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IMPROVING INDICATORS FOR MEASURING SPECIES
THREAT REDUCTION BY 2030 AND IMPLICATIONS FOR
THE 2030 TARGETS OF THE CONVENTION ON
BIOLOGICAL DIVERSITY

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*To Moi Soko Kaisamba, James Maju & Mohamed Kanneh
who have shown me the power of education*

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List of Acronyms

ATT	Average treatment effect on the treated
CBD	Convention on Biological Diversity
CEM	Coarsened Exact Matching
DiD	Difference-in-differences
GBF	Kunming-Montreal Global Biodiversity Framework
GDP	Gross domestic product
IEA	International Energy Agency
IUCN	International Union for the Conservation of Nature
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC	Intergovernmental Panel on Climate Change
LED	Light-emitting diode
MEA	Multilateral environmental agreement
NBSAP	National biodiversity strategies and action plans
PA	Protected area
PADDD	Protected area downgrading, downsizing, or degazettement
SSP	Shared socioeconomic pathways
STAR	Species Threat Abatement and Restoration Metric
UNCTAD	United Nations Trade and Development
VIF	Variance inflation factor
WD-OECM	World database on other effective conservation measures
WDPA	World database on protected areas

Summary

Biodiversity is essential for ecosystem stability and human well-being, but human activity has intensified pressures on nature, leading to biodiversity decline and ecosystem degradation. In response, international efforts have aimed to guide global action through the adoption of the Kunming-Montreal Global Biodiversity Framework. Within the Framework are a series of international biodiversity targets to achieve by 2030 alongside which is a standardised monitoring framework that pairs each target with a series of headline and complementary indicators to assess progress. However, many of these indicators are percentage coverage metrics that can only assess the quantitative aspects of targets without measuring their qualitative characteristics and have been increasingly critiqued for their limited ecological relevance.

Protected areas are an effective instrument for reducing land-use changes associated with biodiversity losses and are among the most widely used conservation strategies worldwide, yet assessing their ability to reduce human pressures remains difficult to measure. Evaluating the impact of protected areas requires methods that can assess what would have happened in the absence of protection such as statistical matching and fixed effect panel regressions. These quasi-experimental approaches help control for confounding variables and correct for biases in protected area placement, offering more reliable estimates of effectiveness.

Effective conservation strategies are shaped by ecological and political dynamics, which are becoming increasingly strained by global geopolitical instability. Scenario planning helps navigate these uncertainties by modelling potential futures and informing adaptive strategies. As urban populations grow and demand for natural resources intensifies, the factors affecting the capacity of protected areas to resist encroachment has become increasingly critical to evaluate. Therefore, the overarching goal of this PhD thesis is to explore how periods of political uncertainty affect long-term conservation outcomes and the achievement of international biodiversity targets, especially related to protected areas. To address this, the research is structured around three core objectives.

The first objective is to assess the influence that geopolitical shifts have on progress toward international biodiversity targets. Through a literature review and expert knowledge, the second chapter presents a policy perspective that discusses the impact of the escalation of the war in Ukraine in early 2022 on the drivers of biodiversity loss. Specifically, international policy changes to global trade routes, agriculture, and energy production made in response to the war were found to potentially impact socioeconomic scenarios used to set and assess biodiversity targets. The policies made in response to the war had immediate and far-reaching impacts on biodiversity, and policies that may seem regionally focused, in fact have worldwide implications through global-to-local-to-global linkages. The disruption to the global geopolitical landscape provides a window of opportunity for policy reform and the radical societal paradigm shift that is needed to

tackle the global biodiversity crisis. This result highlights the importance of re-evaluating the progress made towards goals set in multilateral environmental agreements with more focus on regionalisation scenarios to account for the increased uncertainty in the future storylines. Furthermore, I recommend developing new socioeconomic storylines that reflect the changes made to production and consumption patterns and which focus on a de-globalisation pathway. These would not replace the existing scenarios but would broaden our horizon to ensure that it encapsulates all possible futures, to increase our chances at meeting international biodiversity targets. Finally, I recommend mainstreaming biodiversity so that all policy decisions have a long-term vision that considers nature.

The second objective of this thesis is to evaluate the effectiveness of the global network of terrestrial protected areas on reducing human pressures within their boundaries. To achieve this, Chapter 3 uses nearest neighbour statistical matching at a 1km resolution across the globe to estimate the effect of protected areas on the threats identified on the IUCN Red List threat classification scheme. Overall, protected areas reduce, but do not eliminate threats to wildlife, and strict and small protected areas tend to be most effective even though they are situated in areas with lower pressures. Specifically, protected areas reduce ten of thirteen threats, including the presence of residential and commercial areas, annual and perennial non-timber crops, wood and pulp plantations, livestock farming and ranching, mining and quarrying, the abstraction of surface water, renewable energy, roads and railroads, utility and service lines, and light pollution. One threat, oil & gas drilling, is not significantly different compared to matched control areas, and two threats, fire and dams, have higher levels inside protected areas. Our results show substantial regional heterogeneity in the effectiveness of protected areas and the disconnection between effectiveness and endemic species richness. With these results, I recommend that countries with low protected area coverage should focus on establishing and expanding protected areas, while countries with high coverage should instead prioritize enhancing the effectiveness of existing areas, and this is particularly important in countries with high threatened endemic species richness.

The third objective is to examine the role of economic development and the strength of political systems on the performance of protected areas. Chapter 4 uses statistical matching and a panel dataset from 2000 to 2020 to assess the heterogeneity in protected area effectiveness in preventing urbanisation within their boundaries. It focuses on two aspects of urbanisation, specifically built area and nighttime light, and analyses the influence of the socioeconomic and political context on protected area performance. The results show that globally protected areas are effective at reducing land conversion to built-up areas, but not at limiting light pollution. Furthermore, the rate of economic development affects protected area performance, yet the political context matters more. Stronger protection for minorities through more liberal political institutions, and higher state capacity had the biggest effect on protected area effectiveness by significantly reducing built area and increasing nighttime light inside their boundaries. The political context does not uniformly influence all aspects of urbanisation in PAs but instead shapes

how and where urbanisation occurs. Ensuring the long-term success of PAs requires integrating them into stable, inclusive, and well-governed political systems. The results from this chapter can contribute to improving conservation policy, offering new insights into how regime change and leadership priorities can affect long-term conservation outcomes.

Chapter 5 discusses how the overall findings can assess how periods of political uncertainty affect conservation outcomes and may impact the achievement of international biodiversity targets. While area-based targets like 30×30 are important for setting ambition and guiding national strategies, the percentage-based aspects of them are insufficient in isolation. Integrating threat-based analyses helps bridge this gap by identifying where and how protection efforts contribute to biodiversity outcomes. There is a need to move beyond simply increasing protected area coverage and instead focus on improving management effectiveness and threat mitigation to achieve meaningful biodiversity outcomes. To address these challenges, protected areas must be integrated into broader landscapes and national policies, involve diverse stakeholders, and adapt to dynamic socio-political contexts to ensure long-term conservation success.

Biodiversity conservation must adapt to an increasingly complex and uncertain geopolitical landscape. Addressing the biodiversity crisis requires collective and coordinated global action, however this may become more difficult with increasing international instability with an increase in conflict, shifting alliances, and nationalism. Ultimately, the future of biodiversity conservation will depend not just on meeting fixed targets, but on the ability of global and national actors to adapt to shifting politics while remaining committed to the Kunming-Montreal Global Biodiversity Framework’s 2050 vision of a world of living in harmony with nature.

Chapter 1 – General Introduction

1.1 International frameworks for biodiversity conservation

The diversity of life on earth is essential to the integrity, stability, and resilience of ecosystems. Biodiversity supports a wide range of ecosystem services, including pollination, climate regulation, nutrient cycling, and food security (IPBES 2019). However, the increasing human population has put a strain on key ecosystem functions. Over the past 50 years, the human population has doubled and global trade has grown tenfold, contributing to the unsustainable use of energy and materials (IPBES 2019). This intensification of human activity has resulted in increased pressure on nature, contributing to high rates of species extinction and degradation of ecosystems globally (Ceballos et al. 2015).

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) identifies five direct drivers of biodiversity decline: land and sea use change, direct exploitation, climate change, pollution, and invasive alien species. These direct drivers are influenced by a range of underlying indirect drivers linked to human behaviours such as changes to demographic trends, governance structures, and global conflicts, among others. Tackling the biodiversity crisis requires action at both the national level and through a coordinated and collective international effort to address these drivers.

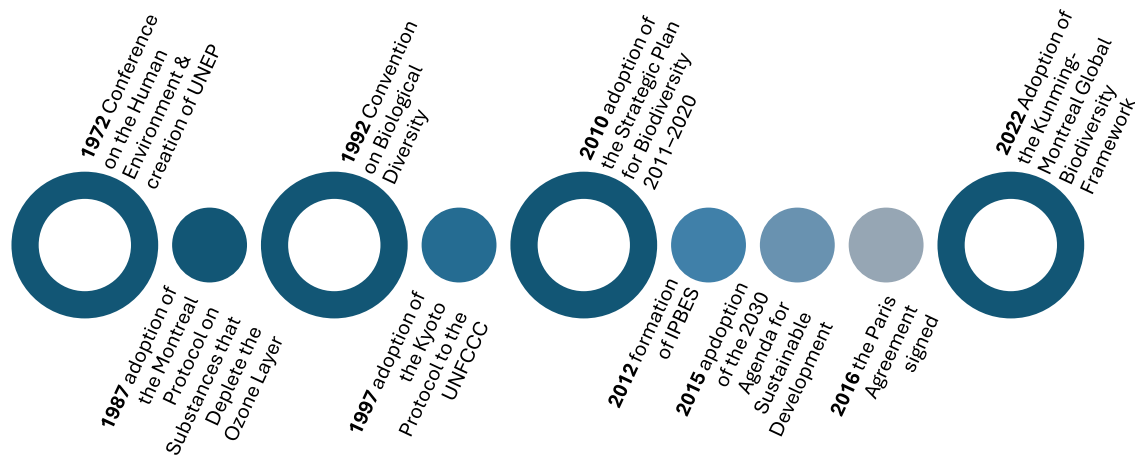


Figure 1.1: Timeline of important multilateral agreements and events that led to these agreements. Those directly related to the conservation agenda are labelled on top of the large circles, whereas those below the little circles show other international agendas that are linked to varying degrees to the international conservation agenda.

The international community has responded to these challenges through a series of multilateral efforts with a rapid increase of regional and global environmental agreements in the 1960s and 1970s. These earlier agreements were focused on the protection of migratory species and the prevention of marine pollution (Kuokkanen et al. 2016). In 1972 the UN held the Conference on the Human Environment and since then over 1500 regional and international agreements have been signed (Figure 1.1). One of the most notable is the Convention on Biological Diversity (CBD), established in 1992, which became the foundation for the next 30 years of international cooperation to safeguard our shared natural resources. In 2010, the CBD adopted the Strategic Plan for Biodiversity 2011–2020, which included the Aichi Biodiversity Targets, developed to advance the “decade on biodiversity”. The Strategic Plan was created to provide a framework to guide national policy in a more coordinated and sustainable direction.

Despite substantial mobilisation of resources and increased policy attention, none of the 20 Aichi Targets were fully achieved at the global level (CBD 2020). Even at the national level there was limited progress particularly with the targets relating to pollution, production and consumption, and traditional knowledge (Maney et al. 2024). However, positive outcomes were realised thanks to the Strategic Plan. For example, more than 90 countries integrated biodiversity values into their national accounting systems, global deforestation declined by approximately one-third relative to the previous decade, and protected area (PA) coverage expanded significantly (CBD 2020). Although there was limited success in achieving the targets, the momentum that the Strategic Plan created enabled the development of an even more ambitious set of goals and targets.

In 2022, the Kunming-Montreal Global Biodiversity Framework (GBF) was adopted as a successor to the Strategic Plan for Biodiversity with a global vision of a world living in harmony with nature by 2050. It consists of four long-term goals for 2050 and 23 targets to achieve by 2030. Included in the GBF are specific targets designed to address each of the five main direct drivers of biodiversity loss (Table 1.1).

However, the achievement of the GBF will require more than incremental policy changes. The global community of policy makers needs to consider and include the knowledge and rights of Indigenous peoples and local communities, who are stewards of some of the most important remaining natural lands (Parks & Tsoumani 2023). The GBF also explicitly calls for “transformative change”, or a fundamental shift in how the anthropogenic world operates including reconfiguring production and consumption patterns, realigning financial and policy incentives, and addressing global inequities (Turnhout et al. 2021).

1.2 Mechanisms and indicators for monitoring the GBF

Achieving transformative change will also depend on learning from past efforts. While the Strategic Plan for Biodiversity introduced a common global framework focused on long-term biodiversity conservation, it had significant limitations in how progress was

Table 1.1: The main direct drivers of biodiversity loss as identified in the Global assessment report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES 2019) are each addressed with a dedicated target within the GBF.

Direct driver	Kunming-Montreal Global Biodiversity Framework target
<i>Land-use change</i>	TARGET 1: Ensure that all areas are under participatory integrated biodiversity inclusive spatial planning and/or effective management processes addressing land and sea use change, to bring the loss of areas of high biodiversity importance, including ecosystems of high ecological integrity, close to zero by 2030, while respecting the rights of Indigenous peoples and local communities.
<i>Overexploitation</i>	TARGET 5: Ensure that the use, harvesting and trade of wild species is sustainable, safe and legal, preventing overexploitation, minimizing impacts on non-target species and ecosystems, and reducing the risk of pathogen spill-over, applying the ecosystem approach, while respecting and protecting customary sustainable use by Indigenous peoples and local communities.
<i>Invasive alien species</i>	TARGET 6: Eliminate, minimize, reduce and or mitigate the impacts of invasive alien species on biodiversity and ecosystem services by identifying and managing pathways of the introduction of alien species, preventing the introduction and establishment of priority invasive alien species, reducing the rates of introduction and establishment of other known or potential invasive alien species by at least 50 per cent, by 2030, eradicating or controlling invasive alien species especially in priority sites, such as islands.
<i>Pollution</i>	TARGET 7: Reduce pollution risks and the negative impact of pollution from all sources, by 2030, to levels that are not harmful to biodiversity and ecosystem functions and services, considering cumulative effects, including: reducing excess nutrients lost to the environment by at least half including through more efficient nutrient cycling and use; reducing the overall risk from pesticides and highly hazardous chemicals by at least half including through integrated pest management, based on science, taking into account food security and livelihoods; and also preventing, reducing, and working towards eliminating plastic pollution.
<i>Climate change</i>	TARGET 8: Minimize the impact of climate change and ocean acidification on biodiversity and increase its resilience through mitigation, adaptation, and disaster risk reduction actions, including through nature-based solution and/or ecosystem-based approaches, while minimizing negative and fostering positive impacts of climate action on biodiversity.

measured and reported (Maney et al. 2024). The insights learned from the Strategic Plan are critical for informing the GBF, ensuring that indicators not only reflect ecological complexity but also support more equitable and effective conservation outcomes.

The wording of conservation targets has a direct influence on their achievement. For example, the Aichi Targets that were more measurable, unambiguous, realistic and scalable were also those that had more progress when assessed by both the Global Biodiversity Outlook and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services reports (Green et al. 2019). Moreover, measurable targets within the Strategic Plan led to better implementation and having a common framework allowed countries to align their national biodiversity strategies and action plans (NBSAPs) leading to more international collaboration (Plumptre et al. 2024; Robinson et al. 2024; McGowan et al. 2024; Burgess et al. 2024). However, many of the indicators used to monitor progress towards the Aichi Targets failed to capture the full complexity of biodiversity challenges and the broader drivers of biodiversity loss (Obura 2023; Maney et al. 2024; McGowan et al. 2024). Some of the Aichi targets have also been criticized for being vague or poorly defined which limited actionable insights and measurable outcomes (Cook et al. 2024; Robinson et al. 2024; McGowan et al. 2024). Unlike climate targets, which rely on a relatively well-defined and easy to measure biophysical metric (e.g., atmospheric CO₂ concentrations), biodiversity targets remain inherently multidimensional and difficult to measure (Carroll & Noss 2022).

Historically, measurable targets such as the phase-out of chlorofluorocarbons under the Montreal Protocol have been more successfully achieved compared to targets that only have qualitative outcomes (Maxwell et al. 2015). Percentage-protected targets (such as Aichi Target 11 which called for 17% protection of land and 10% of sea) appear effective in practice because they are simple to communicate and monitor (Carroll & Noss 2022). However, achieving only the quantitative aspects of the target without measuring the qualitative characteristics, i.e. effective and equitable protection, have been increasingly critiqued for their limited ecological relevance (Geldmann et al. 2021; Carroll & Noss 2022). Moreover, for PAs coverage-based indicators do not inherently reflect improved conservation outcomes (Maron et al. 2021; Pressey et al. 2021). Simply increasing the area under protection, without assessing ecological representation, management effectiveness, or threat reduction, can overestimate conservation success.

The GBF has improved on the previous framework by developing a standardized monitoring framework to stand alongside it. This monitoring framework ensures consistency and comparability across countries, improving transparency and accountability (Plumptre et al. 2024; Maney et al. 2024). It includes a broader range of indicators, addressing equity, financial mobilisation, cross-sector collaboration, and drivers of biodiversity loss (Obura 2023; Burgess et al. 2024). An important improvement is that the indicators are explicitly tied to measurable biodiversity outcomes (Cook et al. 2024; Robinson et al. 2024). For example, species-focused indicators rely on scientifically

validated tools like the Red List Index and the Living Planet Index to track trends in extinction risk and species abundance (McGowan et al. 2024; Burgess et al. 2024).

To complement species-focused indicators, threat-based metrics have gained prominence. Threat mapping involves spatially explicit assessments of factors such as land-use change, exploitation, pollution, and climate hazards (Ridley et al. 2024). The GBF monitoring framework includes some complementary indicators that focus on measuring direct threats to biodiversity, such as the percent of total land area that is under cultivation, and air pollution emissions. These indicators are particularly valuable because they highlight where and how threats are distributed across the landscape.

