging low-cost micro-satellites may improve data accessibility[90]. Although model performance differs across habitats and sensors, Ocholla et al.[90] reported reasonable accuracy and demonstrated that multi-stage transfer learning can mitigate model transferability limitations. Wu et al.[89] developed a pipeline capable of robustly detecting large herds of wildebeest and zebra and argued that continued satellite improvements will enhance multi-species population estimation while generating novel behavioural and ecological datasets. These developments open opportunities for integrating satellite-based wildlife surveys into PA effectiveness assessments, particularly in non-forest ecosystems, such as savannah landscapes.

Though not within the review scope, ground-based tools such as camera traps, passive acoustic sensors, and citizen science platforms contribute to species detection and abundance modelling. Brodie et al.[18] and Cazalis et al.[92] demonstrated that combining such data with EO-derived habitat metrics can quantify PA effects on tropical biodiversity, with PA effectiveness in conserving bird species found to be largely driven by avoided deforestation and forest degradation. New technologies such as automated bird sound identification apps[93] further expand the possibilities for large-scale biodiversity monitoring and real-time biodiversity predictions.

ii. Ecosystem structure

New capabilities in LiDAR technology, ranging from terrestrial to drone and spaceborne acquisitions, provide highly detailed information on ecosystem structural intactness, complexity, and diversity[94,95]. Airborne LiDAR, for example, has become well established for sub-national and national-level ecological applications (e.g., forest inventories and forest management) since it can be used for gathering data not accessible with field methods or optical remote sensing, and is quicker, more accurate, and more cost-efficient than field work[96]. Spaceborne LiDAR missions such as GEDI provide consistent large-scale observations of canopy height, vertical structure, and biomass, but remain limited in their ability to resolve fine-scale within-canopy variation.

Technologies such as terrestrial laser scanning (TLS) offer exceptional detail; as a field-based approach, TLS captures fine-scale three-dimensional forest structure, including stem architecture, understory complexity, and vertical layering largely inaccessible to airborne or satellite observations. While TLS is not scalable, it plays a critical role in calibrating and validating airborne and spaceborne estimates[97] and in improving ecological interpretation of remotely sensed structural metrics. Although new in PA impact assessment, emerging studies using spaceborne LiDAR[62,63]—and also airborne LiDAR coupled with field plot data to estimate forest structure metrics from topographic and Landsat spectral predictors[50]—demonstrate their growing potential: they show that such data and approaches are currently operationally useful for causally robust PA impact evaluation. GEDI started collecting data for scientific use in early 2019, orbiting between ±51.6° latitude, so while long-term time series are not yet available, these data still hold a lot of potential for conservation impact evaluation. Structural attributes derived from these data, such as plant density, canopy height, and canopy cover, can be used to characterise forest structure and heterogeneity. These attributes are linked to ecosystem functioning (e.g., nutrient cycling, resource acquisition, and growth dynamics)[98], but do not directly measure these processes. Together, they provide measures of forest structural diversity or heterogeneity, describing the three-dimensional variation in vegetation structure[99]. Structural diversity has been shown to be a strong proxy for biodiversity and a predictor of key ecosystem functions, including productivity, energy transfer, and nutrient dynamics[100].

Recent developments further expand the capacity to quantify forest structural diversity at large scales. For example, new GEDI-derived products provide spatially explicit metrics of canopy structural complexity and diversity, including indices that integrate vertical stratification and inferred horizontal heterogeneity into a single, globally consistent measure of three-dimensional canopy organisation[101,102]. These advances move beyond single-trait descriptors such as canopy height or leaf area index, enabling a more comprehensive characterisation of structural heterogeneity that is closely linked to biodiversity, ecosystem functioning, and resilience. In parallel, the rapid expansion of spaceborne radar capabilities, including recent missions such as NASA–ISRO's NISAR[103] and ESA's BIOMASS[104], offer complementary sensitivity to canopy structure, biomass distribution, and sub-canopy elements. Although not yet fully exploited for conservation assessments, these radar systems provide an emerging opportunity to integrate structural complexity, biomass dynamics, and disturbance monitoring across spatial scales and cloud-prone regions, broadening the observational toolkit for evaluating ecosystem integrity.

iii. Functional traits and ecosystemic conditions

While EO is limited for individual plant and tree species identification, vegetation functional traits continue to emerge and provide important dimension for assessing ecosystem condition alongside structural traits. Hyperspectral remote sensing, which captures fine contiguous wavelength bands to produce detailed spectral signatures, has emerged as a powerful tool for detecting these traits, revealing leaf biochemical and physiological properties that can serve as early-warning indicators of disturbance in PAs. Recent spaceborne imaging spectroscopy missions, including Italy's PRISMA, launched 2019 with a 29-day repeat cycle and global coverage[105], and Germany's EnMAP, launched 2022 with a 27-day repeat cycle and global coverage[106], now provide high spectral resolution observations suitable for retrieving canopy chlorophyll content, leaf area index, canopy water content, and other biochemical and physiological indicators at landscape scales. These missions build upon earlier airborne and experimental hyperspectral efforts and enable more systematic monitoring of vegetation composition, plant vitality, and ecosystem functioning from space. Forthcoming missions, such as HyperField-1 under the Copernicus program and the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME), promise to significantly expand this capacity by increasing spatial coverage and temporal revisit frequency. However, although individual biochemical and physiological traits can be estimated, consistent inference of functional diversity across ecosystems remains underdeveloped, limiting its routine application in conservation assessments.

Complementing this arsenal, thermal infrared observations from satellites and uncrewed aerial vehicles (UAVs) can detect plant stress long before visible symptoms appear, while also providing a thermal characterisation of habitat conditions. Land surface temperature products and different vegetation indices are already being used to monitor drought stress at regional and global scales and to evaluate the warming impacts of forest loss[107,108]; early applications started well before 2000s, making use of data from NOAA AVHRR sensor series operational since 1978[109]. These approaches are increasingly capable of linking canopy-level signals to physiological processes like stomatal regulation, though challenges remain in scaling measurements from leaves to landscapes[110]. Altogether, the two data streams present contrasting timelines for causal inference: thermal infrared observations would already enable pre- and post-intervention comparisons for long-established PAs, while hyperspectral time series are only now beginning to accumulate—suggesting that a methodological watershed in hyperspectral-based conservation impact evaluation, analogous to the diversification that followed MODIS and Landsat and related data products' availability around 2000, could emerge in the late 2020s as series lengthen and forthcoming missions expand coverage.

iv. Socio-economic outcomes

A promising new direction in PA effectiveness research is using remotely sensed metrics to assess how PA establishment affects nearby human populations. So far, the few studies examining this have relied heavily on household surveys[111,112,113]. However, such surveys are frequently outdated, limited in spatial coverage, and designed primarily for generating nationally representative estimates rather than tracking local-level change over time[114,115,116] Moreover, the underlying data remain with national statistical agencies and are not commonly made publicly available, making integration into research challenging, especially in the Global South[114]. To overcome these constraints, recent initiatives have developed high-resolution estimates of poverty and well-being by modelling relationships between available socio-economic data (e.g., representative household surveys) and satellite or connectivity-based indicators. Examples include nighttime lights[117], roof reflectance[118], and micro-estimates of poverty derived from Facebook activity or mobile phone networks[115]. These approaches offer promising new options for evaluating PA impacts on local communities, yet many of these datasets remain available only as static snapshots rather than consistent time series, limiting their ability to detect socio-economic changes through time. The way forward would thus be to ensure that temporally comparable datasets of socio-economic data will emerge, and new versions of the existing novel openings keep being produced. Moreover, existing EO-based proxies have their own limitations and often struggle to capture meaningful variation in areas with very low development levels. These constraints likely contribute to discrepancies between studies relying on household surveys and those using satellite-derived proxies. E.g., Li et al.[68], using nighttime lights as a proxy for development, found that the majority of PAs globally mitigated deforestation without harming local development. By contrast, Jago et al.[113], using household survey data, reported that trade-offs between conservation and wellbeing outcomes were common in Ethiopia—one of the top-ranked countries in Li et al.'s analysis. A likely explanation is that nighttime lights remain too insensitive to detect subtle changes across many rural areas in the Global South. More comparative studies are needed that directly evaluate the reliability and limitations of emerging EO-based measures against household survey data to clarify how such data can be used to advance understanding of PA effectiveness in relation to equity and justice concerns.

Pairing novel EO and causal designs

Across these four themes, a recurring tension is that several of the most promising EO products have currently too short time series to satisfy the pre-intervention data requirements of DiD, synthetic control, or interrupted time series for most existing PAs. The practical implications differ by theme and method: for example, thermal infrared archives are already long enough to support designs requiring pre-intervention data on long-established PAs, and matching remains viable for most applications when applied and sensitivity-tested carefully—as discussed, e.g., forest structure metrics are ready to be integrated into counterfactual frameworks today. Overall, future potential is high within all of the themes, and looking forward, we expect to see alternative outcomes and metrics increasingly integrated into PA effectiveness evaluation.

Conclusions

The evidence base on PA effectiveness is shaped as much by data availability as by analytical necessity: statistical matching dominates causal inference because it requires no pre-intervention outcome data, and avoided deforestation dominates because forest cover change produces the clearest and most consistent satellite signal. Geographic coverage remains skewed toward tropical forest regions, while non-forest ecosystems and outcomes beyond land cover change—including ecosystem structure, functional traits, and biodiversity—remain underrepresented. Without clarifying how data and methods shape this literature, the conditionality of current PA effectiveness estimates remains underexamined.

The four themes we discussed point toward a coherent expansion. Satellite-based wildlife detection enables large-scale animal-population surveying in non-forest systems; ecosystem structure is becoming a routinely measurable PA outcome; hyperspectral and thermal sensors are opening ecosystem functioning to causal evaluation; and emerging EO-based socio-economic proxies are extending scalable impact assessment to nearby human populations. Together, these trajectories can provide for a shift from single-outcome, forest-centric studies toward multi-outcome designs that combine structure, function, biodiversity, and human well-being within the same counterfactual framework. As EO archives continue to lengthen, methods requiring pre-intervention data will become increasingly viable, enabling cross-method validation that would substantially increase confidence in causal estimates.

The main implications of our findings are to match outcomes to the ecological question; do rigorous reporting of assumptions and more widespread robustness testing and apply multiple methods to the same data if feasible; and treat emerging indicators as complements to land-cover metrics, not replacements. Used this way, EO-based causal inference can contribute to an evidence base that is both methodologically more credible and ecologically more comprehensive, delivering the evidence scientists and policymakers need to drive effective conservation in an era of rapid environmental change.

Acknowledgements

Funding from Faculty of Science, University of Helsinki. J. F. E. acknowledges support from the Kone Foundation (grant no. 201905092) and E.E.M. from the Research Council of Finland (grant no. 363501).

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S1 Review methods

Objective of the review

The objective of this study is to review and synthesise studies that evaluate the impact of protected areas (PA) using a combination of Earth observation (EO) for the measured outcome and applying methods used for causal inference within a counterfactual framework. We examine what data and methods are used, and what outcomes are measured. We focus on terrestrial ecosystems, excluding marine (except for mangroves), other aquatic, intertidal, and unclassified areas. Our data extraction framework includes data corresponding to the following questions:

- What is the state of the evidence—number of studies, study location, study period, ecosystem type (forest vs. non-forest)?
- What remote sensing data are used?
    - What outcomes are measured and how are they measured?
    - What are the data sources?
- What methods are used for causal inference?

Study period

We included all papers published until the end of 2024 (the original searches were done in March 2025). The requirement of EO techniques combined with confounder control eliminated all papers published before 2008, making the de facto study period 2008–2024.

Search language

Only English language publications were reviewed.

Publication databases searched

Web of Science and Scopus were searched in March 2025.

Other sources

To supplement these main searches, Google Scholar was also searched in February 2026. The analysis was limited to peer-reviewed sources.

Search string

Thirteen iterations for search strings were tested in Web of Science (see Appendix 1. Original search string iterations): the final ones are displayed in Table S1. The search string was adapted and elaborated based on Sharma et al. (2020). After the finalisation of testing on Web of Science, the search string was also formatted according to Scopus' search syntax. The searches yielded 2,264 results in Web of Science and 2,222 results in Scopus. The results were tested against a test library selected by the authors as representative examples (Appendix 2. Test library, Table S3).

Table S1. The final search strings.

Search string version 13 (14.3.2025), Web of Science	
Intervention	**All categories of protected areas** TS = ("protected area*" OR "conservation area*" OR "natur* conservation" OR "natur* reserv*" OR "wilderness area*" OR "natural monument*" OR "natural feature*" OR "management area*" OR "protected landscape*" OR "wildlife refuge*" OR "wildlife corridor*" OR "national park*")
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR "control group*" OR "comparison group*" OR counterfactual* OR "random* control* trial*" OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR "double difference*" OR "simple difference*" OR "matching" OR "propensity score*" OR "before after control impact" OR BACI OR "controlled before after" OR "control* evaluation" OR "fixed effect*" OR "synthetic control" OR "regression adjustment" OR "time series" OR "ordinary least squares" OR "panel regression" OR "Bayesian inference" OR "Bayesian network*")
	AND

Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR “socio economic” OR welfare OR income OR inequality OR wellbeing OR well-being OR “social ecological” OR livelihood* OR development)
Note: used Web of Science’s “refine results” feature to include only the publications in English and published before 2025.	
2,264 results	
Version 13.2 (14.3.2025), Scopus	
Intervention	**All categories of protected areas** TITLE-ABS-KEY("protected area*" OR "conservation area*" OR "natur* conservation" OR "natur* reserv*" OR "wilderness area*" OR "natural monument*" OR "natural feature*" OR "management area*" OR "protected landscape*" OR "wildlife refuge*" OR "wildlife corridor*" OR "national park*")
	AND
Outcome	**Impact of conservation** TITLE-ABS-KEY(effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TITLE-ABS-KEY("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR "control group*" OR "comparison group*" OR counterfactual* OR "random* control* trial*" OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR "double difference*" OR "simple difference*" OR "matching" OR "propensity score*" OR "before after control impact" OR baci OR "controlled before after" OR "control* evaluation" OR "fixed effect*" OR "synthetic control" OR "regression adjustment" OR "time series" OR "ordinary least squares" OR "panel regression" OR "Bayesian inference" OR "Bayesian network*")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** AND TITLE-ABS-KEY(environmental OR ecological OR "ecosystem*" OR "eco system" OR "vegetation*" OR "habitat*" OR "*forest" OR "forest*" OR "deforest*" OR "forest loss" OR "woodland*" OR landcover OR "land cover" OR landuse OR "land use" OR "grass*" OR "prairie*" OR "shrub*" OR "savanna*" OR steppe OR "degrad*" OR "fragment*" OR poverty OR economy OR economic OR socioeconomic OR "socio economic" OR welfare OR income OR inequality OR wellbeing OR "well-being" OR "social ecological" OR "livelihood*" OR development)
	AND
Publication year	PUBYEAR < 2025

	AND
Language	(LIMIT-TO (LANGUAGE , "English")
2,222 results	

During the revision, it was brought to our attention that potentially relevant articles had been omitted in the original search. We examined the original search string and found out that all the omissions were due to the Comparison section of the original search string. The Comparison section specified the key terms related to study design i.e., methods for causal inference; in the omitted articles, these terms did not appear in the title, abstract, or keywords and thus, were not picked up by the original search string. We conducted a new search at the manuscript revision stage in February 2026. We tested dropping the Comparison section altogether and redoing the search, which yielded roughly 52,000 results on Web of Science and 57,000 results on Scopus. We tested several alternative search strings and settled on the ones shown in Table S2.