1.3 Monitoring in a turbulent world

Effective monitoring depends on broader political and institutional factors. The global governance landscape is currently undergoing significant shifts, driven by geopolitical tensions and economic instability (Scholz 2023; Vincent et al. 2024). Multilateral environmental agreements (MEAs) including the CBD, face increasing strain in this context. For example, recent geopolitical tensions have worsened climate and environmental governance in the Arctic by limiting transboundary cooperation, including among non-state actors (Guo et al. 2024), highlighting the impact that such changes can have on MEAs.

Ultimately, improving biodiversity indicators is not just a technical task, it is a deeply political effort. It requires alignment between global ambitions and the realities of local contexts, including the capacity to respond to emerging risks, societal values, and long-term development goals. Given the uncertainties surrounding global implementation, scenario planning can help navigate uncertainty by exploring plausible futures under different assumptions about socioeconomic, political, and environmental drivers.

Four major types of scenario approaches are commonly used in biodiversity-related MEAs which are developed by modelling indirect and direct drivers to predict biodiversity trends (IPBES 2016). The first type of scenario approach is by extrapolation from current and historical trends which projects future biodiversity outcomes. This method is used in the Global Biodiversity Outlook (CBD 2020) to assess the implications of business-as-usual pathways and to model future drivers and impacts. The second combines qualitative narratives through plausible socioeconomic storylines with quantitative models to evaluate the impact of different socioeconomic futures. The Shared Socioeconomic Pathways (SSPs), widely used in Intergovernmental Panel on Climate Change (IPCC) assessments, provide a structured framework for this approach (IPCC 2022). The SSPs fall within four broad archetypes that can be mapped on two axes of uncertainty; whether global governance moves towards a more regional or globalised scenario and whether policy is focused on the environment or on the economy. Third, using policy intervention scenarios which build upon socioeconomic pathways such as SSPs, outcomes are predicted by introducing specific policy changes or conservation interventions (Moss et al. 2010). These

are then tested to identify their potential impact and effectiveness on biodiversity outcomes. The fourth scenario type is backcasting from a desired future state where long-term biodiversity or sustainability goals are set for the future (Dreborg 1996), then working backward to identify plausible pathways and enabling conditions for the achievement of those outcomes. Furthermore, the newly developed Nature Futures Framework allows for scenario development that focuses on futures that have positive nature outcomes related to nature's contribution to nature, to people, and to culture (Pereira et al. 2020; Kim et al. 2023).

Although these methods provide an array of possible futures, even the most comprehensive scenario frameworks face limitations in capturing stochastic events, such as pandemics, geopolitical conflicts, or natural disasters, that can substantially modify trajectories (CBD 2020). These events introduce layers of uncertainty that challenge deterministic models and highlight the importance of adaptive, resilient monitoring systems that can respond to unexpected changes.

1.4 Site-based conservation: the role of protected areas in threat mitigation

PAs are clearly defined geographical spaces managed to achieve the long-term conservation of nature, along with associated ecosystem services and cultural values (Dudley 2013). They serve as critical tools for preserving biodiversity by safeguarding habitats, preventing species loss, and maintaining ecological processes. Beyond their ecological importance, PAs also provide co-benefits such as climate regulation, clean water, and support for local livelihoods (Watson et al. 2014).

Within the GBF, PAs have their own dedicated target of protecting at least 30% of the world's land and oceans effectively and equitably by 2030, known as "30x30". Despite this international acceptance of their importance for biodiversity conservation, the effectiveness of PAs in reducing threats to species remains uncertain without robust impact indicators (Geldmann et al. 2021). PAs are widely regarded as the most effective in situ conservation tool to address the ongoing biodiversity crisis at a global scale (Langhammer et al. 2024). However, the assumption that PA coverage directly leads to improved biodiversity outcomes has been increasingly challenged (Pressey et al. 2015).

Metrics such as percentage coverage or total area of PAs can be misleading when used as indicators of conservation success, as they fail to capture the actual biodiversity benefits achieved (Pressey et al. 2015). Higher biodiversity levels within PAs may not be caused by protection itself but may reflect the non-random placement of PAs in remote or inaccessible locations less exposed to human pressures (Joppa & Pfaff 2009). PAs are often designated in areas of inherently low threat, such as at high elevations, distant from roads, or with low agricultural value, which can give the impression of effectiveness. The extent

of this spatial bias was highlighted by Andam et al. (2008), who found that simple inside-outside comparisons led to a 65% overestimation of PA effectiveness.

Moreover, protection alone may not prevent biodiversity loss if it displaces pressures like logging and hunting into unprotected areas, a phenomenon known as leakage (Ewers & Rodrigues 2008). Conversely, well-managed PAs can generate positive spillover effects, enhancing biodiversity in adjacent landscapes (Ribas et al. 2020; Black & Anthony 2022; Brodie et al. 2023). Understanding whether PAs truly contribute to biodiversity conservation requires disentangling the effects of protection from confounding factors like habitat quality and accessibility.

Well-managed PAs are significantly more successful at conserving biodiversity (Leverington et al. 2010), prompting the development of Protected Area Management Effectiveness (PAME) evaluations. These are systematic assessments of how well PAs are achieving their conservation goals (Hockings 2006). Since the 1990s, a variety of PAME methodologies have emerged, many based on the IUCN World Commission on Protected Areas framework which evaluates six elements: context, planning, inputs, process, outputs, and outcomes (Leverington et al. 2010). These methodologies, such as the Management Effectiveness Tracking Tool (METT) and RAPPAM, often use self-assessment surveys supplemented by quantitative data to guide PA managers and improve accountability and conservation outcomes. However, linking management effectiveness with conservation outcomes is difficult both due to a lack of data on trends of biodiversity, and because there is a lack of guidance on how to measure and report the effectiveness of PAs and OECMs (Geldmann et al. 2021). Consequently, the global community has not been able to reliably track whether the PA estate has achieved its conservation objectives in an effective manner.

To better evaluate conservation outcomes, threat mapping has become a valuable tool. Rather than focusing on species distributions, these maps are derived from spatial patterns of threats or pressures, including both anthropogenic drivers (e.g., habitat loss, exploitation) and natural events (e.g., climate change, storms), which are often exacerbated by human influence (Salafsky et al. 2008). Because threats vary across space and taxa, tools like the International Union for the Conservation of Nature (IUCN) Red List threat classification scheme provide a standardised framework to assess historical, ongoing, and future pressures (Kearney et al. 2020; Salafsky et al. 2025). This enables more targeted conservation responses, such as those guided by the STAR (Species Threat Abatement and Restoration) metric, which directly links threat reduction to extinction risk mitigation (Mair et al. 2021). This is particularly important as new PAs are increasingly being designated in more degraded or human-impacted landscapes due to the scarcity of pristine, unprotected habitats (Brodie et al. 2023).

However, not all threats can be addressed by PA establishment alone, as they do not exist in solitude and are open systems integrated into the wider landscape. PAs are embedded in larger ecological and human systems and may fail to shield species from

pervasive threats like land conversion or climate change (Nowakowski et al. 2023). The assumption that coverage by PAs equates to the removal of threats is flawed, underscoring the need to distinguish between coverage and true conservation impact (Pressey et al. 2015).

Efforts to map threats at finer scales, such as those by Harfoot et al. (2021), offer valuable insights by overlaying IUCN species range maps to create generalised threat layers. However, these analyses often overlook the heterogeneity of pressures within species' ranges, potentially misrepresenting where conservation efforts are most urgently needed. Ultimately, for PAs to fulfil their intended conservation role, more nuanced, data-driven evaluations are essential, especially those that consider spatial biases and threat dynamics to assess biodiversity outcomes.

1.5 Counterfactual impact evaluation methods

To understand the impact of an intervention, an evaluation of the outcome that would have occurred in the absence of that intervention, or a counterfactual, is needed. The counterfactual can be measured through baselines, measures of covariates, or control groups (Kleijn & Sutherland 2003). In such evaluations, confounders need to be controlled for since effects may be present that occurred in parallel to the intervention that could have impacted the outcome and hidden the true effect of the intervention (Ferraro & Pattanayak 2006). These could include factors like historical trends or underlying geophysical or socioeconomic factors. Although including a counterfactual in impact evaluation is common in other scientific fields, in conservation biology its uptake has started only in the past two decades with a growing number of calls to increase its use (Ferraro & Pattanayak 2006; Ferraro & Pressey 2015; Baylis et al. 2016; Coetzee & Gaston 2021).

To understand the causal effect of an intervention, it must be compared to a specific alternative, therefore a clearly defined control group or location that does not receive the treatment is required. There are many statistical approaches to identify causal effects and they can all be classified into one of four main categories (Ferraro & Hanauer 2014). The first are experimental designs that rely on researchers randomly assigning the treatment to some units and not others. Its slow adoption in conservation science might be due to the challenge of implementing randomization into experimental design. For example, for financial and political reasons, it is not realistic to set up a conservation program that offers support at random instead of focusing on those places that need it most (Ferraro & Pattanayak 2006). Furthermore, with regards to PA assessments, the designation of a PA is non-random (Joppa & Pfaff 2009) and therefore inhibits the ability to use inside-outside comparisons or random control trials.

The second depends on naturally occurring sources of variation that are unrelated to potential outcomes and includes methods such as instrumental variables and discontinuities. An instrumental variable is something that influences whether a location

or unit receives the program but does not affect the outcome in any other way. However, finding a valid and credible instrument is often very difficult (Ferraro & Hanauer 2014). Even when a valid instrument is available, instrumental variable methods only estimate a local average treatment effect which is the effect of the program on just the subset of units influenced by the instrument. A different instrument would likely identify a different subset, and therefore a different estimate of the effect. This makes it hard to compare findings across studies. Similarly, regression discontinuity designs also take advantage of known rules or thresholds that determine program exposure. While these can be strong designs, they are again limited by data availability and are dependent on the structure of the outcome to have discontinuities (Ferraro & Hanauer 2014).

The third design estimates the treatment through a set of mechanisms by identifying and measuring the steps through which the treatment influences outcomes. This involves first estimating how the program affects an intermediate factor, the mechanism, and then how that factor affects the outcome. This method relies on having a strong understanding of a theory of change about all the variables that may affect the outcome and are highly context specific (Ferraro & Hanauer 2014).

The fourth design relies on statistical tools to define a control using methods like regression, matching, or fixed effects. The key assumption is that any differences affecting outcomes between the treatment and control groups are either observable variables or are unobservable variables that do not change over time. By adjusting for these differences, we can estimate what would have happened without the treatment. Therefore, it is generally more feasible to employ quasi-experimental designs that fall into this design category. However, they may sometimes require advanced and complex statistical analyses, and can be difficult to tease apart the effects from underlying variables and the intervention (Ribas et al. 2020).

This fourth type of quasi-experimental designs are especially useful in conservation science since they can be applied post-intervention by creating a control group based on similar characteristics as the intervention group (Jones & Lewis 2015). This is of particular importance when assessing the impact of PAs since they are known to be biased in their distribution across the landscape, favouring areas that are unsuitable for economic activities (Joppa & Pfaff 2009). Andam et al. (2008) conducted one of the first studies to adopt a counterfactual design in the evaluation of PA impact and found that without this approach the non-random placement of PAs largely overestimated their impact. Since then, studies have continued to highlight the overestimation of impact found by those analyses that do not use a counterfactual, emphasizing their importance for observing a more reliable estimate of impact (Pressey et al. 2015; Ribas et al. 2020; Brodie et al. 2023). In this thesis, two counterfactual methodologies are applied: statistical matching, and fixed effect panel regression, both of which are described in detail in the following sections.

1.5.1. Statistical matching

Statistical matching is a type of quasi-experimental design that creates a control group made up of observations that did not receive the intervention, but are otherwise similar on average to treatment sites (Ferraro & Pattanayak 2006). Matching creates a control group based on observable variables thought to influence receiving the treatment and the outcome of interest (Ferraro 2009). Once an appropriate control group has been identified through matching, the impact of the intervention can be estimated by a t-test on the difference in means (Figure 1.2a), or through a cross-sectional regression (Schleicher et al. 2020).

Matching methods have slowly been increasing in conservation biology over the past 10 years, however the studies have predominantly focused on evaluating the impact of PAs on deforestation in the tropics (Andam et al. 2008; Eklund et al. 2016; Ribas et al. 2021; Black & Anthony 2022), and payments for ecosystem services (Arriagada et al. 2012; Oliveira Fiorini et al. 2020).

1.5.2. Fixed effect panel regression

Panel regressions estimate what would have happened without treatment by tracking how outcomes change over time for both treated and untreated observations, while controlling for unobserved, time-invariant differences between units (Goodman-Bacon 2021). Unlike matching, which builds a control group based on statistical similarity, panel approaches rely on both the timing of the treatment and differences across datapoints to infer the treatment effect (Jones & Lewis 2015).

A difference-in-differences (DiD) model is a type of fixed effect panel regression that defines treatment and control groups to estimate the causal effect of an intervention (Goodman-Bacon 2021). It looks at both the differences in outcomes before and after a treatment as well as between treatment and control groups (Figure 1.2b). To conduct a DiD regression, time-series data is needed on the outcome of interest since data must be available before and after the intervention. The main advantage of this method is that it can control for both observable and unobservable bias between the treatment and control groups (Jones & Lewis 2015).

Although the use of a counterfactual has been growing rapidly in conservation science, relatively few studies have adopted fixed effects panel methods (but see Feng et al. 2021; Cisneros et al. 2022; Li et al. 2024; Martínez & Melo 2025). When using DiD to assess PA effectiveness, it inherently accounts for time-invariant covariates such as soil quality or elevation, as well as observable sources of bias and is therefore more robust than statistical matching (Jones & Lewis 2015). Additionally, using statistical matching as a first step followed by a fixed effects panel regression is one of the most robust methods to estimate the impact of a conservation intervention (Ferraro & Miranda 2017). However, if time-invariant unobservables are not present, matching combined with differences in means

leads to similar estimates of effectiveness as matching combined with fixed effects panel regression (Jones & Lewis 2015).

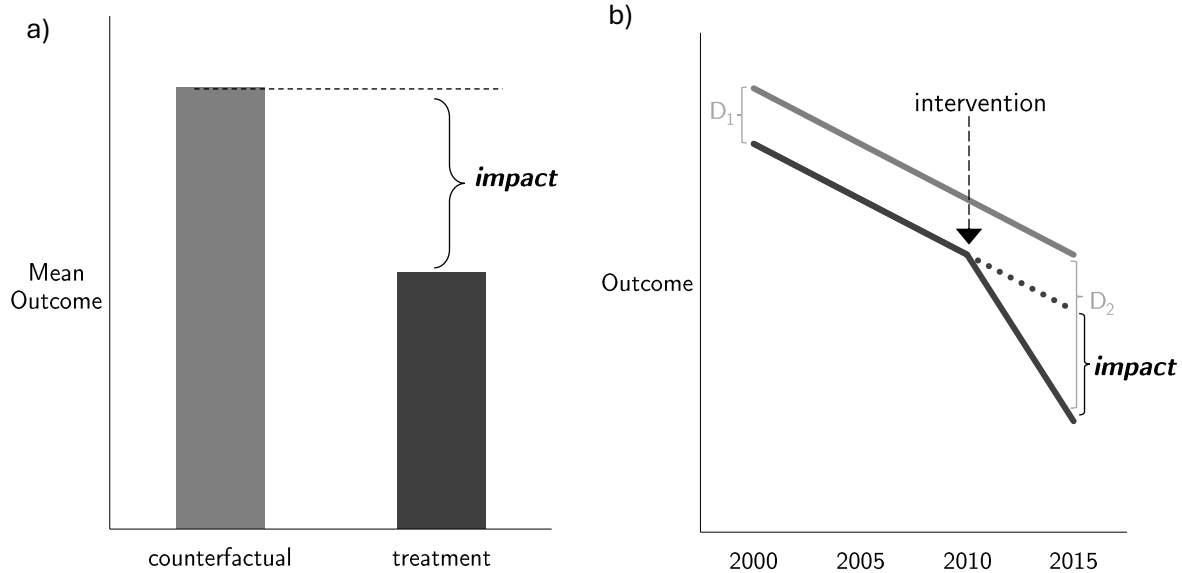


Figure 1.2: Two common methods for estimating impact with a counterfactual. (a) After creating a counterfactual group with statistical matching, the intervention’s impact can be estimated by comparing the difference in mean outcomes (adapted from Pressey et al. 2015). (b) With DiD estimates capture both the temporal changes within groups and the differences between treated and untreated groups. In this case the impact is equal to the difference between D_2 and D_1 , which is why it is called “difference-in-differences”. The lighter grey line is the control site that is never treated, and darker grey received the treatment at the intervention time (adapted from Goodman-Bacon 2021).

A common extension of the DiD approach is the two-way fixed effects model, which allows researchers to study multiple groups over multiple time periods. This method controls for differences across both groups and time by including fixed characteristics of each (Goodman-Bacon 2021). In practice, two-way fixed effects models are widely used to estimate causal effects with panel data, however, if heterogeneity exists it can produce biased results. Treatment effect heterogeneity can occur if the impact of treatment changes over time or has delayed effects (Goodman-Bacon 2021). Specifically for PAs this can be a concern as there is a noted time lag for effects to appear after designation with some studies showing that this varies per PA and can take up to six years (Li et al. 2024). This approach also requires annual data on time-variant variables that are largely missing at a global scale. Although this is a powerful analytical tool, its potential for bias made it unsuitable for assessing the impact of PAs in this thesis.

1.6 Thesis outline

This thesis explores the central question: *How do periods of political uncertainty affect long-term conservation outcomes and the achievement of international biodiversity targets?* To address this, the research is structured around three core objectives:

1. To assess the impact of stochastic geopolitical events on progress toward international biodiversity goals.
2. To evaluate the effectiveness of the global network of terrestrial PAs on reducing human pressure within their boundaries.
3. To examine the influence of the socioeconomic and political context on the performance of PAs, considering how national governance and institutional capacity shape conservation outcomes.

In Chapter 2, I examine how the escalation of the war in Ukraine has impacted the direct drivers of biodiversity loss and created new uncertainties for achieving international biodiversity targets. The chapter underscores the importance of scenario-based approaches for evaluating progress, especially with regards to the GBF, where the direct drivers of biodiversity loss are directly linked to its targets, and SSPs are integrated into the monitoring framework.

Chapter 3 focuses on the role of PAs in reducing pressure on species by evaluating the threats to biodiversity that persist within PA boundaries. Using a matching approach to construct a counterfactual, the chapter assesses how PAs mitigate the threats identified on the IUCN Red List Threat Classification Scheme. The chapter has direct implications for monitoring progress toward GBF Targets 3 (area-based conservation) and 4 (species conservation), providing a more nuanced understanding of how PAs function as a key mechanism for reducing extinction risk.

In Chapter 4, I investigate the growing threat of urbanisation to biodiversity by assessing how effectively PAs limit human encroachment, specifically the expansion of built infrastructure and nighttime light intensity. Using time-series data and DiD panel regression models with a matched dataset, this chapter provides a more rigorous evaluation of PA effectiveness over time, with direct relevance to monitoring progress toward GBF Target 3 (area-based conservation) and Target 12 (inclusive and sustainable urbanisation). The chapter also explores how socioeconomic and political factors, such as GDP growth rate and political stability, shape conservation outcomes, raising questions about how national governments balance environmental protection with development goals.

In the final chapter, I synthesize the findings from the preceding chapters to highlight how the findings may contribute to improved global biodiversity governance. Specifically, I emphasize that global indicators must do more to account for political and economic uncertainty, as these factors significantly influence conservation outcomes but are often

underrepresented in monitoring frameworks. Furthermore, I consider the conservation relevance of the results and how they relate to species extinction risk. Lastly, I discuss the wider policy implications, acknowledging that the biodiversity crisis requires a coordinated and collective international effort that needs to account for an increasingly complex and uncertain world.

Chapter 2 – The war in Ukraine is changing plausible future socioeconomic scenarios leading to an unexplored outlook for biodiversity

Vincent, C., A. Cristiano, I. Cuadros-Casanova, M. Pacifici, C.D. Soria, L. Tedeschi, M. Beekmann, A. D’alessio, P.M. Lucas, D. Nania & C. Rondinini. (2023). The war in Ukraine is changing plausible future socioeconomic scenarios leading to an unexplored outlook for biodiversity. *Conservation Science and Practice*: e13056.

Abstract

SSPs are a key tool in predicting biodiversity scenarios and in the subsequent design of environmental policies. Here, we discuss how recent policy changes to global trade routes, agriculture, and energy production in response to the war in Ukraine are impacting socioeconomic scenarios used to set and assess biodiversity targets. We also discuss how the disruption to the global geopolitical landscape provides a window of opportunity for policy reform and the radical societal paradigm shift that is needed to tackle the global biodiversity crisis. We call for the re-evaluation of biodiversity targets with newly developed scenarios that reflect the changes made to production and consumption patterns. We also recommend establishing national biodiversity working groups to screen proposed policies for their potential risks to the drivers of biodiversity change, since policy decisions made in response to the war that seemingly are far removed from the environment can have lasting impacts on nature.

2.1 Introduction

MEAs, such as the GBF (CBD 2022), and global biodiversity assessments like the Global Biodiversity Outlook 5 (CBD 2020), are some of the main international tools used to address the current biodiversity crisis. MEAs are composed of goals and targets based on a scientific understanding of biodiversity trends and the effects of future changes to drivers and pressures (IPBES 2019).

Progress towards achieving these targets is assessed by modelling direct drivers of biodiversity loss according to future plausible socioeconomic scenarios or by extrapolating data from the past (IPBES 2019). These scenarios are key to understanding the importance of future drivers of change such as climate and land use change, and to design efficient policies to minimize the loss of biodiversity and associated ecosystem services (O’Neill et al. 2014). Currently, five plausible future scenarios, known as the SSPs, have been developed (O’Neill et al. 2014). These scenarios fall within four broad archetypes

that can be mapped on two axes of uncertainty: whether humanity moves towards a more regional or globalised world, and whether policy is focused on protecting the environment or economic interests (Hunt et al. 2012) (Figure 2.1). The storylines used to build these scenarios describe aspects of society that are difficult to project quantitatively, such as political stability and environmental awareness, and provide underlying logic to the quantifiable elements (O'Neill et al. 2017).

Under the context of the war in Ukraine, countries and corporations are drastically changing their policies resulting in a potential shift towards de-globalisation (Mariotti 2022; Coles et al. 2023). Such a reversal of globalisation trends has happened before, as was the case with World War I (Ferguson 2005). De-globalisation could cause a paradigm shift towards socioeconomic scenarios that have been interpreted as quite extreme and therefore less likely. These scenarios include Eco-communalism, which envisions sustainable regionalism with high equity and low economic growth, and Fortress World, that describes a divided world with an authoritarian and inequitable future where human well-being and the environment are sacrificed to meet security demands (Hunt et al. 2012) (Figure 2.1).

Some reactive policy changes linked to global trade, agriculture, and energy production have been introduced and key economic indicators such as Gross Domestic Product and inflation have suffered drastic changes since the escalation of the war with the 2022 invasion of Ukraine (Guenette et al. 2022). These unprecedented changes do not fit properly within the established SSP narratives. We are moving into a new and unexplored plausible scenario which can have knock-on effects on direct drivers of biodiversity change globally, namely climate and land-use change, invasive and alien species, over-exploitation of natural resources, and pollution (Figure 2.2). These changes will distort the interpretation of our collective progress towards achieving biodiversity goals, since the scenarios used to formulate and implement these targets will already be outdated (Nicholson et al. 2019). Additionally, the trends of the past are no longer well placed to forecast the future, and these types of extrapolation analyses now contain more uncertainty.

Here we discuss how short-term policy decisions made in response to the war in Ukraine are impacting the storylines used to create socioeconomic scenarios, and the indirect effects they have on direct drivers of biodiversity loss globally. We focus on the impact of the war in Ukraine because the international policy decisions in response to the war have been immediate, far-reaching, and have influenced the global economy in an unprecedented way (Guenette et al. 2022). We also explore the possible shift in our trajectory along scenario archetypes and the potential that this crisis creates for the transformational change needed to improve the outlook of biodiversity worldwide.

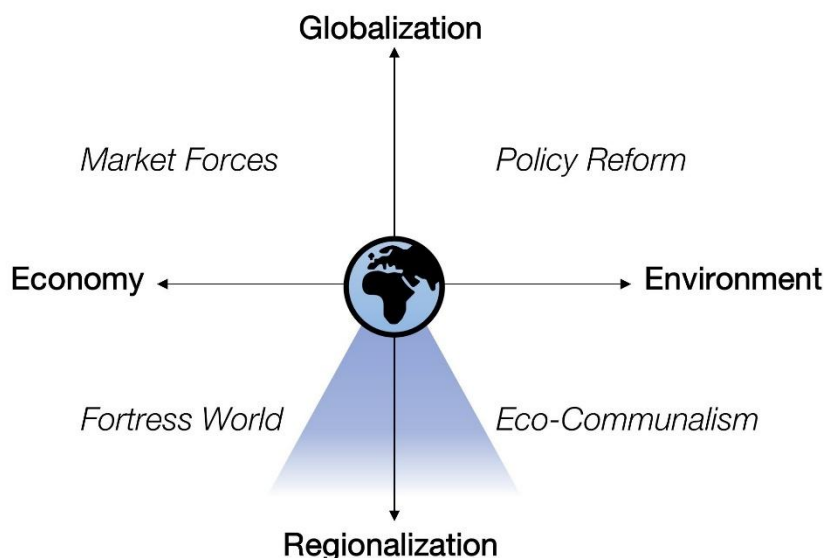


Figure 2.1: Progress towards achieving targets outlined in multilateral environmental agreements is assessed by modelling direct drivers of biodiversity loss according to future plausible socioeconomic scenarios that fall into four broad archetypes (*italic*) along two axes of uncertainty (**bold**). The shaded area shows the world's potential direction along these axes after the consequences of the war in Ukraine.

2.2 Changes to drivers of biodiversity loss

2.2.1. *Disrupted trade routes*

In reaction to the war, various governments have imposed trade sanctions causing significant impacts on international trade relations. In some cases this has led to push-back against long-haul trade, extended supply chains, and over-reliance on single-source suppliers (UNCTAD 2022b). Consequently, there have been significant declines in economic growth and a rapid rise in inflation. A shrinking global economy implies shrinking production, which means less need for raw materials. A similar situation was found during the 2008 Global Financial Crisis, where global domestic material consumption reduced by 1% (Wu et al. 2019). Although after the crisis a rebound effect was seen in certain countries and sectors, at the global level efficiency improvements through technological progress reduced material use and alleviated the environmental burden (Wu et al. 2019). Therefore, to keep natural resource use levels low, investments must be made in technological advances that can lead to reduced resource inputs.

Trade and transport are also recognised as the most relevant indirect determinants of invasive alien species' potential impact as a driver of biodiversity decline (IPBES 2019). We therefore expect that the alterations in trade modes and global transportation networks could lead to novel source pools of alien species, new pathways of introduction, and changes to the frequency of invasion events. For instance, numerous invasive alien

species have already been introduced following the construction of international trade and transport infrastructure. This was the case for the Mourning gecko (*Lepidodactylus lugubris*), whose first record in the Americas came from Panama just two years after the canal's opening (Nania et al. 2020), and for marine species migrating across the Suez Canal to the Mediterranean Sea (Galil et al. 2015). Moreover, human migrations have been associated with increased spread of alien species (Essl et al. 2020), and therefore the human migration crisis that the conflict has caused could increase the spread of such species. However, a closed border policy combined with reduced movement of goods may help contain already established species and reduce the risk of a secondary spread (Tedeschi et al. 2022).

As projections to the future are based on past trends and often underestimate stochastic events such as pandemics or wars, changes in international trade routes will influence the projected patterns of biological invasions. Before the war, the number of alien species was projected to increase from 2005 levels by an average of 36% globally by 2050 (Seebens et al. 2021). While it is still too early to foresee how the war will affect the number of invasions, potential changes in rates and pathways of introductions and a potential lower risk of secondary spread should be accounted for.

Box 2.1. Unintended consequences of trade sanctions on nature: an example from Colombia

Colombia is one of Germany's biggest coal suppliers, providing it with 2.3 million tons of coal in 2021. In the wake of European sanctions against Russia, Colombia has agreed to increase its supply of coal to Germany. About 90% of coal production in Colombia is extracted from El Cerrejón, a 69,000 ha coal mine located in La Guajira department, which is home to Indigenous communities and one of the few remnants of the dry forest ecosystem in Colombia. The mine was scheduled to close in 2021 due to slowing global demand for coal, but the recent request from Germany and other EU countries has triggered its reactivation (El Espectador 2022). The dry forest is a critical ecosystem with endemic and endangered species in Colombia. It has lost more than 90% of its original cover and is expected to lose about 155 ha more due to the expansion of the coal mine (CCRC 2017). As part of the expansion, a permit to permanently deviate the Bruno creek, one of the main tributaries of the Rancheria River, was requested. This recent development is expected to have a major impact on the dry forest ecosystem since the Rancheria River is the only river in the arid region, with expected changes to the local fauna and vegetation, its freshwater diversity, and the fragile hydrological equilibrium of the region. Human rights groups have also warned that this will cause irreparable damage to the Indigenous communities that use the river as one of their only sources of water and for which the river represents a sacred site.

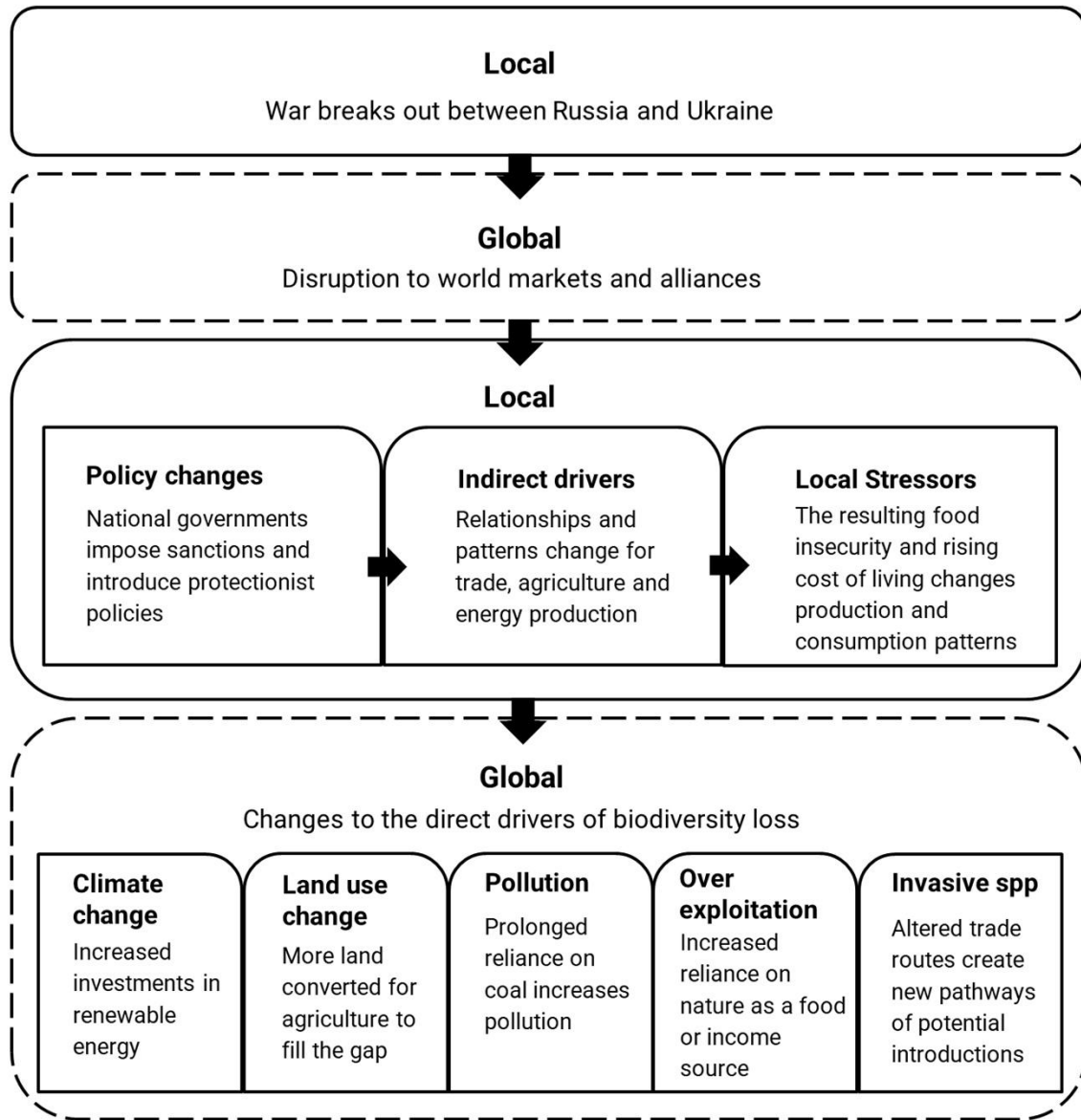


Figure 2.2: Global-to-local-to-global linkages of the international response to the war in Ukraine. This framework presents an example of the unintended consequences of local policy decisions made in response to the war on the direct drivers of biodiversity loss at a global scale. An example of how the conflict is changing the direct drivers of biodiversity loss is provided for each driver.

2.2.2. Interrupted agricultural production

The war generated shockwaves to the global food market, reducing the availability of staple foods like wheat and sunflower oil and skyrocketing global food prices by 34% compared to a year prior to the invasion (UNCTAD 2022b). Both Russia and Ukraine play a key role in global food production, accounting for 53% of the world's sunflower oil,

27% of the wheat, and 23% of the barley (UNCTAD 2022b). Russia and Belarus also account for 20% of global fertilizer exports (UNCTAD 2022b), and the fertilizer shortage in countries that have imposed sanctions against them will further drive up food prices as a direct effect of reduced yields. This has the potential to exacerbate food insecurity globally. We expect these changes to global agriculture to impact four drivers of biodiversity loss.

First, more land might be converted to agricultural production in some regions to fill the gap. For example, South Korea has introduced new policy to become wheat self-sufficient by aiming to increase wheat crops by 12,000 ha in 2023 (Yoona Jeon 2023). Additionally, the European Commission is allowing European farmers to plant food and feed crops on farmland normally set aside for biodiversity under the Common Agricultural Policy (European Commission 2022a). This change could lead to increased use of pesticides and reduce semi-natural habitats, such as fallow land and hedgerows, which has already been identified as a key driver of the decline of farmland birds (Strange et al. 2022). This is especially concerning since there has also been an indefinite delay to legalizing the EU's Farm-to-Fork policy to reduce pesticide use by half by 2030. We therefore expect this to increase pressure on farmland biodiversity across Europe, despite the commitments to protect the environment and biodiversity set under the European Green Deal. However, after World War II, Europe underwent land use change due to land abandonment and reforestation programs which led to an increase in large mammal populations across the continent (Fuchs et al. 2013). Therefore, there is hope that any short-term reductions could be reversed with the appropriate planning and policies in place.

Second, a global change to the main food producing countries may promote the spread of invasive species, pests, and pathogens. Such was the case in 2016 when wheat grains from Brazil imported to Bangladesh to make flour were instead planted for local production. This led to the invasion of wheat blast, a devastating fungal disease that can halve average yields in affected areas (Ceresini et al. 2019). Under a scenario of altered agricultural production, the occurrence of analogous cases is not unlikely, and may further aggravate food insecurity.