Table S2. The new search strings.

Web of Science, 17.2.2026	**Scopus, 17.2.2026**
TS = ("protected area*" OR "conservation area*") AND TS = ("effective*" OR efficacy) [note: studies limited to <2025 and English only using filters]	TITLE-ABS ("protected area*" OR "conservation area*") AND TITLE-ABS ("effective*" OR efficacy) AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE , "English"))
9,836 results	**8,944 results**

To ensure the thoroughness of our results, we performed searches on Google Scholar ("remote sensing" AND "protected area effectiveness", 824 results; "Earth observation" AND "protected area effectiveness", 172 results; both sorted by relevance and limited to 2008–2024) and screened the results, along with screening the newly added articles’ references in case they contained papers that our new searches had not caught. The results were tested against the articles flagged as omitted during the review (Appendix 2. Test library, Table S4).

Screening

The original search

The references were exported from both databases and imported to EndNote. 1,583 duplicates were identified, after which 2,903 articles remained. The first screening was based on their titles, after which the remaining articles were evaluated based on their abstracts and when necessary, full text. The ones evaluating area-based[1] conservation impacts by applying methods used for causal inference within a counterfactual framework and an air- or spaceborne remote sensing outcome in any terrestrial ecosystem or mangroves were included. This process led to the inclusion of 187 articles. Their reference lists were screened for potentially additional relevant articles, and as a result, 13 more articles were included. After a final screening, 18 articles were discarded e.g., due to the conservation measure not being area-based (e.g., payment for ecosystem services-type schemes where the project boundaries were not clearly defined) or the study not establishing a clear comparison for the effectiveness estimation (e.g., time series analyses inside a protected area without an interruption component). The original search yielded 182 articles. In the revision stage, this initial list of included articles was revised and 11 articles (13 studies) were further excluded (nine time series studies that have an interrupted time series-like study design but, strictly examined, do not qualify; and three regression-based (e.g., Bayesian network) studies that do control for typical confounders but in a way that, in a strict sense, does not allow for establishing causality).

The new search

The references were exported from both databases. After the identification of duplicates (n = 7,401), the final number of references found with the new searches was 11,369. We screened

[1] We included all categories of protected areas, including private and community protected areas. Payments for environmental services schemes were included when the areas benefitting from the system had clear geographical boundaries defined and were mapped. Other effective area-based conservation measures (OECMs) were not included.

these references based on their titles and, when needed, abstracts, and identified 625 references for further inspection. This set was further narrowed down to 85, and after reviewing full texts, 17 articles were identified as matching our criteria.

The supplementary search results on Google Scholar were screened based on titles and, when needed, abstracts. The bibliographies of the newly included articles were also screened for relevant references. With these additional measures, we found one more article that matched our inclusion criteria. Therefore, the final number of added articles is 18. After revising the original set of included articles and adding the new ones, the total number of articles included in the review is 189 (275 studies). All reviewed articles are listed in the Excel file provided as Supplementary Material (S2 List of reviewed articles).

Data extraction

Data extraction was done using a spreadsheet-based data extraction framework. Five categories were established, and the following variables were collected from all articles:

- Article information
    - UID (Unique Identifier)
    - Title
    - Year [of publication]
    - Author(s)
    - Journal
    - DOI (Digital Object Identifier)
- General
    - Key findings
    - Study period start
    - Study period end
    - Study area

    - Scope / Ecosystem type (forest vs. non-forest)
- Response variable
    - Response variable(s)
    - Response variable: data name
        - Note: extracted if available, i.e., if a pre-processed data product was used
    - Response variable: data provider
    - Response variable: data source
        - Note: satellite / sensor
    - Effect estimation method(s)
- Confounder control
    - Method(s)
    - Methods (specific details if available and relevant)
    - Confounding factors
        - Note: e.g., matching variables
- Additional analysis
    - Additional analysis (methods)
    - Covariates (if different from confounding factors)

As many of the 189 articles had several response variables, they were further split into 275 studies where each response variable corresponds to one study. All the analyses, except for the temporal distribution of articles described in panel C of Figure 1 in the manuscript, were done on a study basis.

The extracted data were processed, analysed, and visualised using Microsoft Excel, R 4.5.2, and QGIS 3.34.8.

References

Sharma, R., et al. The impact of terrestrial protected areas on vegetation extent and condition: a systematic review protocol. *Environmental Evidence* **9**, 8 (2020).

Appendix 1. Original search string iterations

Version 1	
Intervention	**All categories of protected areas** TS = (protect* OR conserv* OR reserve* OR preserv* OR "wilderness area*" OR monument* OR "natural feature*" OR "management area*" OR landscape* OR refuge* OR park* OR "botanical garden" OR sanctuar* OR corridor*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
	Studies that use Earth observation to quantify the effectiveness TS = (“Earth observation” OR “remote sens*” OR “remotely sens*” OR satellite* OR aerial OR imagery OR ALS OR LiDAR OR laser OR photogramm*)
	AND
Outcome	**Impact of protection** TS = (effectiveness OR impact* OR performance)
7,946 results – intended interventions poorly present	
Version 2	
Intervention	**All categories of protected areas** TS = (protected area* OR conservation* OR reserve*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND

	Studies that use Earth observation to quantify the effectiveness TS = ("Earth observation" OR "remote sens*" OR "remotely sens*" OR satellite* OR aerial OR imagery OR ALS OR LiDAR OR laser OR photogramm*)
	AND
Outcome	**Impact of protection** TS = (effectiveness OR impact* OR performance)
5,652 results – intended interventions poorly present	
Version 3	
Intervention	**All categories of protected areas** TS = ("protected area* effectiveness" OR "national park* effectiveness" OR "biosphere reserve* effectiveness" OR "nature reserve* effectiveness" OR "effectiveness of protected area*" OR "effectiveness of national park*" OR "effectiveness of biosphere reserve*" OR "effectiveness of nature reserve*" OR "protected area* impact*" OR "national park* impact*" OR "biosphere reserve* impact*" OR "nature reserve* impact*" OR "impact* of protected area*" OR "impact* of national park*" OR "impact* of biosphere reserve*" OR "impact* of nature reserve*")
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR "control group*" OR "comparison group*" OR counterfactual* OR "counter factual*" OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR "diff in diff" OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR "control* evaluation" OR "fixed effect*" OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
	Studies that use Earth observation to quantify the effectiveness TS = ("Earth observation" OR "remote sens*" OR "remotely sens*" OR satellite* OR aerial OR imagery OR ALS OR LiDAR OR laser OR photogramm*)
19 results – too few results due to EO-related terms	
Version 4	
Intervention	**All categories of protected areas** TS = ("protected area* effectiveness" OR "national park* effectiveness" OR "biosphere reserve* effectiveness" OR "nature reserve* effectiveness" OR "effectiveness of protected area*" OR "effectiveness of national park*" OR "effectiveness of biosphere reserve*" OR "effectiveness of nature reserve*" OR "protected area* impact*" OR "national park* impact*" OR "biosphere reserve* impact*" OR "nature reserve* impact*" OR "impact* of protected area*" OR "impact* of national park*" OR "impact* of biosphere reserve*" OR "impact* of nature reserve*")
	AND

Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
132 results– too few results	
Version 5	
Intervention	**All categories of protected areas** (TS = (protected area* OR conserv* OR reserve* OR preserv* OR "wilderness area*" OR monument* OR "natural feature*" OR "management area*" OR landscape* OR refuge* OR park* OR "botanical garden" OR sanctuar* OR corridor*) AND TS = (effect* OR impact* OR perform*))
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR nightlight* OR night light* OR wellbeing OR well-being OR human development OR social-ecological OR livelihood*)
32,455 results – too many results from other fields due to e.g, *preserv** in Intervention	
Version 6	
Intervention	**All categories of protected areas** TS = (“protected area*” OR “conservation area*” OR “conserved area*” OR “nature conservation” OR “nature reserve*” OR reservation OR "wilderness

	area*" OR monument* OR "natural feature*" OR "management area*" OR landscape* OR refuge OR refuges OR “natur* park“ OR "botanical garden" OR sanctuar* OR corridor*)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR nightlight* OR “night light*” OR wellbeing OR well-being OR “human development” OR social-ecological OR livelihood*)
6,335 results – still too many unrelated results due to e.g., *landscape* in Intervention	
Version 7	
Intervention	**All categories of protected areas** TS = (“protected area*” OR “conservation area*” OR “conserved area*” OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR monument* OR "natural feature*" OR "management area*" OR “natur* landscape*” OR refuge OR refuges OR “natur* park“ OR "botanical garden" OR sanctuar* OR “natur* corridor*” OR “wildlife corridor*” OR biosphere)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in

	difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR nightlight* OR “night light*” OR wellbeing OR well-being OR “human development” OR social-ecological OR livelihood*)
2,108 results	
Version 8 – finetuning	
Intervention	**All categories of protected areas** TS = (“protected area*” OR “conservation area*” OR “conserved area*” OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR refuge OR refuges OR “natur* park“ OR sanctuar* OR “natur* corridor*” OR “wildlife corridor*” OR biosphere)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR wellbeing OR well-being OR “human development” OR social-

	ecological OR livelihood* OR development OR deprivation OR shortage OR impoverishment OR *population*)
2,329 results	
Version 9 – finetuning	
Intervention	**All categories of protected areas** TS = (“protected area*” OR "conservation area*" OR “conserved area*” OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR "wildlife refuge*" OR “natur* park“ OR sanctuar* OR “natur* corridor*” OR “wildlife corridor*” OR biosphere)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR wellbeing OR well-being OR “human development” OR social-ecological OR livelihood* OR development OR deprivation OR shortage OR impoverishment OR *population*)
2,142 results	
Version 10 – finetuning	
Intervention	**All categories of protected areas** TS = (“protected area*” OR "conservation area*" OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR "wildlife refuge*" OR “wildlife corridor*”)

	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR “counter factual*” OR "random* control* trial*" OR RCT OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR “diff in diff” OR "double difference" OR "simple difference" OR "matching" OR "propensity score*" OR PSM OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR wellbeing OR well-being OR “human development” OR social-ecological OR livelihood* OR development OR deprivation OR shortage OR impoverishment OR *population*)
1,431 results	
Version 11 – testing dropping Comparisons	
Intervention	**All categories of protected areas** TS = (“protected area*” OR "conservation area*" OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR "wildlife refuge*" OR “wildlife corridor*”)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR rangeland OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR socio-economic OR welfare OR income OR inequality OR wellbeing OR well-being OR “human development” OR social-

	ecological OR livelihood* OR development OR deprivation OR shortage OR impoverishment OR *population*)
30,594 results – deemed unfeasible	
Version 12	
Intervention	**All categories of protected areas** TS = (“protected area*” OR "conservation area*" OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR "wildlife refuge*" OR “wildlife corridor*”)
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)
	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR "random* control* trial*" OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR "double difference*" OR "simple difference*" OR "matching" OR "propensity score*" OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series")
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR “socio economic” OR welfare OR income OR inequality OR wellbeing OR well-being OR “social ecological” OR livelihood* OR development)
1,600 results	
Version 13 (14.3.2025), published before 2025, English only	
Intervention	**All categories of protected areas** TS = (“protected area*” OR "conservation area*" OR “natur* conservation” OR “natur* reserv*” OR "wilderness area*" OR “natural monument*” OR "natural feature*" OR "management area*" OR “protected landscape*” OR "wildlife refuge*" OR “wildlife corridor*” OR "national park*")
	AND
Outcome	**Impact of conservation** TS = (effect* OR impact* OR perform* OR evaluat*)

	AND
Comparisons	**Studies that use a comparison group to measure impact. The search keywords are related to studies that use quantitative methods for evaluation.** TS = ("quasi experiment*" OR "impact evaluation*" OR "impact analysis" OR "impact study" OR "empirical evidence" OR "empirical comparison*" OR causal OR causation OR “control group*” OR “comparison group*” OR counterfactual* OR "random* control* trial*" OR "instrumental variable*" OR "regression discontinuity" OR "difference in difference*" OR "double difference*" OR "simple difference*" OR "matching" OR "propensity score*" OR "before after control impact" OR BACI OR "controlled before after" OR “control* evaluation” OR “fixed effect*” OR "synthetic control" OR "regression adjustment" OR "time series" OR "ordinary least squares" OR "panel regression" OR "Bayesian inference" OR "Bayesian network*”)
	AND
Context	**Change or conversion of terrestrial vegetation types and socio-economic outcomes** TS = (environmental OR ecological OR ecosystem* OR “eco system” OR vegetation* OR habitat* OR *forest* OR deforest* OR “forest loss” OR woodland* OR landcover OR “land cover” OR landuse OR “land use” OR grass* OR prairie* OR shrub* OR savanna* OR steppe OR degrad* OR fragment* OR poverty OR economy OR economic OR socioeconomic OR “socio economic” OR welfare OR income OR inequality OR wellbeing OR well-being OR “social ecological” OR livelihood* OR development)
Note: used Web of Science’s “refine results” feature to include only the publications in English and published before 2025.	
2,264 results	

Appendix 2. Test library

Table S3. The test library used to validate the results of the original search string.

Author(s)	Title	Year	Journal
Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A.	Measuring the effectiveness of protected area networks in reducing deforestation	2008	PNAS
Gaveau, D. L. A., et al.	Evaluating whether protected areas reduce tropical deforestation in Sumatra	2009	Journal of Biogeography
Andam, K. S., Ferraro, P. J., Sims, K. R. E., Healy, A., & Holland, M. B.	Protected areas reduced poverty in Costa Rica and Thailand	2010	PNAS
Honey-Rosés, J., Baylis, K., & Ramírez, M. I.	A Spatially Explicit Estimate of Avoided Forest Loss	2011	Conservation Biology
Joppa, L. N. & Pfaff, A.	Global protected area impacts	2011	Proceedings of the Royal Society B-Biological Sciences
Nelson, A. & Chomitz, K. M.	Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods	2011	Plos One
Nolte, C. & Agrawal, A.	Linking Management Effectiveness Indicators to Observed Effects of Protected Areas on Fire Occurrence in the Amazon Rainforest	2013	Conservation Biology
Carranza, T., Balmford, A., Kapos, V. & Manica, A.	Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: The Brazilian Cerrado	2014	Conservation Letters
Hanauer, M. M. & Canavire-Bacarreza, G.	Implications of heterogeneous impacts of protected areas on deforestation and poverty	2015	Philosophical Transactions of the Royal Society B-Biological Sciences
Shah, P. & Baylis, K.	Evaluating Heterogeneous Conservation Effects of Forest Protection in Indonesia	2015	Plos One
Eklund, J., et al.	Contrasting spatial and temporal trends of protected area effectiveness in mitigating deforestation in Madagascar	2016	Biological Conservation
Schleicher, J., Peres, C. A., Amano, T., Llactayo, W., & Leader-Williams, N.	Conservation performance of different conservation governance regimes in the Peruvian Amazon	2017	Scientific Reports
Sarathchandra, C., et al.	Effectiveness of protected areas in preventing rubber expansion and deforestation in Xishuangbanna, Southwest China	2018	Land Degradation & Development