Third, the rising global food prices might increase the rate of natural resource exploitation especially in financially stressed regions. Researchers found that the financial impacts of the COVID-19 pandemic caused an increase in the level of illegal hunting in tropical regions (Anagnostou et al. 2021), and that the 2008 Global Financial Crisis caused an increase in wildlife crime in Greece (Troumbis & Zevgolis 2020). Currently, over 1 billion people, mainly concentrated across the tropics where there are many hotspots of biodiversity (Hillebrand 2004), are at risk of financial stress due to the recent increase in food prices (UNCTAD 2022b). Therefore, as the price of staple foods keeps growing, so too will the pressure on natural resources that become vital for human sustenance and as an alternative income source.

Fourth, pollution from agricultural runoff might decrease in the short-term, giving temporary respite to biodiversity. Nitrogen-phosphorus fertilizers are known to negatively impact terrestrial biodiversity by slowing microbial growth and blocking decomposition in soils, as well as harming freshwater and marine biodiversity through eutrophication (IPBES 2019). The price of fertilizers was already increasing due to the COVID-19 pandemic and has skyrocketed since the invasion. As a result, its use decreased in 2021 and 2022, especially in Africa and West Asia where it declined by 19% and 18% respectively (International Fertilizer Association 2022). There is potential for the high price of fertilizer to incentivize farmers to move away from synthetic fertilizers, or towards crops that are less fertilizer intensive like soybeans. However, agricultural intensification and the use of fertilizers has been documented to increase in times of financial stress (Sayer et al. 2012). Government subsidies and incentives that help promote the transition away from synthetic inputs are one of the most effective potential tools to alleviate the impact of pollution on biodiversity.

2.2.3. Energy transition

Russia has historically been a top exporter of natural gas, oil, and coal, but sanctions imposed by many western countries are causing them to shift away from importing Russian energy (UNCTAD 2022b). For example, Europe released the REPowerEU plan to phase out the import of Russian fossil fuels (European Commission 2022b) with the long-term vision for Europe to move to renewable energy. Yet, the short-term strategies to replace Russian energy sources include importing liquefied natural gas from the United States, oil from the Middle East, and reverting coal-fired power plants to full capacity. These strategies could lead to a prolonged reliance on fossil fuels, resulting in further greenhouse gas emissions.

The extremely rapid post-COVID economic recovery and the increase in gas prices already caused an increase in coal use in 2021. The result is that global CO₂ emissions from the energy and other industrial sectors, which account for almost 90% of total global emissions, increased in 2022 to reach levels never recorded before (IEA 2023). Although renewable energy and nuclear power provided their largest ever share of electricity generation in 2022, and the global use of natural gas declined, this improvement was outpaced by the record high emissions from coal (IEA 2023). Gas-to-coal switching led by increases in Asian emerging markets and developing economies was the main driver of increased emissions (IEA 2023).

An increase in the use of coal can directly impact biodiversity through pollution and land-use change (Harfoot et al. 2018). A heightened European demand for coal is anticipated to drive the opening or expansion of coal mines in countries like Colombia (Box 2.1). Future areas of extraction of coal in Africa and Latin America are expected to overlap with areas of high species richness and range rarity (Harfoot et al. 2018). Pollution from coal mining also impacts freshwater biodiversity and is known to increase aqueous

solute concentrations in downstream ecosystems leading to disrupted osmoregulation and the death of stream biota (Giam et al. 2018).

Nevertheless, the high price of fossil fuels can add pressure to reduce demand, incentivize more efficient production, and can make renewable energy prices more competitive (UNCTAD 2022a). However, there needs to be strong policies in place to attract investment to expand clean energy, especially with support to developing economies where renewable energy investments must increase by four times their current rate to achieve the Paris Agreement (UNCTAD 2022a). This is a realistic ambition since in reaction to the effects of the war, the EU has already made their emissions targets more ambitious, moving from a 40% reduction to a 57% reduction (Coles et al. 2023). Additionally, between 2020 and 2022, global economic recovery packages included over 1.2 billion USD in clean energy investments, which is twice as much as was made to this sector after the 2008 Global Financial Crisis (IEA 2023).

These changes can directly affect the outlook for biodiversity since climate change currently stands as one of the main drivers of biodiversity loss and can interact with, and exacerbate, other drivers such as habitat loss, over-exploitation, and biological invasions (IPBES 2019), causing shifts in species' distribution, phenology, and physiology. The severity of climate change's impacts on biodiversity increases with each degree of temperature rise. For example, the projected median percentage of species at high risk of extinction due to climate change increases from 9% (max 14%) at 1.5°C to 10% (max 18%) at 2°C, and to 15% (max 48%) at 5°C (IPCC 2022). Therefore, it is of utmost importance for biodiversity that policies and investments to push the green transition are realised.

2.3 An opportunity to redefine our future?

We discussed the potential indirect drivers that could intensify and those that could alleviate the drivers of biodiversity loss but found that the overall impact is more likely to exacerbate threats if biodiversity is ignored in new policy decisions. Nonetheless, the war in Ukraine is ongoing at the time of writing and therefore the impact on global drivers of biodiversity loss remains unknown.

If the biodiversity crisis is not addressed with rapid transformative changes to our social and economic systems, the future of biodiversity and the vital services it provides to humans is at risk. However, there is still scope for policy decisions for the medium and long term to be made now that could push us away from a future scenario that falls within the Fortress World archetype (Figure 2.1). Societal paradigm shifts, such as a transition from one socioeconomic storyline to another, have historically required a period of transformation that is often chaotic and turbulent before arriving at a new normal (Global Scenario Group 2002). This conflict has created a shock to the geopolitical system that could provide the period of transformation needed for a shift in our trajectory along the environment-economy axis (Figure 2.1) if policy decisions are made now that can benefit

biodiversity. This type of change requires adaptation from all institutions with public pressure playing an important part in setting our desired path towards an equitable and sustainable future (Global Scenario Group 2002).

Tackling the biodiversity crisis requires action at both national and international levels. However, the potential for this conflict to create a multipolar world, where global influence is split between different groups of countries, would result in less soft power to steer the world in one clear direction. Political tensions can have a direct impact on MEAs, for example the conflict in Ukraine has blocked the United Nations Nuclear Non-Proliferation Treaty (United Nations 2022) when Russia rejected the wording referencing the war. Specifically, the war threatens the governance system for biodiversity conservation due to changes in international and domestic policy priorities (Gallo-Cajiao et al. 2023). The war could also reduce the amount of funding available for the sustainability agenda as governments grapple with minimizing the societal impacts of the conflict (Gallo-Cajiao et al. 2023). However, it is promising that agreement was reached in December 2022 with the adoption of the GBF. With many other negotiations failing to reach consensus, it is hopeful that agreement was reached on this crucial global issue.

Socioeconomic scenarios play a key role in designing and informing effective conservation targets, and evaluating the actions needed to achieve them (Nicholson et al. 2019). Therefore we recommend re-evaluating the progress made towards goals set in MEAs with more focus on the regionalisation scenarios that were previously deemed unlikely. Additionally, we recommend developing new socioeconomic storylines that reflect the changes made to production and consumption patterns and that focus on a de-globalisation pathway. This would provide an updated view of what challenges we might face in the coming years to reverse the biodiversity crisis. We also stress the need for mainstreaming biodiversity and recommend that policy decisions in response to the war, including temporary and short-term changes, have a long-term vision to conserve nature. This could include at the national level establishing and empowering an inter-ministerial biodiversity working group that can screen and analyse proposed policies for their potential impact on the drivers of biodiversity change, and to ensure policies are aligned with existing national environmental commitments. As we discussed here, many policy decisions that superficially do not seem to be associated with nature can have large impacts on the drivers of biodiversity change. Without a specialised biodiversity lens assessing these policy changes, some of their impacts may go unnoticed until it is too late. There is potential for governments to shift from fossil fuel to renewable energy, from destructive agriculture to sustainable agrifood systems, and from exploitative to equitable supply chains. But we cannot delay. Biodiversity is the life insurance of humanity in the long term (IPBES 2019), and we cannot afford to ignore it in the policy decisions we make now.

Chapter 3 – Effectiveness of the global protected area network in mitigating threats to biodiversity

Vincent, C., Cisneros, E., & Rondinini, C. (2025). Effectiveness of the global protected area network in mitigating threats to biodiversity.

Abstract

Human activity impacts natural biodiversity globally, threatening the survival of endemic species. PAs are an effective instrument for reducing land-use changes associated with biodiversity losses. Nonetheless, little evidence exists on the ability of PAs to mitigate other threats to wildlife. We use nearest neighbour matching at a 1km resolution across the globe to estimate the effect of terrestrial PAs on the threats identified on the IUCN Red List threat classification scheme. Here we show that PAs reduce ten of thirteen threats, specifically the presence of residential and commercial areas, annual and perennial non-timber crops, wood and pulp plantations, livestock farming and ranching, mining and quarrying, renewable energy, the abstraction of surface water, roads and railroads, utility and service lines, and light pollution. The threat of oil & gas drilling is not significantly different compared to matched control areas, and two threats, fire and dams, showed higher levels inside PAs. Our results show substantial regional heterogeneity in the effectiveness of PAs, with smaller and more strictly managed areas generally performing better. Additionally, PA effectiveness is partly disconnected from endemic species richness. Impacts can be improved by enhancing effectiveness or expanding PA networks, depending on the national context. Our results highlight the importance of site-based conservation in meeting the global biodiversity goals set in the GBF.

3.1 Introduction

Biodiversity is declining globally, primarily driven by human activities through direct exploitation of biological resources or through indirect impacts like habitat loss (IPBES 2019). Human pressures lead to biodiversity loss and can also alter the composition of biological communities, highlighting that all human pressures need to be considered when attempting to reverse biodiversity loss (Keck et al. 2025). The IUCN Red List of Threatened Species evaluates the extinction risk across various taxonomic groups, identifying threats that contribute to the decline of species. These threats are classified using a standardized classification scheme, which helps monitor changes in extinction risk and guides conservation interventions aimed at improving the status of species (Salafsky et al. 2008, 2025). This framework allows for a more nuanced understanding of the ongoing

and potential future drivers of species decline and the role of conservation efforts in mitigating these pressures (Salafsky et al. 2008).

PAs are an effective tool for conservation in situ for improving the state of biodiversity within their boundaries (Langhammer et al. 2024). This has been reinforced through the adoption of Target 3 of the GBF, which aims to effectively and equitably protect 30% of the planet by 2030 (CBD 2022), commonly referred to as ‘30x30’. Despite the importance of PAs, there remains a lack of a reliable indicator to measure their effectiveness in mitigating threats to biodiversity (Geldmann et al. 2021). While PAs can contribute to reducing certain pressures, not all the threats listed on the IUCN threat classification scheme can be addressed by their establishment. A critical issue is that PAs do not exist in solitude; they are linked to larger systems and cannot always shield species from stressors that originate outside their boundaries (Nowakowski et al. 2023), and they often lack adequate resources for their enforcement (Coad et al. 2019). More than half of the threats in the classification scheme, such as pollution run-off, climate change, and invasive species, require additional inputs like effective site management or larger-scale landscape management (Pressey et al. 2015; Kearney et al. 2020).

Measuring the effectiveness of PAs at a global scale has been limited due to the different conservation objectives of sites (Coad et al. 2015), the heterogeneous impact of threats affecting species (Thomson et al. 2020), and the resolution and availability of data needed to assess impact (Ridley et al. 2024). Past research has primarily focused on biological indicators, such as species abundance and habitat quality (Geldmann et al. 2013; Gray et al. 2016; Ji et al. 2022), or management effectiveness, which evaluates factors like staffing, governance, and legal frameworks (Leverington et al. 2010; Geldmann et al. 2018). However, quantitative assessments of PA effectiveness are essential for optimizing conservation interventions with limited resources. PA coverage alone is not sufficient to remove all threats, and impact can only be assessed in relation to avoided threats or avoided loss of biodiversity (Pressey et al. 2015).

Moreover, PAs are not placed randomly across landscapes; they are often located in remote and less economically valuable areas (Andam et al. 2008; Joppa & Pfaff 2009). If PAs improve biodiversity simply because they are located in remote, undisturbed habitats, expanding PA networks alone may not achieve the desired biodiversity outcomes (Brodie et al. 2023). Consequently, simple ‘inside-outside’ comparisons are prone to bias, often overestimating the impacts on threats simply because they are located in low-pressure areas (Brodie et al. 2023). Simple ‘before-after’ comparisons can be falsely interpreted as a lack of impact when threat levels stay constant, although this could indicate a high impact if threats in comparable areas increased (Pressey et al. 2015).

To address these challenges, there has been an increase in counterfactual impact assessment methods, such as statistical matching, in the field of conservation biology (Ribas et al. 2021; Chen et al. 2023). Statistical matching creates a control group that can be compared to PAs based on similarities in observable variables (Ferraro 2009).

Previous studies assessing the effectiveness of PAs in reducing threats to biodiversity have been small-scale (Cisneros et al. 2022), lacked counterfactual comparisons (Spracklen et al. 2015), or have not assessed the IUCN Red List threats individually (Andam et al. 2008; Li et al. 2024). Some threat specific studies have found that PAs can reduce the Temporal Human Pressure Index in forested landscapes (Geldmann et al. 2019), and can reduce the rate of habitat loss by 4.2% (Li et al. 2024). However, there has yet to be a comprehensive and statistically robust evaluation of the individual threats on the IUCN Red List classification scheme across the global network of terrestrial PAs.

Here, we evaluate the effect of PAs on 13 threats identified on the IUCN Red List threat classification scheme at 1km resolution globally. We used statistical matching to compare the level of each threat inside PAs to matched control sites to account for potential bias in PA placement. Our analysis provides insights into the overall global patterns of threat mitigation, as well as trends at national and regional scales, and assesses the differences between types of PAs based on size and management categories.

3.2 Methods

3.2.1. *Classifying grid cells as protected and unprotected*

Grid cells are defined as treated when covered by a PA¹ in March 2022. We combined the World Database on Protected Areas (WDPA) and the World Database on Other Effective Area-based Conservation Measures (WD-OECM) (UNEP-WCMC & IUCN 2022a, 2022b) retaining national, regional, and international terrestrial sites designated between 2000 and 2020. We exclude UNESCO-MAB Biosphere Reserves from the WDPA because these sites include a buffer and transition zone that, in many cases, do not act as PAs (UNEP-WCMC 2019). PAs without a recorded boundary are stored as points in the WDPA, and we included these PAs as polygons by applying a buffer to the site’s centroid based on the reported area of the site to preserve its size, however the boundaries are inexact. Some countries choose to restrict their data by making them unavailable to the public. To account for this, the 2016 version of the WDPA is added for China, Estonia, India, and Turkey when the spatial information for their PAs was still publicly available.

For areas where PAs overlap, we retain only one PA using the SAGA Rasterize tool Version: 7.8.2 in QGIS Version 3.32.3-Lima. We retain the most appropriate attribute information keeping the earliest designation year, the strictest IUCN PA Management Categories, and the largest PA size. We classify PAs as strictly protected (IUCN categories Ia - IV) or multi-use (IUCN categories V and VI) and categorize PAs into four bins according to their size: less than 10 km², 10-500 km², 500-2000 km², and over 2000 km².

Control units are defined as areas that did not fall within the complete PA network from the March 2022 version of the WDPA and the WD-OECM regardless of designation

¹ In this study, “PA” is used to describe both protected areas and other effective area-based conservation measures for simplicity.

year. We also removed all areas within a 10 km buffer around PAs. This buffer is excluded from both the control and treatment datasets because of the potential for leakage or spillover effects from PAs (Baylis et al. 2016; Brodie et al. 2023). The final map was rasterized to 1x1 km cells and each pixel converted to a point in GRASS GIS v8.3.

3.2.2. Threat data preparation

We used the most recently published publicly available global pressure maps that corresponded to each of the threats on the IUCN Red List threat classification scheme (Salafsky et al. 2008) that can potentially be addressed by PAs (Table 3.1). They were standardised to 1 km² resolution and reprojected to Mollweide equal-area projection in GRASS GIS v8.3. The datasets used for each threat are described below.

For residential & commercial development (Threats 1.1 and 1.2), we used the Global Human Settlement Layer (GHS-BUILT-S - R2023A) which maps built-up surfaces derived from Sentinel2 and Landsat data from 2020 (Pesaresi & Politis 2023). The values ranged from 0 - 655,503 m² of built area per 1 km² pixel.

To assess annual and perennial non-timber crops (Threat 2.1), a map was created from the cropland extent data from 2016 to 2019 assigning a value from 0 to 1 for the proportion of croplands per pixel (Potapov et al. 2022). For wood and pulp plantations (Threat 2.2), we used a global map of planting years (Du et al. 2022), where pixels were assigned a value of 1 for plantations established between 1982 and 2019, and all other pixels were assigned 0. Livestock farming and ranching (Threat 2.3) was estimated from the Gridded Livestock of the World v4 dataset (GLW4; (Gilbert et al. 2018), which provides the distribution of livestock in 2015. The dataset was aggregated to 1 km² grid cells by selecting the maximum value from smaller pixels, with values ranging from 0 to 88,735 cattle per pixel.

For oil and gas drilling (Threat 3.1), data was mapped from the Global Oil and Gas Extraction Tracker dataset (Global Energy Monitor 2022) which includes sites with a production start year of 1934 to 2020. The dataset was rasterized to 1 km² grid cells after removing “discovered” sites and those without exact coordinates. Mining and quarrying (Threat 3.2) was rasterized from the global mining footprint of 2017 map (Tang & Werner 2023), where pixels overlapping the mining footprint were assigned a value of 1 and all other pixels were 0. To create a map of renewable energy (Threat 3.3) we combined the Global Wind Power Tracker data (Global Energy Monitor 2023) and the renewable energy types extracted from the Global Power Plant Database (Global Energy Observatory et al. 2019) which included geothermal power production, solar farms, wind farms, and tidal farms. Dams were excluded from this dataset as they are addressed separately under Threat 7.2.9.

The presence of roads and railroads (Threat 4.1) was rasterized from a combination of the Global Roads Inventory Project (GRIP4) (Meijer et al. 2018) and the Global Railways dataset (World Food Programme 2019) for 2015, with pixels assigned a value of

1 if they intersected a road or railway. Utility and service lines (Threat 4.2) was derived from the Global Power System map (Arderne et al. 2020) with data from 2015 to 2019, and rasterized so that pixels overlapping power lines received a value of 1.

Due to the lack of a global pressure map for hunting and collecting terrestrial animals (Threat 5.1), we used the defaunation index from Bogoni et al. (2020), which compares mammal assemblages in protected and unprotected areas to estimate the impact of PAs on hunting. Similarly, for logging and wood harvesting (Threat 5.3), results in Table 1 are presented from Li et al. (2024) who looked at the effect of PAs on deforestation rates using counterfactual methods.

For fire (Threat 7.1), we used the MODIS burned area products from January and June 2020 (Giglio et al. 2018). Pixels were assigned a value of 1 if they were burned in either month. To capture the abstraction of surface water (Threats 7.2.1–7.2.4) we use the Global Surface Water Explorer (Pekel et al. 2016) which tracks surface water changes from 2000 to 2020 at 30-metre resolution. We create a map for 2020 with values ranging from -100 to 99 where positive values indicate the percentage of water lost since 2000, negative values indicate gains, and 0 indicate no change. To map dams (Threats 7.2.9–7.2.11), we combined the Global Georeferenced Database of Dams (GOODD; (Mulligan et al. 2020) with dams from the Global Power Plant Database (Global Energy Observatory et al. 2019), assigning a value of 1 to pixels containing dams.

Lastly, light pollution (Threat 9.6.1) was derived from the harmonized global nighttime light dataset for 2018 (Li et al. 2020), where each pixel was assigned a radiance value ranging from 0 to 63 DN, with higher values indicating greater light intensity.

3.2.3. Counterfactual matching method

Statistical matching was used to account for confounding factors as it is designed to evaluate the effects of a treatment with purely observational data. Matching reduces the bias associated with unequal covariate distribution between treatment (here PAs) and non-treatment groups (Ferraro 2009).

Based on previous studies (Andam et al. 2008; Eklund et al. 2016; Geldmann et al. 2019) and due to the biased placement of PAs in the landscape where they tend to be in places that are at high elevations and in areas that are not important for economic activities (Joppa & Pfaff 2009), we chose the following matching covariates: agricultural suitability, human population density, travel time to nearest city of 50,000 or more people, elevation, slope, total annual precipitation, mean annual temperature, biome and country. All the covariate datasets were from the year 2000 or before to ensure they represent the pre-treatment state. It should be noted that we avoided obvious confounding variables, for example soil type, soil fertility, soil quality index, and soil nutrient levels since they are all related to agricultural suitability. Each of the nine matching covariates was assessed and the reasoning for inclusion is provided in the Appendix Table A1.2.

We tested for multicollinearity between covariates using Variance Inflation Factors (VIF) on a random 10% sample of our data ($n = 10,410,175$) with R package ‘car’ (Fox & Weisberg 2019). All nine covariates have a VIF score of less than 5 (Appendix Table A1.3), therefore there is a low likelihood of high correlation between the variables. Additionally, collinearity among covariates is not as problematic with matching as in other methods used for impact evaluation such as parametric regression models (Ribas et al. 2021). After this assessment we deemed it appropriate to retain all nine covariates. We standardised the data to Mollweide equal-area projection at 1x1 km resolution in GRASS GIS v8.3.

We tested three matching methods on a sample of the dataset and Coarsened Exact Matching (CEM) with the Mahalanobis distance metric provided the best balance, with the smallest standardised mean differences and variance ratios closest to one. As well as providing good balance, the Mahalanobis distance accounts for potential collinearity among the variables considered at each pixel (Eklund et al. 2016). Matching analyses were performed using the MatchIt package (Ho et al. 2011) in R 4.2.0 with one treatment to one control point without replacement. Exact matching was used for biome and country, meaning that each matched pair of treatment and control points were from within the same biome and country. The final dataset retained 3,279,545 matched pairs across 166 countries (Appendix Table A1.4 & Figure A1.1).

3.2.4. Threat level in protected and unprotected grid cells

We assessed a total of 13 threats, the remaining threats on the Red List are either assumed to not be impacted by the presence of PAs such as geological events like earthquakes (Kearney et al. 2020), or they have already been estimated with similar methods or a global map of the threat does not exist (e.g. hunting, deforestation).

We calculated the difference between PAs (treatment) and matched unprotected areas (control) as the average treatment effect on the treated (ATT) where a positive value indicates a higher threat occurrence inside PAs. For each threat, the average value was calculated for the treatment and control groups at a global scale and compared with a two-sided paired Wilcoxon signed rank test with continuity correction. The signed rank test is the nonparametric alternative to the paired t-test designed to assess comparisons in paired data like matched data (Keele 2010). This analysis was repeated to look at differences based on PA characteristics, specifically IUCN PA Management Categories, size, and national differences. To compare across threats with different units, the results were converted to normalized differences (Imbens & Wooldridge 2009) with the following formula:

$$(X_t - X_c) / \sqrt{S_c^2 + S_t^2} \quad (3.1)$$

where X is the average value for treatment (t) and control (c) groups, and S is the standard deviation.

Table 3.1: A description of the threat datasets used in this study. The threat category follows the IUCN Red List threat classification scheme version 3.3 as defined by Salafsky et al (2008).

IUCN Threat Category	Threat year	Dataset
1 Residential & commercial development [m ²]		
1.1 Housing & urban areas	2020	Global Human Settlement Layer (GHS-BUILT-S - R2023A) (Pesaresi & Politis 2023)
1.2 Commercial & industrial areas		
2 Agriculture & aquaculture		
2.1 Annual & perennial non-timber crops [%]	2016 - 2019	Cropland extent (Potapov et al. 2022)
2.2 Wood & pulp plantations [%]	2019	Global map of planting years (Du et al. 2022)
2.3 Livestock farming & ranching [No. of cattle]	2015	Gridded Livestock of the World v4, GLW4 (Gilbert et al. 2018)
3 Energy production & mining [%]		
3.1 Oil & gas drilling	2020	Global Oil and Gas Extraction Tracker (Global Energy Monitor 2022)
3.2 Mining & quarrying	2017	Global mining footprint (Tang & Werner 2023)
3.3 Renewable energy	2020	Global Wind Power Tracker (Global Energy Monitor 2023) & Global Power Plant Database (Global Energy Observatory et al. 2019)
4 Transportation & service corridors [%]		
4.1 Roads & railroads	2015	Global Roads Inventory Project (GRIP4) (Meijer et al. 2018) & Global Railways dataset (World Food Programme 2019)
4.2 Utility & service lines	2019	Global Power System (Arderne et al. 2020)
5 Biological resource use		No global map exists
6 Human intrusions & disturbance		No global map exists
7 Natural system modifications [%]		
7.1 Fire & fire suppression	2020	MODIS burned area products (Giglio et al. 2018)
7.2.1 - 7.2.4 Abstraction of surface water	2020	Global Surface Water Explorer (Pekel et al. 2016)
7.2.9 - 7.2.11 Dams	2020	Global Georeferenced Database of Dams, GOODD (Mulligan et al. 2020) & Global Power Plant Database (Global Energy Observatory et al. 2019)
8 Invasive & other problematic species, genes & diseases		No global map exists
9 Pollution		
9.6.1 Light pollution [DN]	2018	Harmonized global nighttime light (Li et al. 2020)
10 Geological events		Not related to PA effectiveness
11 Climate change & severe weather		Not related to PA effectiveness
12 Other options		No global map exists

Finally, as a sensitivity test we calculated E-values for the normalized difference of means with the *EValue* package in R (VanderWeele & Ding 2017). E-values provide the minimum strength that an unmeasured covariate, in this case those used for the matching algorithm, would need to have for the effect to not be causal (VanderWeele & Ding 2017). The results from the sensitivity analysis are provided in the Appendix Table A1.1.

3.2.5. Threatened and endemic species richness

We retrieved data on the number of threatened and endemic species per country from the IUCN Red List version 2024-2 (IUCN 2024). We included all species assessed on the global Red List that are threatened with extinction (i.e. Vulnerable, Endangered, and Critically endangered species), and we added a filter to retain only endemic species. The resulting dataset has 37,674 species and was downloaded with information on the country in which each species occurs. The number of threatened and endemic species per country were then mapped in QGIS Version 3.32.3-Lima.

3.3 Results

3.3.1. Global results

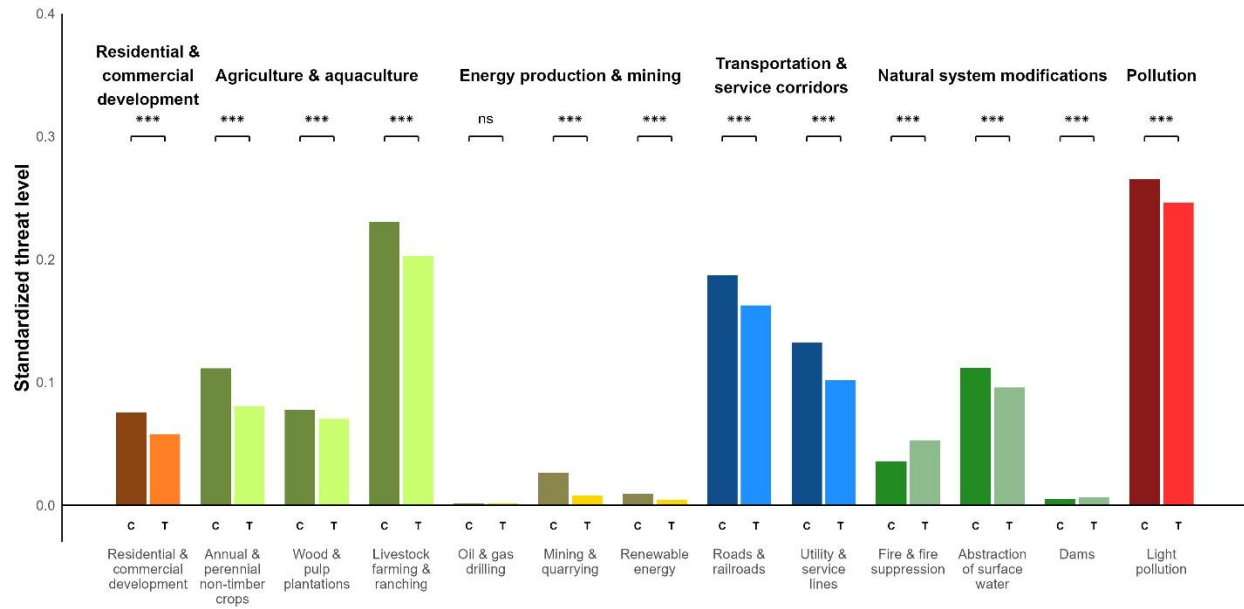
We found a significant effect of PAs for 12 of the 13 IUCN Red List threats assessed in this study at the global level. The threat with no significant difference between treatments and controls is oil and gas drilling (Figure 3.1). Two threats from natural system modifications, dams, and fire and fire suppression, measured as the burned area of each pixel, are both significantly worse inside PAs at the global scale (Figure 3.1b). The remaining ten threats have a significantly lower rate inside PAs when compared to the matched control areas (Figure 3.1 & Appendix Table A1.5).

Additionally, the level of occurrence for each threat per pixel is low for all threats in both control and treatment points (Appendix Table A1.5). The presence of roads and railroads is the threat that covered the largest average proportion of the treatment pixels at 9.3% (std. error = 0.02).

3.3.2. The effect of PA size on threat mitigation

Most of the threats have an inverse relationship between PA size and threat level with the smallest PAs, and their matched control points, having higher threat occurrence than larger PAs (Appendix Figure A1.2). Yet when considering ATT, large PAs are found to be less effective at reducing threats from agricultural activities, despite their lower levels of threat presence (Figure 3.2a & Appendix Table A1.6). Additionally, PAs between 10-500 km² most effective at reducing cropland, livestock farming, roads & railroads, and utility & service lines (Figure 3.2a & Appendix Table A1.6).

(a)



(b)

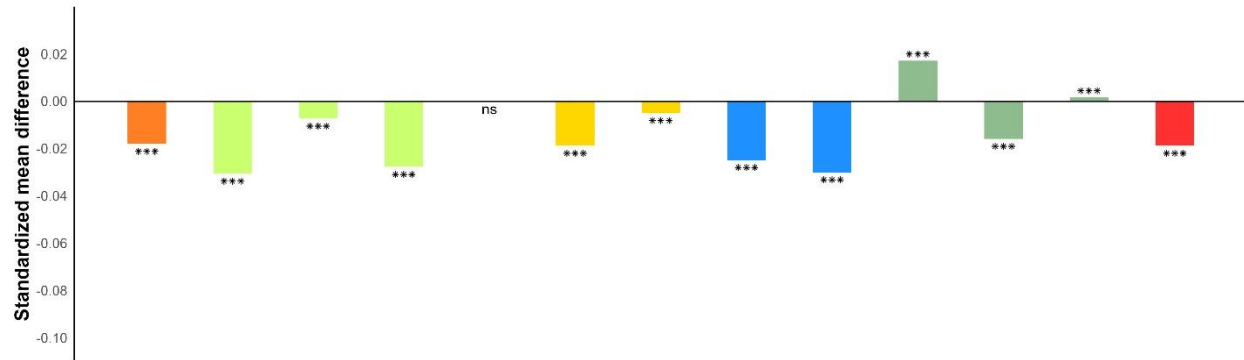


Figure 3.1: Protected area effects on biodiversity threats. (a) Threat levels are standardized by the standard deviations of control (*C*) and protected area units (*T*). (b) The standardized mean differences with negative values indicating a reduction in threats within protected areas compared to their matched controls. Appendix Table A1.5 shows the non-standardized regression results. */**/** denote significance levels at 10/5/1 percent respectively.

However, this trend is not universal across all threats. Larger PAs are more effective for reducing wood and pulp plantations (ATT = -0.20 %pt., std. error = 0.004, $p < 0.01$), and PAs between 500-2000 km² in size are best at mitigating pressures from mining & quarrying and light pollution (ATT = -0.12 %pt., std. error = 0.004, $p < 0.01$; ATT = -0.34 DN, std. error = 0.01, $p < 0.01$, respectively). Oil & gas drilling did not differ between treatments and controls for any size class.

The rate of fires did not follow the same trend as we found more burned areas inside PAs over 500 km² than in smaller sites (Appendix Figure A1.2d). Fire is higher inside PAs of all size classes compared to their controls, with PAs of 500-2000 km² performing the worst (ATT = 0.42 %pt., std. error = 0.01, $p < 0.01$).

3.3.3. The effect of PA management on threat mitigation

Ten of the threats have a significantly lower rate inside both strict and multi-use PAs compared to their matched controls, with strict PAs performing better than multi-use ones (Figure 3.2b). Livestock farming & ranching, and the abstraction of surface water have the inverse result with multi-use PAs reducing the threat significantly more than in strict PAs. However, the chance of occurrence of livestock is similar inside both strict and multi-use PAs (Appendix Figure A1.2h), and the surface water use was lower inside strict PAs even if they have a lower ATT (Appendix Figure A1.2m).

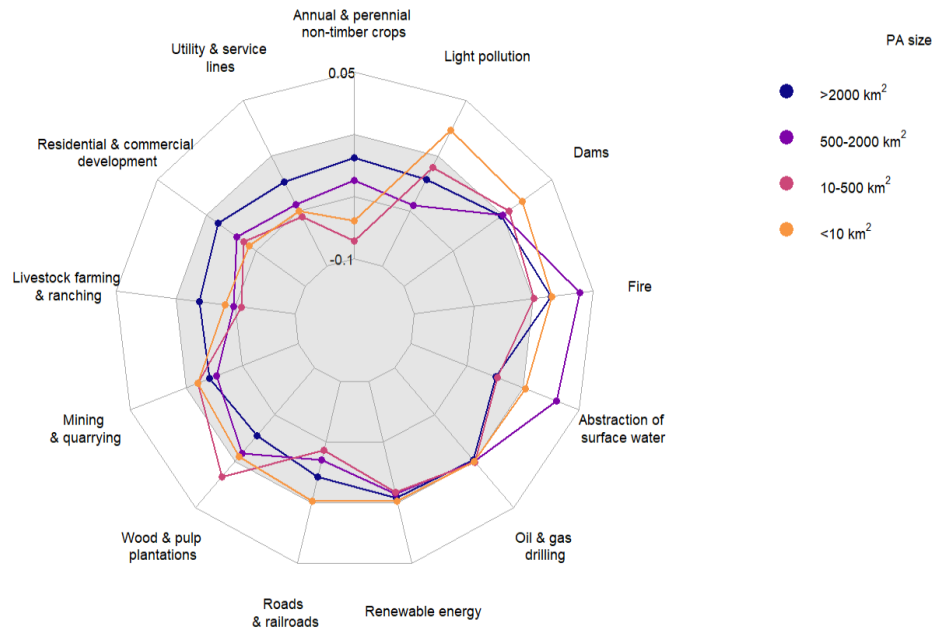
The average burned areas inside strict PA pixels is 0.71 % and is higher than multi-use areas where it is only 0.40 % (Appendix Figure A1.2d). Additionally, there is a higher chance of burned areas inside strict PAs compared to their controls (ATT = 0.32 %pt., std. error = 0.005, $p < 0.01$) and this is worse than in multi-use PAs (ATT = 0.10 %pt., std. error = 0.004, $p < 0.01$). For neither strict nor multi-use PAs is the difference between treatments and controls significant for the threats of oil & gas drilling, or dams (Appendix Table A1.6).