Author(s)	Title	Year	Journal
Geldmann, J., Manica, A., Burgess, N. D., Coad, L., & Balmford, A.	A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures	2019	PNAS
Naidoo, R., et al.	Evaluating the impacts of protected areas on human well-being across the developing world	2019	Science Advances
Zhao, H. W., et al.	Individual-level performance of nature reserves in forest protection and the effects of management level and establishment age	2019	Biological Conservation
Shi, H., et al.	Global protected areas boost the carbon sequestration capacity: Evidences from econometric causal analysis	2020	Science of the Total Environment
Rodríguez-Rodríguez, D., Larrubia, R., & Sinoga, J. D.	Are protected areas good for the human species? Effects of protected areas on rural depopulation in Spain	2021	Science of the Total Environment
Auliz-Ortiz, D. M., Arroyo-Rodríguez, V., Mendoza, E., & Martínez-Ramos, M.	Are there trade-offs between conservation and development caused by Mexican protected areas?	2023	Land Use Policy
Alberto, R., Zavalloni, M., & Pagliacci, F.	The environmental and socioeconomic impacts of the Italian National Parks: Time and spillover effects across different geographical contexts	2024	Global Environmental Change-Human and Policy Dimensions

Table S4. Additional test articles for the new search.

Author(s)	Title	Year	Journal
Brodie, J., et al.	Landscape-scale benefits of protected areas for tropical biodiversity	2023	Nature
Cazalis, V., et al.	Effectiveness of protected areas in conserving tropical forest birds	2020	Nature Communications
Ceccherini, G., et al.	Spaceborne LiDAR reveals the effectiveness of European Protected Areas in conserving forest height and vertical structure	2023	Communications Earth & Environment
Duncanson, L., et al.	The effectiveness of global protected areas for climate change mitigation	2023	Nature Communications
Muise, E., Coops, N., Hermosilla, T., & Ban, S.	Assessing representation of remote sensing derived forest structure and land cover across a network of protected areas	2022	Ecological Applications

S2 List of reviewed articles

Author(s)	Title	Year	Journal
Abman, R.	Rule of Law and Avoided Deforestation from Protected Areas	2018	Ecological Economics
Agarwal, S., Sairorkham, B., Sakitram, P., & Lambin, E. F.	Effectiveness of community forests for forest conservation in Nan province, Thailand	2022	Journal of Land Use Science
Aguirre, J., Guerrero, E., & Campana Y.	How efective are protected natural areas when roads are present? An analysis of the Peruvian case	2021	Environmental Economics and Policy Studies
Alejo, C., et al.	Are indigenous territories effective natural climate solutions? A neotropical analysis using matching methods and geographic discontinuity designs	2021	PLOS One
Alejo, C., Walker, W. S., Gorelik, S. R., & Potvin, C.	Community Managed Protected Areas Conserve Aboveground Carbon Stocks: Implications for REDD+	2022	Frontiers in Ecology and Evolution
Alix-Garcia, J. M., Shapiro, E. N., & Sims, K. R. E.	Forest Conservation and Slippage: Evidence from Mexico's National Payments for Ecosystem Services Program	2012	Land Economics
Alves-Pinto, H. N., et al.	The role of different governance regimes in reducing native vegetation conversion and promoting regrowth in the Brazilian Amazon	2022	Biological Conservation
Ament, J. M. & Cumming, G. S.	Scale dependency in effectiveness, isolation, and social-ecological spillover of protected areas	2016	Conservation Biology
An, L., Shen, L., Zhong, S., Li, D., & Zhu, Y.	Conservation effects of transboundary protected areas on mitigating anthropogenic pressure across China’s borders	2024	Resources, Conservation & Recycling
Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A.	Measuring the effectiveness of protected area networks in reducing deforestation	2008	PNAS
Andam, K. S., Ferraro. P. J., & Hanauer, M. M.	The effects of protected area systems on ecosystem restoration: a quasi-experimental design to estimate the impact of Costa Rica’s protected area system on forest regrowth	2012	Conservation Letters
Anderson, E. & Mammides, C.	The role of protected areas in mitigating human impact in the world’s last wilderness areas	2020	Ambio
Arriagada R. A., Echeverria C. M., & Moya D. E.	Creating Protected Areas on Public Lands: Is There Room for Additional Conservation?	2016	PLOS One

Author(s)	Title	Year	Journal
Assaf, C., Adams, C., Ferreira, F. F., & França, H.	Land use and cover modeling as a tool for analyzing nature conservation policies – A case study of Juréia-Itatins	2021	Land Use Policy
Auliz-Ortiz D. M., Arroyo-Rodríguez V., Mendoza E., & Martínez-Ramos M.	Conservation of forest cover in Mesoamerican biosphere reserves is associated with the increase of local non-farm occupation	2022	Perspectives in Ecology and Conservation
Auliz-Ortiz, D. M., Arroyo-Rodríguez, V., Mendoza, E., & Martínez-Ramos, M.	Are there trade-offs between conservation and development caused by Mexican protected areas?	2023	Land Use Policy
Bebber, D. P. & Butt, N.	Tropical protected areas reduced deforestation carbon emissions by one third from 2000–2012	2017	Scientific Reports
Beresford, A. E., et al.	Protection Reduces Loss of Natural Land-Cover at Sites of Conservation Importance across Africa	2013	PLOS One
Beresford, A. E., et al.	Correlates of long-term land-cover change and protected area performance at priority conservation sites in Africa	2017	Environmental Conservation
Biswas, S., Vadrevu, K. P., Lwin, Z. M., Lasko, K., & Justice, C. O.	Factors Controlling Vegetation Fires in Protected and Non-Protected Areas of Myanmar	2015	PLOS One
Black B., & Anthony, P. B.	Counterfactual assessment of protected area avoided deforestation in Cambodia: Trends in effectiveness, spillover effects and the influence of establishment date	2022	Global Ecology and Conservation
Blackman, A.	Strict versus mixed-use protected areas: Guatemala's Maya Biosphere Reserve	2015	Ecological Economics
Blackman, A. & Villalobos, L.	Clear, but don't invest: protected areas discourage some land uses more than others	2019	Environmental Research Letters
Blackman, A., Pfaff, A., & Robalino, J.	Paper park performance: Mexico's natural protected areas in the 1990s	2015	Global Environmental Change
Bonilla-Mejía, L. & Higuera-Mendieta, I.	Protected Areas under Weak Institutions: Evidence from Colombia	2019	World Development
Bowker, J. N., De Vos, A., Ament, J. M., & Cumming, G. S.	Effectiveness of Africa's tropical protected areas for maintaining forest cover	2016	Conservation Biology
Bragina, E. V., Radeloff, V. C., Baumann, M., Wendland, K., Kuemmerle, T., & Pidgeon, A. M.	Effectiveness of protected areas in the Western Caucasus before and after the transition to post-socialism	2015	Biological Conservation