3.3.4. National differences

There are notable national differences in the presence of pressures inside PAs, with substantial variation observed across countries. Certain threats are universally lower inside PAs across multiple countries. Specifically, annual & perennial non-timber crops, livestock farming & ranching, utility & service lines, light pollution, and residential & commercial development are consistently found to be significantly lower inside PAs in over 75 countries (Appendix Table A1.7).

Although the global analysis does not show a significant effect for oil & gas drilling, it is found to be significantly higher inside PAs in Canada (ATT = 0.002 %pt., sd = 0.004, $n = 778,830$, $p = 0.04$). Similarly, while the presence of dams is not significantly different on a global scale, national differences are found. For example, dams are found to be significantly lower inside PAs in Cambodia (ATT = -0.04 %pt., sd = 0.01, $n = 28,928$, $p = 0.02$) and Sri Lanka (ATT = -0.76 %pt., sd = 0.07, $n = 2,354$, $p = 0.01$), while the presence of dams is significantly higher inside PAs in Japan (ATT = 0.61 %pt., sd = 0.06, $n = 3,270$, $p < 0.01$) and Italy (ATT = 0.14 %pt., sd = 0.03, $n = 35,404$, $p < 0.01$).

(a)



(b)

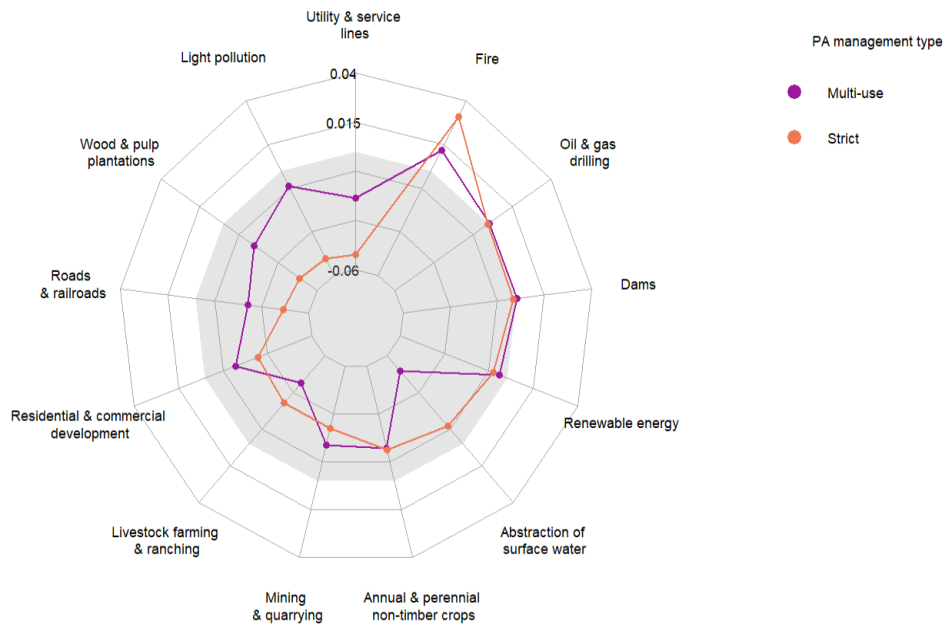


Figure 3.2: Normalized mean difference between PAs and controls for each threat by PA characteristic. Data are grouped based on PA size (a) and management category (b) where strict protection includes IUCN categories Ia-IV, and multi-use includes IUCN categories V-VI. Values closer to the centre of the plot indicate a greater mitigation effect of PAs. Gray shading designates ATT values lower than 0 where the PAs perform better than controls.

A total of 53 countries reduced the presence of threats inside PAs without having any pressure higher inside PAs than in the control points. In contrast, 15 countries have no threats with significantly lower levels inside PAs: Mauritania, Guinea-Bissau, Angola, Djibouti, Greenland, Israel, Jamaica, Lesotho, Liberia, Mauritius, Puerto Rico, Samoa, Sao Tome and Principe, Solomon Islands, and Turkey (Appendix Table A1.7). Most countries that have threat levels not significantly different between treatment and control points have lower pressures from these threats nationally.

Regional patterns further emphasize these differences. Southeast Asia, the Middle East, and South America show particularly favourable outcomes, with lower levels of threats inside PAs. Europe and Central Asia show mixed results in terms of threat reduction inside PAs while Africa has less favourable outcomes (Figure 3.3a). When comparing this to the map of threatened and endemic species richness, we found higher richness in South-East Asia, and North and South America with mixed rates in the rest of the world (Figure 3.3b). The countries with the highest richness of threatened and endemic species are Madagascar, Ecuador, Indonesia, Mexico, Brazil, Malaysia, and the United States, each with over 2,000 species. However, not many of the countries with the most effective PAs also have the highest levels of threatened and endemic species. Notably, some countries with the greatest threatened and endemic species richness have poorly performing PAs, like Colombia, the Democratic Republic of Congo, Guinea, Honduras, and Papua New Guinea.

3.4 Discussion

Our results show that the majority of the threats affecting species on the IUCN Red List threat classification scheme are reduced inside PAs compared to matched control sites globally. However, we find no difference in the likelihood of the presence of oil and gas infrastructure. Additionally, dams and the burned areas from fires are significantly higher inside PAs compared to control sites globally. Knowledge of these threat levels is important for conservation planning for over 85,000 terrestrial species assessed on the IUCN Red List for which threat information is recorded.

Strict PAs have a greater impact on most threats compared to multi-use PAs including from residential & commercial development, light pollution, utility & service lines, and roads & railroads, likely due to multi-use sites allowing permanent human settlements within their boundaries (Dudley 2013). When not accounting for controls, the presence of most threats is similar in these two types of PAs. Furthermore, for all the assessed threats, except for fires, large PAs have lower levels of threat presence than small PAs, but for most threats the difference between large PAs and their matched controls is not as extensive as for small PAs.

Threats that are typically associated with extensive rather than localised impacts are consistently lower inside PAs across multiple countries. This result highlights that conservation policies are more effective at reducing large-scale land-use threats within

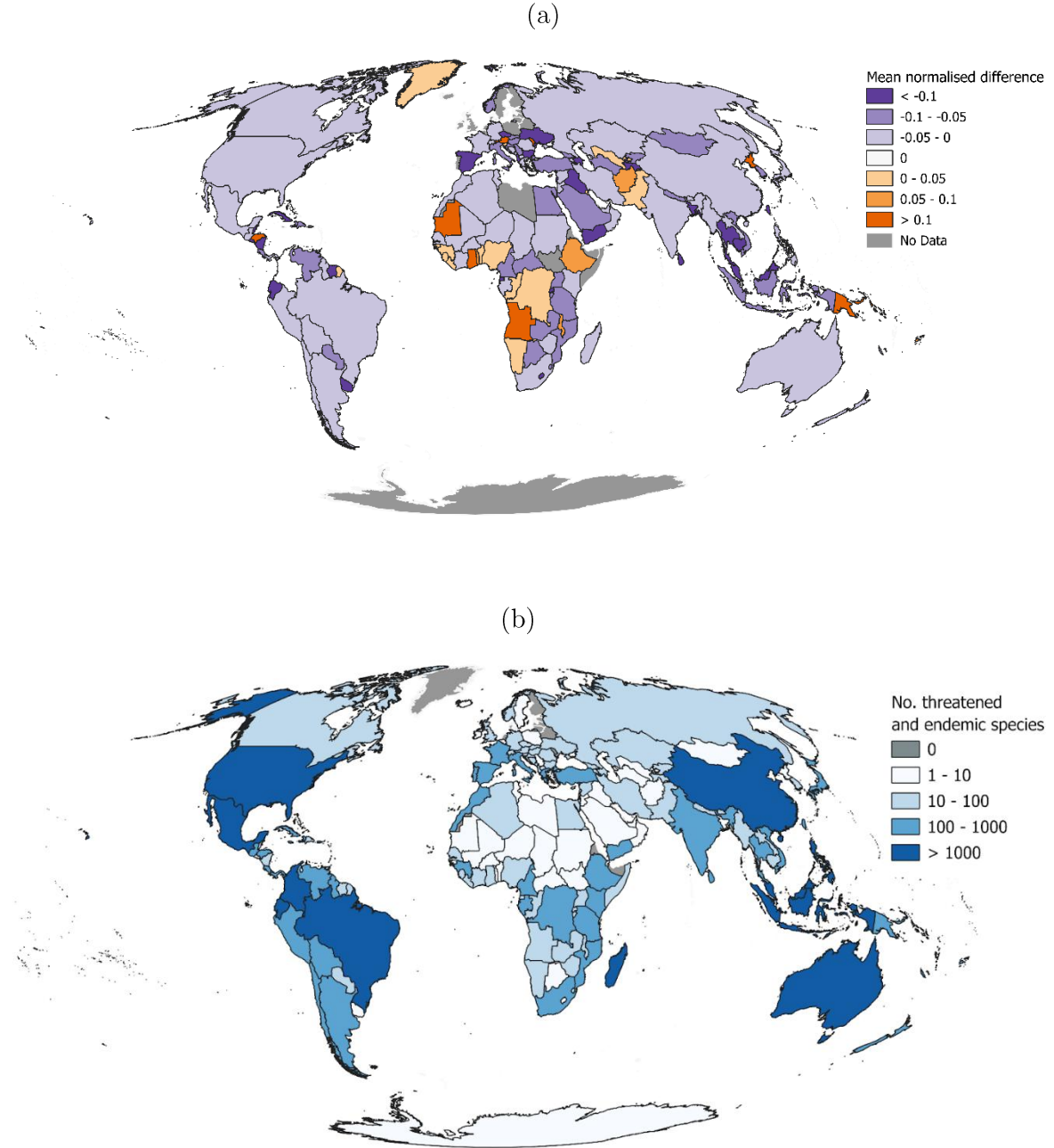


Figure 3.3: National heterogeneity in threat mitigation and biodiversity importance. (a) An aggregate PA threat mitigation score is presented as the average normalised mean difference between PAs and control points across all 13 threats per country. Negative values indicate a lower threat level inside PAs implying better effectiveness. (b) National values of threatened and endemic species richness.

PAs, while more localised and high-revenue activities, like oil drilling, dams, and mining, are harder to regulate due to their economic importance. The significant resources and power held by these industries can enable expansion into ecologically sensitive areas, creating challenges in regulation, particularly in low-income countries, where corporate influence often leads to insufficient protection for vulnerable ecosystems (Lamb et al. 2024).

3.4.1. Threat-specific performance of PAs

Annual & perennial non-timber crops is the sub-threat affecting the most species on the Red List, and although it has previously been identified as representing 18% of all human impacts inside PAs and is more prevalent in countries with higher population density and lower income inequality (Vijay & Armsworth 2021), we found that it is the threat with which PAs have the most impact. Countries with higher levels of cropland also have a higher PA impact, such as Moldova and Ukraine, demonstrating that intensively farmed countries can have a strong benefit from PAs.

Similarities are found between threats from agricultural activities with smaller PAs and their controls experiencing higher levels of annual & perennial non-timber crops, livestock farming & ranching, and wood & pulp plantations which tend to enter wilderness areas through encroachment and edge effects (Vijay & Armsworth 2021; Li et al. 2024). Although large PAs are recognised as vital for preserving vulnerable biodiversity and are more cost-effective than smaller ones (Armsworth et al. 2011), when compared to matched controls with similar characteristics, large PAs are less effective, despite their lower levels of threat presence. Strict PAs are more effective than multi-use PAs in limiting wood & pulp plantations. We found strict PAs were less effective than multi-use PAs for the presence of livestock farming & ranching which is of concern since high livestock density and expansion of rangelands are the most important factors negatively affecting habitat availability for terrestrial mammals (Pacifi et al. 2023).

Currently, residential & commercial development is listed as a threat on the Red List to over 26,000 species, almost half of which are threatened with extinction, and species with more highly-urbanised ranges are more likely to be threatened on the IUCN Red List (McDonald et al. 2008). Importantly, we found that urbanisation-related threats, including residential & commercial development, roads & railroads, light pollution, and utility & service lines, are significantly lower inside PAs compared to controls. These pressures are inversely related to PA size with smaller PAs and their controls experiencing higher levels, likely due to their proximity to human populations. Germany, Ghana, and Pakistan are outliers with higher urbanisation pressures inside PAs. This could be explained by the rush to build cross-border roads in countries undergoing rapid economic growth (Liu et al. 2020), where housing infrastructure tends to be developed along these new roads (Engert et al. 2025). For the case of Germany, it may be due to the rapid urbanization rates between 2009-2012 observed inside their Natura2000 sites (Concepción 2021).

Mining is a major threat to biodiversity known to cause deforestation (Sonter et al. 2017) and pollution (Lamb et al. 2024), and is also a threat to PAs being the cause of more than three quarters of global PA downgrading, downsizing, or degazettement (PADDD) events between 2000 and 2018 (Golden Kroner et al. 2019). Encouragingly, we found that PAs are effective in minimising mining & quarrying globally, with Suriname, where mining is the predominant economic activity (Love et al. 2007), showing the best performance. PAs also reduce the likelihood of renewable energy infrastructure, although the probability of such development is generally low in both PAs and control sites. Greece has the best performing PAs, reducing renewable energy, likely due to their existing legislation that calls for avoidance of PAs in the development of photovoltaic systems (Economou 2010).

Dams are known to be present in PAs and 14% of planned future dams worldwide fall within PAs (Thieme et al. 2020). However, our analysis suggests that globally the likelihood of a dam being inside a PA is slightly higher than their matched control sites. Oil and gas fields have been found to cover over 30,000 km² of protected lands globally (Harfoot et al. 2018), however we found that the likelihood of oil and gas drilling occurrence did not differ significantly between PAs and control sites at the global scale, nor did it vary across different size or protection categories. The probability of occurrence is generally close to zero, likely due to limited availability of public data on the precise locations of drilling sites. However, in Canada, where oil and gas extraction constitutes a major contributor to its GDP and is often permitted on a case-by-case basis in PAs (Hoesen et al. 2023), oil and gas drilling is found to be more likely within PAs.

An increase in fire frequency and intensity is identified as a threat to over 10,000 species assessed on the Red List and almost half of those species have been identified by experts as requiring land protection to improve their conservation status (IUCN 2024). However, our results show that at a global scale, land protection increases the risk of burned areas from fires. Multi-use PAs are found to be more effective than strict PAs, a trend also observed in tropical forests (Nelson & Chomitz 2011). When fighting wildfires there is a priority given to protect people and property over wild areas which may contribute to the higher levels of burned area inside PAs. Our results support results from Australia where burned area is higher in large or strict PAs which tend to be more wild than smaller or multi-use sites (D'alessio 2020; Ward et al. 2020). Notably, the burned area data was from 2020 which corresponded to the COVID-19 pandemic when an increase of 76-248% was seen in the fire incidence in Madagascar that year (Eklund et al. 2022). Furthermore, during this time there was a potential suspension of management activities in some PAs potentially contributing to the poor performance of PAs.

However, this adverse effect of protection is not universal with some countries, like Benin and Senegal, exhibiting lower fire rates inside PAs. The government of Senegal has implemented fire management strategies from as early as 1965, and The Forestry Department uses controlled burns early in the dry season to minimize the occurrence and

strength of later fires (Goldammer & Ronde 2004), and fires are banned in Benin after December 15th for the same reasons. This highlights the positive impact that effective management strategies and policies can have in reducing pressures on biodiversity. It underscores the importance of improving the management of existing PAs and stresses that simply establishing a PA without sufficient funding, proper management, or community involvement is insufficient to mitigate threats to wildlife.

3.4.2. Impact on biodiversity

We looked at national threatened and endemic species richness and compared that to threat mitigation to assess the impact of PAs on biodiversity conservation. We focused on species that are both threatened and endemic because the countries in which these species are found are independently responsible for their survival. We found that Madagascar has the highest number of threatened and endemic species, however it only has two threats significantly lower inside PAs. This highlights the need for improved effectiveness of PAs in Madagascar to safeguard these species since they do not occur in other countries. On the other hand, the United States and Indonesia have high threatened and endangered species richness, and their PAs successfully mitigate most threats analysed, with no threats higher inside PAs. This underscores the critical role these areas play in biodiversity conservation.

Our results can also guide national conservation investment strategies. For example, countries exhibiting both high effectiveness and high threatened and endemic species richness, such as the United States and Indonesia represent priority regions where PA expansion is likely to yield substantial conservation benefits. Conversely, in countries where threatened and endemic species richness is also high, but PA effectiveness is low, such as Madagascar and Papua New Guinea, priority should instead be given to improving the management effectiveness of existing PAs. Such targeted strategies can benefit global conservation outcomes by aligning investments with specific needs and capacities at a national scale, thereby maximizing impact in biodiversity conservation planning.

3.4.4. Limitations and further research

In this study, we presented a comprehensive and statistically robust analysis of the impact of PAs on threats to biodiversity identified on the IUCN Red List. Despite these strengths, some limitations should be acknowledged. First, a lack of time series data for most of the pressures at a global scale prevented us from including sufficient “before” data and therefore we focused only on control-impact comparisons. We accounted for this by ensuring that the pressure maps were from after PA establishment in nearly all cases. We only considered PAs designated after 2000, so our estimates might be conservative given the known time lag in the performance of PAs which can take up to 6 years to become apparent (Li et al. 2024). Additionally, the absence of global pressure maps for some threats on the IUCN Red List threat classification scheme made a comprehensive assessment impossible. However, we filled some of these gaps with findings from similar

studies, for example with hunting (Bogoni et al. 2020). Second, we defined our treatment and control groups at a pixel level which may overlook spatial characteristics of PAs which would be retained in polygon-based comparisons. Third, we analysed threats individually and did not consider potential interactions between them. The combined effects of multiple pressures on wildlife often cannot be predicted reliably from the individual effects of each stressor (Pirodda et al. 2022), meaning that our findings might not fully inform site- or species-specific conservation interventions. Importantly, threat levels can be proxies for measuring conservation success, however targeting conservation resources to threats alone will not necessarily translate to the most benefit to biodiversity (Pressey et al. 2015).

Our results emphasize that the designation of PAs on its own is insufficient to eliminate threats from an area. This aligns with previous studies which found that wildlife populations are declining within PA networks (Nowakowski et al. 2023). These findings can inform and improve the implementation of the GBF ‘30x30’ target by highlighting the need for PAs to be ‘effectively conserved and managed’, rather than solely focusing on expansion to meet the coverage statistics. While earlier drafts of the GBF included a focus on ‘strict protection’ and the EU Biodiversity Strategy for 2030 aims for 10% coverage by strict PAs, our results highlight that multi-use PAs can also play a significant role in reducing threats. In some cases, such as the presence of renewable energy infrastructure and fire risks, multi-use areas may even be more effective than strict PAs.

Our analysis shows considerable room for improvement in the management of existing PAs, as many threats persist inside existing PAs. Our results emphasize that the focus for achieving this ‘30x30’ target should depend on how much land is already protected. For countries with low PA coverage, the focus should be on establishing and expanding PAs, while countries with high coverage should instead prioritize enhancing the effectiveness of existing areas as suggested by Dudley & Solton (2022). We extend this further and highlight the need to consider threatened and endemic species richness to maximize the impact on biodiversity outcomes. Moving forward, balancing expansion and improving the management effectiveness of PAs will be essential for meeting global biodiversity targets.

Chapter 4 – The political economy of protected area effectiveness

Vincent, C. & Cisneros E. (2025). The political economy of protected area effectiveness.

Abstract

PAs are among the most widely used conservation strategies world-wide, yet assessing their ability to reduce human pressures remains difficult to measure. As urban populations grow and demand for natural resources intensifies, the factors affecting the capacity of PAs to resist encroachment has become increasingly critical to evaluate. Here, we use statistical matching and a panel dataset from 2000 to 2020 to assess the heterogeneity in PA effectiveness in preventing urbanisation. We focus on two aspects of urbanisation, specifically built area and nighttime light, and analyse the influence of socioeconomic and political contexts on PA performance. We find that globally PAs are effective at reducing land conversion to built-up areas, but not at limiting light pollution. PAs in more rapidly developing economies have more built area and nighttime light within their boundaries. Notably, the political context matters more than economic development. Stronger protection for minorities through more liberal political institutions, and higher state capacity had the biggest effect on PA effectiveness by significantly reducing built area and increasing nighttime light. The political context does not uniformly influence all aspects of urbanisation in PAs but instead shapes how and where urbanisation occurs. Ensuring the long-term success of PAs requires integrating them into stable, inclusive, and well-governed political systems.

4.1 Introduction

The ongoing biodiversity crisis, driven by habitat loss, climate change, and human activity, is leading to unprecedented rates of species extinction and ecosystem degradation worldwide (IPBES 2019). PAs are one of the best tools for addressing the biodiversity crisis in situ, however their effectiveness in absolute terms has historically been difficult to measure (Geldmann et al. 2021). While PAs can contribute to reducing certain human pressures such as deforestation (Andam et al. 2008), assessing their effectiveness on protecting biodiversity is difficult due to their non-random placement favouring areas that are less important for human exploitation (Joppa & Pfaff 2009). If PAs improve biodiversity simply because they are located in remote, undisturbed habitats, expanding PA networks alone may not achieve desired biodiversity outcomes (Brodie et al. 2023).

Furthermore, the effectiveness of individual PAs is variable depending on size, management type, and country (see Chapter 3), and the effectiveness of the global PA network on habitat loss is dependent on underlying biophysical factors (Li et al. 2024).

Additionally, a national study in Mexico showed that socioeconomic drivers such as road density and human population density were stronger predictors of forest loss than PA age and management effectiveness (Powlen et al. 2023).

Urbanisation is a major threat to wildlife, drastically reducing available habitats through fragmentation which increases edge effects and reduces connectivity (McDonald et al. 2020). Urban population growth is projected to expand urban areas by 1.2–1.8 million km² between 2000 and 2030 of which 290,000 km² is in natural habitat (McDonald et al. 2020). Sensitive and endemic species with limited habitat ranges are particularly vulnerable to urbanisation (Simkin et al. 2022). Urban areas tend to support more invasive species, with the proportion of invasive species increasing with the degree of urbanisation (McKinney 2006). Additionally, pollution from urban areas, including water contamination and greenhouse gas emissions, further degrades ecosystems and affects species survival (McDonald et al. 2020). These increased pressures can lead to the displacement of native species, changes in community composition (Shochat et al. 2010), and even local extinctions (McDonald et al. 2020).

Remotely sensed built area data provides insights into land cover changes and the physical expansion of urban areas. Nighttime light data captures the presence and intensity of artificial lighting, which serves as a proxy for electrification. Together, these indicators can monitor two characteristics of the urbanisation process integrating both structural and functional aspects of urban growth (Stokes & Seto 2019). Artificial light can significantly impact species' behaviour and physiology in various ways. For example, light pollution can interfere with predator-prey dynamics, reproductive behaviours, and species interactions even at low levels of nighttime light pollution (Gaston et al. 2013; Levin et al. 2020). Given its widespread ecological consequences, especially in urban and coastal regions, artificial light must be carefully managed to protect wildlife and ecosystem health (Levin et al. 2020).

PA coverage on its own is insufficient to eliminate human pressures on wildlife, and conservation impact can only be assessed in relation to avoided threats or avoided loss of biodiversity through the use of a counterfactual (Pressey et al. 2015; Ribas et al. 2020). The enabling conditions required to create successful PAs, such as the environmental, economic, governance, and cultural factors that increase the likelihood of successful conservation outcomes, are diverse, dynamic and intertwined, and therefore can be difficult to pinpoint (Huber-Stearns et al. 2017). Additionally, PAs require well understood use rights, clear land tenure, and improved patrolling strategies in order for them to provide positive outcomes for biodiversity (Nolte 2016). Therefore, the national socio-political context likely contributes to the effectiveness of PAs and likely dictates where and how urbanisation occurs. In a time of political uncertainty and regime change it is more important than ever to understand how these factors can affect long term conservation in situ.

Here, we investigate the impact of PAs on urbanisation using a 1-by-1 km grid-cell globally over a time period of 21 years (2000-2020) through statistical matching combined with a DiD panel regression. We use this framework to investigate the global heterogeneity in PA effectiveness and the underlying socioeconomic and political factors that impact the rate of urbanisation inside PA boundaries.

4.2 Data

Treatment points were derived from a combination of the March 2022 versions of the World Database on Protected Areas (WDPA) (UNEP-WCMC & IUCN 2022a) and the World Database on Other Effective Area-based Conservation Measures (WD-OECM) (UNEP-WCMC & IUCN 2022b), the combined dataset is referred to hereafter as “PAs” for simplicity. National, regional, and international terrestrial sites designated between 2000 and 2020 were retained. UNESCO-MAB Biosphere Reserves were removed from the WDPA because these sites include a buffer and transition zone that in many cases do not act as PAs (UNEP-WCMC 2019). PAs recorded as points, when their exact boundaries were not available, were included by applying a buffer to the site’s centroid so that the area of the site is preserved, however the boundaries are inexact. Some countries choose to restrict their data by making it unavailable to the public. To account for this, the 2016 version of the WDPA was added for China, Estonia, India and Turkey when the spatial information for their PAs was still publicly available. To consider the spatial overlap of some PAs in the database we retained only one of the PAs where they overlapped using the SAGA Rasterize tool Version: 7.8.2 in QGIS Version 3.32.3-Lima. We retain the strictest IUCN PA Management Categories in cases where there were overlaps. PA management categories are described in Appendix Table A2.1.

Control units were defined as areas that did not fall within the PA network. We also removed UNESCO-MAB Biosphere Reserves from potential control points and removed controls from a 10 km buffer around the PAs. This buffer was excluded from both the control and treatment datasets because of the potential for leakage or spillover effects from PAs (Baylis et al. 2016; Brodie et al. 2023). Both the final control and PA maps were independently rasterized to 1 km² resolution, and then each pixel was transformed into a potential control or treatment point, respectively, in GRASS GIS v8.3.

Our outcome of interest was urbanisation. To estimate the rate of urbanisation we looked at built area as well as nighttime light as outcome variables. Built area was taken from the Global Human Settlement Layer (GHS-BUILT-S - R2023A) which maps built-up surfaces derived from Sentinel2 and Landsat data at 5 years intervals from 2000 to 2020 (Pesaresi & Politis 2023). The values ranged from 0 to 638,883 m² of built area per 1 km² pixel. Artificial light was derived from the harmonized global nighttime light dataset (Li et al. 2020), where each 1 km² pixel was assigned a radiance value ranging from 0 DN (no light) to 63 DN (saturation), with higher values indicating greater light intensity. The global data was retained annually from 2000-2018.

To study the socioeconomic drivers of PA effectiveness we looked at pre-treatment values of employment in agriculture as the percentage of total employment (The World Bank 2024a), and GDP growth rate (The World Bank 2024b), and the human population growth rate (The World Bank 2024c) as percentage per year.

We considered four political factors at the national level. Rule of law ranges from 0 to 1 and captures the extent to which the government complies with the law, courts are independent, laws transparent, justice accessible, corruption absent, and bureaucracy impartial (Kaufmann et al. 2010). Political stability measures perceptions of the likelihood of political instability or politically motivated violence, including terrorism. Each country is scored on the aggregate indicator, in units of a standard normal distribution ranging from approximately -2.5 to 2.5 (Kaufmann et al. 2010). Liberal political institutions combines information on individual and minority rights, equality before the law, and limits on the governments' power on the courts. It ranges from 0 to 1 with higher scores indicating more liberal institutions (V-Dem 2025). Finally, the state capacity index captures the extent to which the state controls its territory, sustainably raises sufficient resources, and has skilled and impartial security forces and public servants (Hanson & Sigman 2021). Higher scores mean more capacity and scores range from -1 to 3. For all these factors, each treatment point was assigned a value for the country in which it fell, one year before it was designated as a PA. Control points were assigned the same value as their matched treatment since they were always paired within the same country.

We included all 14 terrestrial biomes, and assigned each point to the biome in which it fell (Figure A2.1; Olson et al. 2001). Biomes are large-scale ecological units characterised by distinctive climate conditions, vegetation types, and associated animal communities, serving as a framework for understanding patterns of biodiversity and ecosystem function globally.

4.3 Empirical approach

4.3.1. *Matching*

Statistical matching was done to account for confounding factors as it is designed to evaluate the effects of a treatment with purely observational data. Matching reduces the bias associated with unequal covariate distribution between treatment (here PAs) and non-treatment groups (Ferraro 2009).

Based on previous studies (Andam et al. 2008; Eklund et al. 2016; Geldmann et al. 2019) and due to the biased placement of PAs in the landscape where they tend to be in places that are at high elevations and in areas that are not important for economic activities (Joppa & Pfaff 2009), we chose the following matching covariates: agricultural suitability, human population density, travel time to nearest city of 50,000 or more people, elevation, slope, total annual precipitation, mean annual temperature, biome and country.

All the covariate datasets were from the year 2000 or before to ensure they represent the pre-treatment state.

We tested for multicollinearity between covariates using VIFs on a random 10% sample of our data ($n = 10,410,175$) with R package *car* (Fox & Weisberg 2019). All nine covariates had a VIF score of less than 5 (Table A2.2), therefore there is a low likelihood of high correlation between the variables. Additionally, collinearity among covariates is not as problematic with matching as in other methods used for impact evaluation such as parametric regression models (Ribas et al. 2021). After this assessment we deemed it appropriate to retain all nine covariates. We standardised the data to Mollweide equal-area projection at 1x1 km resolution in GRASS GIS v8.3.

We tested three matching methods on a sample of the dataset and CEM with the Mahalanobis distance metric provided the best balance, with the smallest standardised mean differences and variance ratios closest to one. As well as providing good balance, the Mahalanobis distance accounts for potential collinearity among the variables considered at each pixel (Eklund et al. 2016). Matching analyses were performed using the *MatchIt* package (Ho et al. 2011) in R 4.2.0 with one treatment to one control point without replacement. Exact matching was used for biome and country, meaning that each matched pair of treatment and control points were from within the same biome and country. The final dataset retained 3,279,545 matched pairs across 166 countries (Figure 4.1 & Table A2.3).

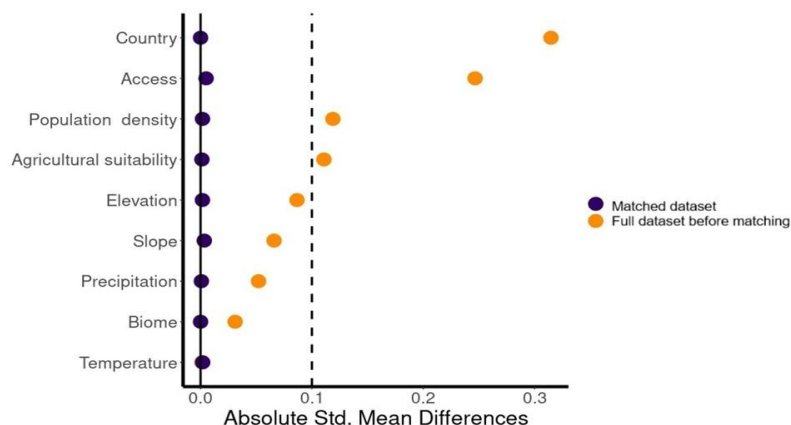


Figure 4.1: Covariate balance showing differences in the absolute standard mean differences of covariates before (light orange) and after (dark purple) coarsened exact matching. For determining imbalance we used a threshold of > 0.1 (dashed line).

4.3.2. Panel estimations

We assessed the effect of protection on urbanisation by using the panel structure of our matched grid cell database which spans 21 years from 2000-2020. We do this with a DiD model that considers both the difference in the outcome variable between periods before

and after PA designation and between treatment and control groups. We use the following fixed effect panel regression for estimates of two urbanisation outcomes (U), done separately for built area and nighttime light, per 1x1km pixel i per year t :

$$U_{icbt} = \delta PA_{icbt} + \mu_i + \alpha_t + \lambda_{ct} + \eta_{bt} + \varepsilon_{icbt} \quad (4.1)$$

Where PA is the treatment indicator, which turns to one after the designation of a PA at that pixel. The treatment coefficient δ measures the average treatment effect, or the average change in urbanisation due to the establishment of a PA for all years after treatment. We include cell fixed effects which capture unobserved time-invariant characteristics (μ_i), such as underlying geological and environmental conditions, and year fixed effects (α_t) that control for common macroeconomic and policy shocks.

To consider the heterogeneity of urbanisation pressure in different national and biophysical contexts, we controlled for country (c) and biome (b) fixed effects. We also controlled for common environmental shocks as well as national political changes with the interactions of biome-year (η_{bt}) and country-year (λ_{ct}) fixed effects. The error term, ε_{icbt} , is the idiosyncratic error. In all cases, we cluster the standard error at the cell level.

To investigate the heterogeneity of the socioeconomic and political factors contributing to the effect of protection on urbanisation we add an observed time-invariant variable to the equation. Specifically, we add the pre-treatment values of GDP growth rate, population growth rate, and employment in agriculture to estimate the effect of development pressure. We also look at pre-treatment values of rule of law, political stability, liberal political institutions, and state capacity to estimate the political influence on PA effect.

4.4 Results

4.4.1. Global impacts

The estimates of the average effect of PAs on built area are reported in Panel A of Table 4.1. The first column shows the results using the basic model with only pixel and year fixed effects, which indicates a 39 m² annual reduction of built area after the designation of a PA. When controlling for macroeconomic shocks and political changes at the country level (column 2) we find a similar result although the rate of reduction is slightly lower at a 36 m² reduction per year. When adding biomes to control for the ecological landscape (column 3), we again get a similar result of a 34 m² reduction per year, indicating that the impact of PAs on built area is only slightly dependent on the country and biome in which it is found. In all cases we clustered the standard errors at the cell-level and the impact is significant at 1.3 m².

For the estimates of the average effect of PAs on nighttime light, the inclusion of country and biome differential year fixed effects has more importance (Panel B of Table 4.1). We find that without the inclusion of either the country-year or biome-year fixed

effects, the model suggests that PAs reduce the rate of artificial light by 0.02 DN per year (column 1). However, when we control for the country in which a PA is found, the impact estimate changes sign, pointing to a 0.01 DN increase in radiance (column 2). This estimate increases with the addition of the biome-year fixed effect to a 0.02 DN annual increase of radiance inside PAs (column 3). In all cases we clustered the standard errors at the cell-level and the impact is significant at 0.001 DN.

Table 4.1: Baseline exposure of PAs to urbanisation.

	(1)	(2)	(3)
PANEL A: <i>Dep.var.</i> : Built area [m ²]			
Protected area	-38.894*** (1.254)	-35.780*** (1.298)	-34.322*** (1.304)
Mean (control)			
No. observations	30,336,495	30,336,495	30,336,495
No. cells	6,002,791	6,002,791	6,002,791
Adj. R ²	0.972	0.973	0.973
PANEL B: <i>Dep.var.</i> : Nighttime light [DN]			
Protected area	-0.022*** (0.001)	0.012*** (0.001)	0.024*** (0.001)
Mean (control)			
No. observations	114,804,840	114,804,840	114,804,840
No. cells	5,978,060	5,978,060	5,978,060
Adj. R ²	0.732	0.765	0.787
Cell & year FE	Yes	Yes	Yes
Country-year FE		Yes	Yes
Biome-year FE			Yes

The dependent variable is built area in Panel A and nighttime light in Panel B. The dataset is based on one-to-one coarsened exact matching without replacement. Clustered standard errors at the cell level are reported in round brackets. */**/** denote significance levels at 10/5/1% respectively.

PA effectiveness is also dependent on the management interventions at the site level. When looking at the effect per PA management categories, we find that the category III natural monuments and the category IV habitat management areas are the most effective at reducing built area by -53.2 m² and -22.1 m² respectively (Figure 4.2a). Additionally, we find that the multi-use protected landscapes, category V, performed worse and increased built area by 64.7 m².