Author(s)	Title	Year	Journal
Brandt, J. S., Butsic, V., Schwab, B., Kuemmerle, T., & Radeloff, V. C.	The relative effectiveness of protected areas, a logging ban, and sacred areas for old-growth forest protection in southwest China	2015	Biological Conservation
Braza, M.	Effectiveness of conservation easements in agricultural regions	2017	Conservation Biology
Bruggeman, D., Meyfroidt, P., & Lambin, E. F.	Impact of land-use zoning for forest protection and production on forest cover changes in Bhutan	2018	Applied Geography
Brum, F. T., Pressey, R. L., Bini, L. M., & Loyola, R.	Forecasting conservation impact to pinpoint spatial priorities in the Brazilian Cerrado	2019	Biological Conservation
Brun, C., et al.	Analysis of deforestation and protected area effectiveness in Indonesia: A comparison of Bayesian spatial models	2015	Global Environmental Change
Butsic, V., Baumann, M., Shortland, A., Walker, S., & Kuemmerle, T.	Conservation and conflict in the Democratic Republic of Congo: The impacts of warfare, mining, and protected areas on deforestation	2015	Biological Conservation
Butsic, V., et al	The effect of protected areas on forest disturbance in the Carpathian Mountains 1985–2010	2016	Conservation Biology
Carranza, T., Balmford, A., Kapos, V., & Manica, A.	Protected area effectiveness in reducing conversion in a rapidly vanishing ecosystem: the Brazilian cerrado	2013	Conservation Letters
Chen, J., Shi, H., Wang, X., Zhang, Y., & Zhang, Z.	Effectiveness of China's Protected Areas in Mitigating Human Activity Pressure	2022	International Journal of Environmental Research and Public Health
Chen, Y., Fiankor, D. D. D, Kang, K., & Zhang, Q.	Assessing the role of institutional effectiveness on carbon sequestration: the case of China's nature reserve policy	2023	China Agricultural Economic Review
Cheng, Y., Wu, H., & Yang, B.	Conserving habitat and ecosystem in protected areas amid increasing intensive human modification: A case study of China's Pan-Pearl River Delta	2023	Ecological Indicators
Cisneros, E., Börner, J., Pagiola, S., & Wunder, S.	Impacts of conservation incentives in protected areas: The case of Bolsa Floresta, Brazil	2022	Journal of Environmental Economics and Management
Clemente, C. M. S., Espírito-Santo, M. M. D., & Leite, M. E.	Estimates of deforestation avoided by protected areas: a case study in Brazilian tropical dry forests and Cerrado	2020	Landscape Research

Author(s)	Title	Year	Journal
Clements, T. & Milner-Gulland, E. J.	Impact of payments for environmental services and protected areas on local livelihoods and forest conservation in northern Cambodia	2014	Conservation Biology
Condro, A. A., Prasetyo, L. B., Rushayati, S. B., Santikayasa, I. P., & Iskandar, E.	Protected areas slow down tropical rainforest disturbance in the Leuser Ecosystem, Indonesia	2022	Journal of Land Use Science
Cuenca, P., Arriagada, R., & Echeverría, C.	How much deforestation do protected areas avoid in tropical Andean landscapes?	2016	Environmental Science & Policy
Cuenca, P., Robalino, J., Arriagada, R., & Echeverría, C.	Are government incentives effective for avoided deforestation in the tropical Andean forest?	2018	PLOS One
D'Alberto R., Zavalloni M., & Pagliacci F.	The environmental and socioeconomic impacts of the Italian National Parks: Time and spillover effects across different geographical contexts	2024	Global Environmental Change
De Assis Barros, L., Venter, M., Ramírez-Delgado, J. P., Coelho-Junior, M. G., & Venter, O.	No evidence of local deforestation leakage from protected areas establishment in Brazil's Amazon and Atlantic Forest	2022	Biological Conservation
De Los Rios, C.	The double fence: Overlapping institutions and deforestation in the Colombian Amazon	2022	Ecological Economics
Desbureaux, S. & Damania, R.	Rain, forests and farmers: Evidence of drought induced deforestation in Madagascar and its consequences for biodiversity conservation	2018	Biological Conservation
Donnelly, A. & Rodríguez-Rodríguez, D.	Effectiveness of protected areas against land development in coastal areas of the Mediterranean global biodiversity hotspot	2022	Global Ecology and Conservation
Duncanson, L., et al.	The effectiveness of global protected areas for climate change mitigation	2023	Nature Communications
Eklund, J., Coad, L., Geldmann, J., & Cabeza, M.	What constitutes a useful measure of protected area effectiveness? A case study of management inputs and protected area impacts in Madagascar	2019	Conservation Science and Practice
Eklund, J., et al.	Contrasting spatial and temporal trends of protected area effectiveness in mitigating deforestation in Madagascar	2016	Biological Conservation
Elleason, M., et al.	Strictly protected areas are not necessarily more effective than areas in which multiple human uses are permitted	2021	Ambio

Author(s)	Title	Year	Journal
Feng, C.-T., et al.	Improving protected area effectiveness through consideration of different human-pressure baselines	2022	Conservation Biology
Feng, Y., et al.	Assessing the effectiveness of global protected areas based on the difference in differences model	2021	Ecological Indicators
Ferraro, P. J. & Hanauer, M. M.	Protecting Ecosystems and Alleviating Poverty with Parks and Reserves: 'Win-Win' or Tradeoffs?	2011	Environmental and Resource Economics
Ferraro, P. J., et al.	More strictly protected areas are not necessarily more protective: evidence from Bolivia, Costa Rica, Indonesia, and Thailand	2013	Environmental Research Letters
Ferraro, P. J., et al.	Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation	2015	Proceedings of the National Academy of Sciences
Ferraro, P. J., Hanauer, M. M., & Sims, K. R. E.	Conditions associated with protected area success in conservation and poverty reduction	2011	Proceedings of the National Academy of Sciences (PNAS)
Ford, S. A., et al.	Deforestation leakage undermines conservation value of tropical and subtropical forest protected areas	2020	Global Ecology and Biogeography
Gao, Y., et al.	Control selection for the assessment of protected areas in the Hengduan Mountains: A case study in Yunlong Tianchi National Nature Reserve, China	2020	Global Ecology and Conservation
Gaveau, D. L. A., et al.	Examining protected area effectiveness in Sumatra: importance of regulations governing unprotected lands	2012	Conservation Letters
Gaveau, D. L., et al.	Evaluating whether protected areas reduce tropical deforestation in Sumatra	2009	Journal of Biogeography
Gaveau, D. L., et al.	Reconciling Forest Conservation and Logging in Indonesian Borneo	2013	PLOS One
Geldmann, J., Manica, A., Burgess, N. D., Coad, L., & Balmford, A.	A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures	2019	PNAS
Ghoddousi, A., et al.	Effectiveness of protected areas in the Caucasus Mountains in preventing rangeland degradation	2024	Conservation Biology
Giudice, R., Börner, J., Wunder, S., & Cisneros, E.	Selection biases and spillovers from collective conservation incentives in the Peruvian Amazon	2019	Environmental Research Letters
Gizachew, B., Shirima, D. D., Rizzi, J., Kukunda, C. B., & Zahabu, E.	Conservation and Avoided Deforestation: Evidence from Protected Areas of Tanzania	2024	Forests

Author(s)	Title	Year	Journal
Gonçalves-Souza, D., Vilela, B., Phalan, B., & Dobrovolski, R.	The role of protected areas in maintaining natural vegetation in Brazil	2021	Science Advances
Graham, V., et al.	Southeast Asian protected areas are efective in conserving forest cover and forest carbon stocks compared to unprotected areas	2021	Scientific Reports
Gu, C., et al.	Forest Cover Change and the Effectiveness of Protected Areas in the Himalaya since 1998	2020	Sustainability
Hagen, S., et al.	Understanding variation in impacts from private protected areas across regions and protection mechanisms to inform organizational practices	2024	Conservation Biology
Hanauer, M. M. & Canavire-Bacarreza, G.	Implications of heterogeneous impacts of protected areas on deforestation and poverty	2015	Philosophical transactions B
Haruna, A., Pfaff, A., Van den Ende, S., & Joppa, L.	Evolving protected-area impacts in Panama: impact shifts show that plans require anticipation	2014	Environmental Research Letters
He, W., et al.	Inferring Economic Impacts from a Program's Physical Outcomes: An Application to Forest Protection in Thailand	2023	Environmental and Resource Economics
Henriksen, L. F., et al.	Strong collaborative governance networks support effective Forest Stewardship Council-certified community-based forest management: Evidence from Southeast Tanzania	2023	Global Environmental Change
Hernandez, S., Barnes, M. D., Duce, S., & Adams, V. M.	The impact of strictly protected areas in a deforestation hotspot	2021	Conservation Science and Practice
Herrera, D., Pfaff, A., & Robalino, J.	Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian Amazon	2019	Proceedings of the National Academy of Sciences
Honey-Rosés, J., Baylis, K., & Ramírez, M. I.	A Spatially Explicit Estimate of Avoided Forest Loss	2011	Conservation Biology
Hua, T., Zhao, W., Cherubini, F., Hu, X., & Pereira, P.	Upgrading protected areas can improve or reverse the decline in conservation effectiveness: Evidence from the Tibetan Plateau, China	2023	Science of the Total Environment
Huang, L., Shao, Q., & Liu, J.	Assessing the conservation effects of nature reserve networks under climate variability over the northeastern Tibetan plateau	2019	Ecological Indicators

Author(s)	Title	Year	Journal
Jagger, P., Sellers, S., Kittner, N., Das, I., & Bush, G. K.	Looking for Medium-term Conservation and Development Impacts of Community Management Agreements in Uganda's Rwenzori Mountains National Park	2018	Ecological Economics
Jenke, M.	Community-based forest management moderates the impact of deforestation pressure in Thailand	2024	Land Use Policy
Jiang M., et al.	Assessment of the conservation effectiveness of nature reserves on the Qinghai-Tibet plateau using human activity and habitat quality indicators	2024	Ecological Informatics
Jones, K. W. & Lewis, D. J.	Estimating the Counterfactual Impact of Conservation Programs on Land Cover Outcomes: The Role of Matching and Panel Regression Techniques	2015	PLOS One
Jones, K. W., et al.	Forest conservation incentives and deforestation in the Ecuadorian Amazon	2017	Environmental Conservation
Joppa, L. N. & Pfaff, A.	Global protected area impacts	2011	Proceedings of the Royal Society
Jusys, T.	Quantifying avoided deforestation in Pará: Protected areas, buffer zones and edge effects	2016	Journal for Nature Conservation
Jusys, T.	Changing patterns in deforestation avoidance by different protection types in the Brazilian Amazon	2018	PLOS One
Kere, E. N., et al.	Addressing Contextual and Location Biases in the Assessment of Protected Areas Effectiveness on Deforestation in the Brazilian Amazônia	2017	Ecological Economics
Kim, D.-H. & Anand, A.	Effectiveness of Protected Areas in the Pan-Tropics and International Aid for Conservation	2021	Geomatics
Koskimäki, T., Eklund, J., Moulatlet, G. M., & Tuomisto, H.	Impact of individual protected areas on deforestation and carbon emissions in Acre, Brazil	2021	Environmental Conservation
Koulgi, P. S., Clinton, N., & Karanth, K. K.	Extensive vegetation browning and drying in forests of India’s Tiger Reserves	2019	Scientific Reports
Kukkonen, M.O. & Tammi, I.	Systematic reassessment of Laos' protected area network	2019	Biological Conservation
Lamba, A., et al.	Climate co-benefits of tiger conservation	2023	Nature Ecology & Evolution
Lessmann, J., Geldmann, J., Fajardo, J., & Marquet, P. A.	The role of funding in the performance of Latin America’s protected areas	2024	PNAS

Author(s)	Title	Year	Journal
Li, B. V., Wu, S., Pimm, S. L., & Cui, J.	The synergy between protected area effectiveness and economic growth	2024	Current Biology
Li, G., et al.	Mixed effectiveness of global protected areas in resisting habitat loss	2024	Nature Communications
Li, Y. & Song, Z.	Have protected areas in China achieved the ecological and economic “win-win” goals? Evidence from the Giant Panda Reserves of the Min Mont Range	2022	Forest Policy and Economics
Liang, M., et al.	Assessing protected area’s carbon stocks and ecological structure at regional-scale using GEDI lidar	2023	Global Environmental Change
Liévano-Latorre, L. F., Brum, F. T., & Loyola, R.	How effective have been guerrilla occupation and protected areas in avoiding deforestation in Colombia?	2021	Biological Conservation
Liu, Y., Zhao, W., Zhang, Z., Hua, T., & Ferreira, C.	The role of nature reserves in conservation effectiveness of ecosystem services in China	2023	Journal of Environmental Management
Lonn, P., Mizoue, N., Ota, T., Kajisa, T., & Yoshida, S.	Using Forest Cover Maps and Local People’s Perceptions to Evaluate the Effectiveness of Community-based Ecotourism for Forest Conservation in Chambok (Cambodia)	2019	Environmental Conservation
Loveridge, R., et al.	Certified community forests positively impact human wellbeing and conservation effectiveness and improve the performance of nearby national protected areas	2021	Conservation Letters
Lwin, K. K., Ota, T., Shimizu, K., & Mizoue, N.	A country-scale analysis revealed effective landuse zoning affecting forest cover changes in Myanmar	2020	Journal of Forest Research
Mammides, C., Zotos, S., & Martini, F.	Quantifying the amount of land lost to artificial surfaces in European habitats: A comparison inside and outside Natura 2000 sites using a quasi-experimental design	2024	Biological Conservation
McNicol, I. M., et al.	Protected areas reduce deforestation and degradation and enhance woody growth across African woodlands	2023	Communications Earth & Environment
Meng, J., et al.	Anthropogenic vulnerability assessment of global terrestrial protected areas with a new framework	2023	Biological Conservation
Meng, Z., et al.	Post-2020 biodiversity framework challenged by cropland expansion in protected areas	2023	Nature Sustainability
Meyer, M., Klingelhoeffer, E., Naidoo, R., Wingate, V., & Börner, J.	Tourism opportunities drive woodland and wildlife conservation outcomes of community-based conservation in Namibia's Zambezi region	2021	Ecological Economics

Author(s)	Title	Year	Journal
Miranda, J. J., Corral, L., Blackman, A., Asner, G., & Lima, E.	Effects of Protected Areas on Forest Cover Change and Local Communities: Evidence from the Peruvian Amazon	2016	World Development
Miteva, D. A. & Pattanayak, S. K.	The effectiveness of protected areas in the context of decentralization	2021	World Development
Miteva, D. A., Ellis, P. W., Ellis, E. A., & Griscom, B. W.	The role of property rights in shaping the effectiveness of protected areas and resisting forest loss in the Yucatan Peninsula	2019	PLOS One
Mohebalian, P. M. & Aguilar, F. X.	Beneath the Canopy: Tropical Forests Enrolled in Conservation Payments Reveal Evidence of Less Degradation	2018	Ecological Economics
Mohebalian, P. M. & Aguilar, F. X.	Additionality and design of forest conservation programs: Insights from Ecuador's Socio Bosque Program	2016	Forest Policy and Economics
Mondal, P. & Southworth, J.	Evaluation of conservation interventions using a cellular automata-Markov model	2010	Forest Ecology and Management
Montoya-Zumaeta, J., Rojas, E., & Wunder, S.	Adding rewards to regulation: The impacts of watershed conservation on land cover and household wellbeing in Moyobamba, Peru	2019	PLOS One
Moreno, A., Neumann, M., Mohebalian, P. M., Thurnher, C., & Hasenauer, H.	The Continental Impact of European Forest Conservation Policy and Management on Productivity Stability	2019	Remote Sensing
Morgans, C. L., et al.	Improving well-being and reducing deforestation in Indonesia’s protected areas	2024	Conservation Letters
Muise, E. R., Coops, N. C., Hermosilla, T., & Ban, S. S.	Assessing representation of remote sensing derived forest structure and land cover across a network of protected areas	2022	Ecological Applications
Muñoz Brenes, C. L., Jones, K. W., Schlesinger, P., Robalino, J., & Vierling, L.	The impact of protected area governance and management capacity on ecosystem function in Central America	2018	PLOS One
Neal T.	Estimating the effectiveness of forest protection using regression discontinuity	2024	Journal of Environmental Economics and Management
Negret, P. J., et al.	Effects of spatial autocorrelation and sampling design on estimates of protected area effectiveness	2020	Conservation Biology
Nelson, A. & Chomitz, K. M.	Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods	2011	PLOS One

Author(s)	Title	Year	Journal
Neugarten, R. A., Rasolofoson, R. A., Barrett, C. B., Vieilledent, G., & Rodewald, A. D.	The effect of a political crisis on performance of community forests and protected areas in Madagascar	2024	Nature Communications
Nolte, C. & Agrawal, A.	Linking Management Effectiveness Indicators to Observed Effects of Protected Areas on Fire Occurrence in the Amazon Rainforest	2012	Conservation Biology
Nolte, C., Agrawal, A., & Barreto, P.	Setting priorities to avoid deforestation in Amazon protected areas: are we choosing the right indicators?	2013	Environmental Research Letters
Nolte, C., Agrawal, A., Silvius, K., & Soares-Filho, B.	Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon	2013	PNAS
Ota, T., Lonn, P., & Mizoue, N.	A country scale analysis revealed effective forest policy affecting forest cover changes in Cambodia	2020	Land Use Policy
Pacheco, A. & Meyer, C.	Land tenure drives Brazil's deforestation rates across socio-environmental contexts	2022	Nature Communications
Paiva, R. J. O., Brites R. S., & Machado R. B.	The Role of Protected Areas in the Avoidance of Anthropogenic Conversion in a High Pressure Region: A Matching Method Analysis in the Core Region of the Brazilian Cerrado	2015	PLOS One
Panlasigui, S., Rico-Straffon, J., Pfaff, A., Swenson, J., & Loucks, C.	Impacts of certification, uncertified concessions, and protected areas on forest loss in Cameroon, 2000 to 2013	2018	Biological Conservation
Papunen, S. & Eklund, J.	Comparing the performance of three satellite-based data products for assessing protected area effectiveness	2024	Global Ecology and Conservation
Pessôa, A. C. M., et al.	Protected areas are effective on curbing fires in the Amazon	2023	Ecological Economics
Pfaff, A., Robalino, J., Herrera, D., & Sandoval, C.	Protected Areas' Impacts on Brazilian Amazon Deforestation: Examining Conservation – Development Interactions to Inform Planning	2015	PLOS One
Pfaff, A., Robalino, J., Lima, E., Sandoval, C., & Herrera, L.	Governance, Location and Avoided Deforestation from Protected Areas: Greater Restrictions Can Have Lower Impact, Due to Differences in Location	2014	World Development
Pfaff, A., Robalino, J., Sanchez-Azofeifa, G. A., Andam, K. S., & Ferraro, P. J.	Park Location Affects Forest Protection: Land Characteristics Cause Differences in Park Impacts across Costa Rica	2009	The B.E. Journal of Economic Analysis & Policy

Author(s)	**Title**	**Year**	**Journal**
Pfaff, A., Robalino, J., Sandoval, C., & Herrera, D.	Protected area types, strategies and impacts in Brazil’s Amazon: public protected area strategies do not yield a consistent ranking of protected area types by impact	2015	Philosophical Transactions B
Pfaff, A., Santiago-Ávila, F., & Joppa, L.	Evolving Protected-Area Impacts in Mexico: Political Shifts as Suggested by Impact Evaluations	2016	Forests
Poor, E. E., Frimpong, E., Imron, M. A., & Kelly, M. J.	Protected area effectiveness in a sea of palm oil: A Sumatran case study	2019	Biological Conservation
Potapov, P., et al.	The last frontiers of wilderness: Tracking loss of intact forest landscapes from 2000 to 2013	2017	Science Advances
Powlen, K. A., Gavin, M. C., & Jones, K. W.	Management effectiveness positively influences forest conservation outcomes in protected areas	2021	Biological Conservation
Putraditama, A., Kim, Y. S., & Meador, A. J. S	Community forest management and forest cover change in Lampung, Indonesia	2019	Forest Policy and Economics
Rahman, M. F., & Islam, K.	Effectiveness of protected areas in reducing deforestation and forest fragmentation in Bangladesh	2021	Journal of Environmental Management
Ramirez-Reyes, C., Sims, K. R., Potapov, P., & Radeloff, V. C.	Payments for ecosystem services in Mexico reduce forest fragmentation	2018	Ecological Applications
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S3 Overview of counterfactual methods

Box 1 provides an overview of key counterfactual methods, including matching, difference-in-differences (DiD), synthetic control, regression discontinuity, instrumental variables, and interrupted time series. While these methods differ in their assumptions and data requirements (pre- or post-intervention data on outcomes available for treatment/control areas), they share the common goal of isolating the causal effects of PAs by addressing confounding factors. Interested readers are directed to O'Garra et al.[1] for a comprehensive typology of impact evaluation methodologies and how to choose between them.

Box 1. Overview of counterfactual methods, with a focus on quasi-experimental methods, for evaluating conservation impact

Counterfactual methods encompass diverse approaches aimed at investigating the causal relationships between interventions and their outcomes. This is done by contrasting actual outcomes following an intervention with projected outcomes of what would have happened had the intervention not taken place[2,3]. The hypothetical scenarios generated in this process are referred to as counterfactuals. For evaluating PAs, the focus has been on applying quasi-experimental methods that use different identification strategies to isolate the causal effect of protection by accounting for non-random PA placement.

Quasi-experiments: Quasi-experimental designs employ statistical techniques to address confounders and alternative explanations for observed treatment effects. These approaches are particularly useful when randomisation is not feasible, such as in cases where interventions have already been implemented in a non-random manner. Various quasi-experimental designs exist, and they vary in how the counterfactual is constructed, the underlying assumptions, and data requirements[1].

Matching can be used to pair each treated unit with an untreated unit that is as similar as possible in terms of covariates (i.e., factors affecting both the treatment assignment and the outcome). Matching assumes there are no unobserved confounders, but sensitivity tests can reveal how strong the effect of omitted variables would need to be to affect the results. The appeal of matching lies in its ability to use only post-intervention data, a crucial advantage for evaluating PAs established before satellite data became available.

Difference-in-differences (DID) is used to compare changes in outcomes over time between treatment units and their identified controls. Data before and after treatment implementation is needed; the controls can be identified using matching. Ideally, multiple pre-intervention observations are needed to validate that treatment and control groups would have followed similar trends if it were not for the intervention (parallel trend assumption).

The synthetic control method (SCM) can be used to create a comparison for a single treatment unit by combining several non-treated sites into a comparison unit called the synthetic control that mimics the treated unit before the intervention. Useful when only a single (or very few) treated observations exist but requires both pre- and post-intervention time series data.

Regression discontinuity design (RDD) uses a cutoff point that corresponds to an eligibility criterion for receiving the treatment to estimate the impact of an intervention. It then compares the outcomes for units just above or below this cutoff point. PA borders have been used as such a cutoff point. Like matching, does not require pre-intervention data, but can be used on it (e.g., dynamic RDD).

The Instrumental Variable (IV) approach introduces a variable i.e., the instrument, that predicts the treatment but does not independently affect the outcome of interest. This allows for uncovering the causal effect of the treatment variable on the dependent variable. Especially useful if there are omitted variables or reverse causal relationships.

Interrupted time series (ITS) is used to infer causality if data is only available for treatment sites. It requires long-term data both pre- and post an intervention and the counterfactual is constructed by extending the pre-treatment trend and comparing the observed trend to this projection.

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