We find that the category Ia strict nature reserves, category Ib wilderness areas, and the multi-use sites of categories V and VI are most effective at reducing nighttime light pollution (Figure 4.2b). In this case we find that category II national parks and category IV habitat management areas are least effective increasing light pollution by 0.4 DN and 0.7 DN respectively.

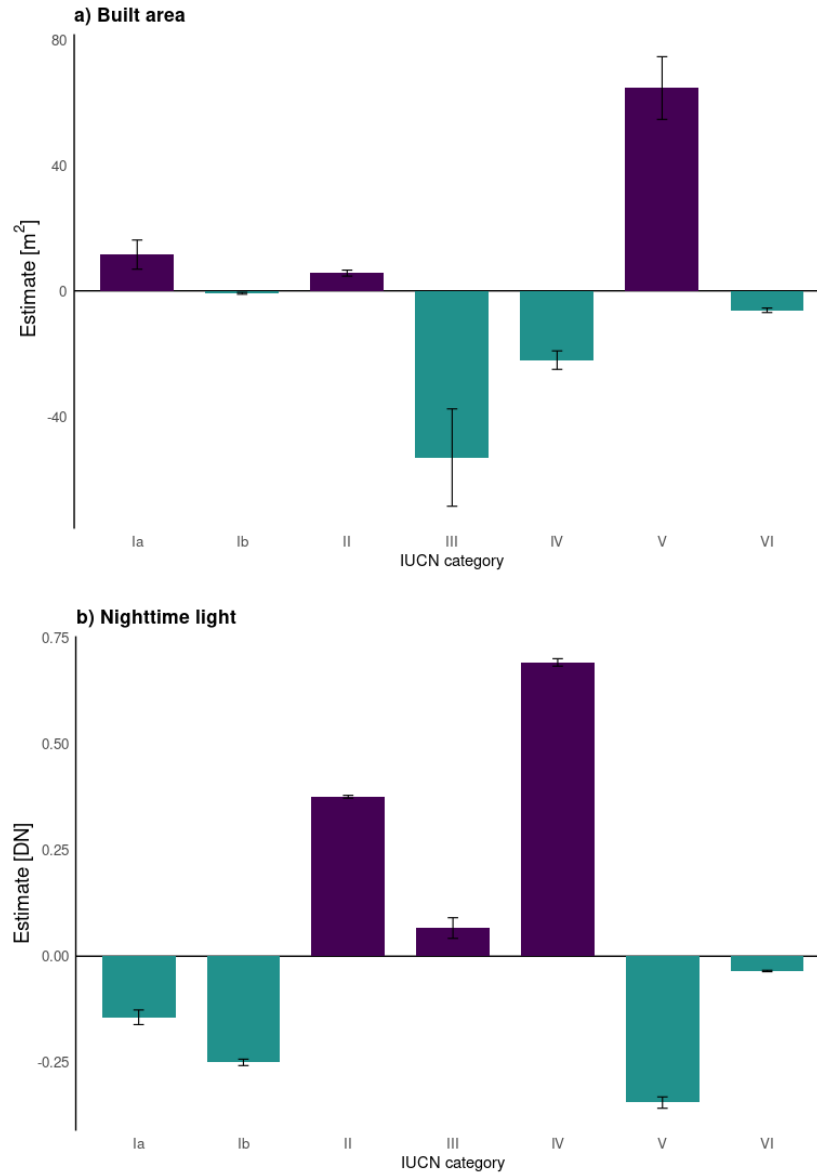


Figure 4.2: The average treatment effect for each PA IUCN management category on two indicators of urbanisation: built area (a) and nighttime light (b). The effect per category was calculated from model 4.1 with pixel, year, country, biome, country-year and biome-year fixed effects using the matched dataset. Light green bars indicate a lower rate inside PAs compared to controls, and dark purple indicates a higher rate inside PAs. Built area is measured in m^2 per pixel, and nighttime light is measured in DN per pixel. Clustered standard errors at the cell level are shown.

4.4.2. Diverse effectiveness across the globe

PA effectiveness is heterogeneous across the globe with large variation at the national level. PAs significantly reduce the rate of built area in 87 countries, whereas in 13 countries the rate is significantly higher after PA designation ($p < 0.05$), and the remaining countries had no significant difference of treatment (Figure 4.3a). Regionally, North America and Southeast Asia perform well with mixed effects found across Africa and Europe. In South America there are numerous countries with no significant effect of protection on built area.

For nighttime light we found a significant reduction by PAs in 70 countries, whereas 52 countries had significantly higher radiance after PA designation with the remaining countries showing no significant difference (Figure 4.3b). Few regional patterns emerged with mixed estimates in most of the world, and poor PA performance in parts of Asia.

We found contrasting effectiveness in 28 countries which have a significantly lower rate of built area and a significantly higher rate of nighttime light after treatment. France is the only country where the opposite is observed with significantly higher rates of built area and lower rates of nighttime light. Overall, 46 countries show a significantly negative effect of protection for both outcomes of urbanisation, indicating strong PA effectiveness in over a quarter of the analysed countries.

4.4.3. Robustness

We performed an event study analysis on a subsample of our panel dataset to test for the absence of urbanisation trends prior to PA designation. An event study analysis is needed since the year of PA designation was staggered across time (Sun & Abraham 2021), and it can show whether the effect of urbanisation would have changed anyway in the absence of PA designation. The results from the event study analysis are provided in the Appendix (Figure A2.2) and confirms the absence of pre-treatment trends. For both built area and nighttime light, the pre-treatment trend is constant and at the time of PA designation there is an immediate negative effect of protection, meaning that the rate of urbanisation slows as soon as the PA is designated. This negative effect continues for the remainder of the treated years, although with nighttime light the effect reduces after 10 years.

To account for potential other unobservable confounding factors specific to PAs, we conduct a placebo test demonstrating that there are no underlying differences between the areas. Placebo tests mean that insignificant effects would be expected when treatment interventions are randomly reassigned. Table A2.4 shows that the effects of PAs do not owe to inherent differences in receiving treatment.

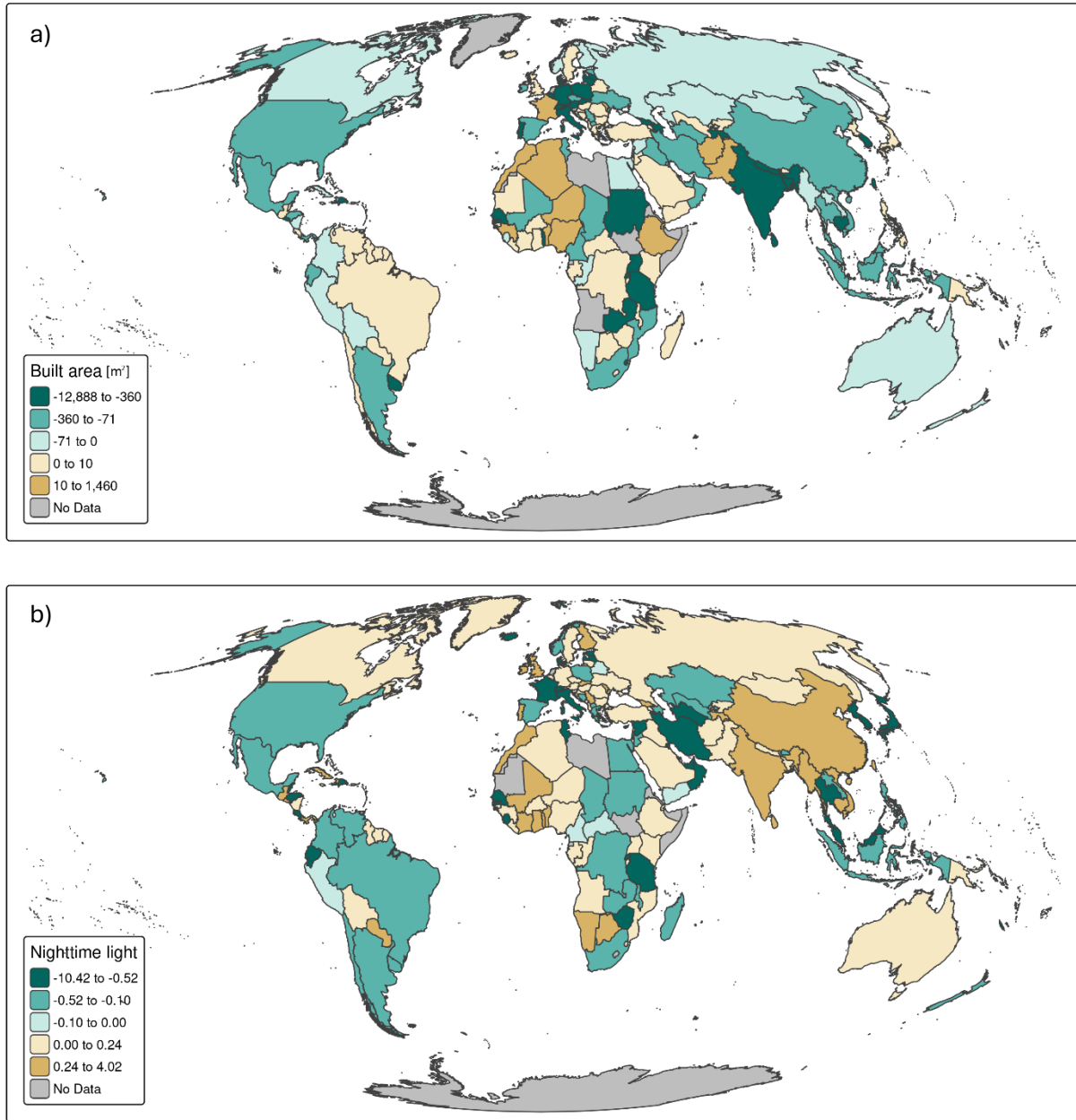


Figure 4.3: The average national treatment effect of PAs on two indicators of urbanisation: built area (a) and nighttime light (b). The effect per country was calculated from model 4.1 with pixel, year, country, biome, country-year and biome-year fixed effects using the matched dataset. The colours indicate the average annual effect across PA pixels in reducing urbanisation with negative values indicating a lower rate inside PAs compared to controls. Built area is measured in m² per pixel, and nighttime light is measured in DN per pixel.

4.4.4. Development moderately reduces the effectiveness of PAs

Rapid rates of urban growth can destroy natural habitats to make room for the expanding human population (McDonald et al. 2020). Countries with a rapidly growing GDP and human population convert more land for urbanisation (Seto et al. 2011), and countries with lower employment in agriculture have smaller urban populations. Therefore, we test the effect of these factors on the effectiveness of PAs in the face of urbanisation pressure. We test for the effect of these three national measures of development and present the results in Table 4.2.

Countries with higher rates of economic development have a moderate but significant increase in built area inside PAs. With every percent increase of GDP growth rate, we see an increase of 0.3 m² protected land converted to infrastructure (column 1). A similar trend was found with the other socioeconomic factors. With every percent increase in employment in agriculture and human population growth rate there was a 1.1 m² and 4.2 m² increase in built area inside PAs respectively (columns 2 & 3). Similarly, higher GDP growth rates and employment in agriculture marginally increased nighttime light intensity inside PAs by 0.001 and 0.003 DN respectively (columns 4 & 5). However, population growth rate had the opposite effect on nighttime light inside PAs, where it is reduced by 0.04 DN with every percent of growth (column 6). For both built area and nighttime light, human population growth rate had the strongest effect on PAs of all the socioeconomic variables tested.

Table 4.2: Socioeconomic drivers of PA effectiveness

Mediator	Built area			Nighttime light		
	GDP Growth rate (1)	Empl. in Agricul. (2)	Pop. Growth Rate (3)	GDP Growth rate (4)	Empl. in Agricul. (5)	Pop. Growth Rate (6)
Protected area	-34.476*** (1.310)	-33.053*** (1.312)	-34.786*** (1.309)	0.024*** (0.001)	0.025*** (0.001)	0.027*** (0.001)
Protected area × Mediator	0.298*** (0.021)	1.055*** (0.031)	4.250*** (0.276)	0.001*** (0.000)	0.003*** (0.000)	-0.035*** (0.001)
Cell & year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Biome-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,183,005	30,160,925	30,195,155	114,221,578	114,137,674	114,267,748
No. cells	5,986,179	5,981,763	5,988,609	5,961,448	5,957,032	5,963,878
Adj. R ²	0.973	0.973	0.973	0.787	0.787	0.787

The dependent variable is built area (m²) per 1 km² cell measured at 5-year intervals from 2000-2020 (left) and nighttime light radiance (DN) per cell measured annually from 2000-2018 (right) globally. Samples are based on one-to-one coarsened exact matching without replacement. Clustered standard errors at the cell level are reported in round brackets. */**/** denote significance levels at 10/5/1% respectively.

4.4.5. The political context matters

PAs are known to be more effective when they are actively managed and well resourced (Coad et al. 2019), therefore we expect treatment effects to be highest in countries with stronger political structures. We test for the effect of four national measures of government functioning on PA effectiveness and present the results in Table 4.3.

We found that with increasing rule of law, liberal political institutions, and state capacity, PAs were more effective at avoiding built area inside their boundaries (Panel A). However, we found that PAs performed worse with stronger levels of these same political factors for avoiding nighttime light (Panel B). When considering the effect of political stability, we found the opposite effect for both outcomes. Specifically, countries that were more politically stable had significantly more built area inside PAs by 5 m², however PAs lowered nighttime light by -0.05 DN (column 2). Overall, there was a mixed effect of stronger political institutions on urbanisation rates inside PAs, however the effect was stronger than that of the socioeconomic factors.

Table 4.3: Political drivers of PA effectiveness

Mediator	Rule of law	Political Stability	Liberal Political Institutions	State capacity
	(1)	(2)	(3)	(4)
PANEL A: <i>Dep.var.</i> : Built area [m ²]				
Protected area	-34.469*** (1.311)	-34.472*** (1.311)	-34.527*** (1.312)	-32.463*** (1.312)
Protected area × Mediator	-0.875 (3.573)	5.062*** (0.345)	-6.779*** (1.930)	-10.200*** (0.567)
Observations	30,147,505	30,149,015	30,147,525	30,114,095
No. cells	5,979,079	5,979,381	5,979,083	5,972,397
Adj. R ²	0.973	0.973	0.973	0.973
PANEL B: <i>Dep.var.</i> : Nighttime light [DN]				
Protected area	0.021*** (0.001)	0.025*** (0.001)	0.027*** (0.001)	0.012*** (0.001)
Protected area × Mediator	0.414*** (0.004)	-0.048*** (0.000)	0.429*** (0.003)	0.037*** (0.001)
Observations	114,086,678	114,092,416	114,086,754	113,959,720
No. cells	5,954,348	5,954,650	5,954,352	5,947,666
Adj. R ²	0.787	0.787	0.787	0.788
Cell & year FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
Biome-year FE	Yes	Yes	Yes	Yes

The dependent variable is built area per 1 km² cell measured at 5-year intervals from 2000-2020 (Panel A) and nighttime light radiance (DN) per cell measured annually from 2000-2018 (Panel B) globally. Samples are based on one-to-one coarsened exact matching without replacement. Clustered standard errors at the cell level are reported in round brackets. */**/** denote significance levels at 10/5/1% respectively.

4.5 Discussion

Our analysis found that on average PAs have a significant effect on reducing the amount of built area inside their borders, yet they do not protect against artificial light globally. These contrasting results suggest that built area expansion and electrification are driven by different underlying processes and occur at varying rates depending on local and national contexts. The lack of correlation between these two pressures highlights the need to consider them as distinct dimensions of urbanisation. We also observed substantial national-level variation in PA effectiveness as well as between PA management categories. While the global trends for built area and nighttime light differed, over a quarter of the countries analysed exhibited strong PA performance in mitigating both pressures. These findings prompted further analysis to investigate the heterogeneity contributing to these national differences in PA effectiveness.

We found increased encroachment in PAs in countries with more rapidly developing economies and populations, supporting previous global projections that suggest there will be a significant expansion of urban land near PAs in the coming decades, especially in developing countries and emerging economies (Elmqvist et al. 2013). Further, it has been suggested that these countries have lower institutional capacity to manage new anthropogenic pressures (McDonald et al. 2008), as well as lower capacity for formal governance, which may limit conservation effectiveness (Elmqvist et al. 2013). We tested this assumption, and our results confirm that countries with more institutional capacity are more effective at reducing rates of built area inside their PAs, and state capacity had the strongest effect of any heterogeneous factor analysed in this study.

Furthermore, countries characterised by stronger protections for minority and Indigenous rights, and broader principles of equality before the law had lower rates of built area in PAs. Case studies have shown that when conservation interventions are viewed as inequitable, illegal resource use increases and managers must rely on enforcement to ensure results (Schreckenberg et al. 2016). Generally, equitable governance structures are associated with more positive ecological and social outcomes (Dawson et al. 2024), whereas top-down interventions that disregard local practices can spark conflict between rural communities and powerful state actors (Dawson et al. 2021; Zhang et al. 2023). Our result supports the need for political legitimacy for the local communities near PAs (Schreckenberg et al. 2016) to create enabling conditions that reduce encroachment pressures on PAs.

In contrast, our analysis found that PAs in more politically stable countries were, on average, less effective at preventing built area encroachment. Interestingly, the opposite effect was seen with nighttime light. One possible explanation is that during periods of stability, lower-income populations may feel more secure investing in land and property, including within or near PAs. However, these communities may lack the resources for full electrification, leading to minimal nighttime light emissions despite increased physical development. Additionally, in rapidly developing regions, political stability often attracts

international investments which then dictate development (Elmqvist et al. 2013). This influx of investment can in some cases lead to increased pressure on the environment (Henderson 2021), underscoring the complex relationship between governance, development, and environmental protection.

Overall, we found small but higher rates of light pollution inside PAs. Globally, brightly lit areas are relatively rare, and radiance levels are low outside of large cities (Kyba et al. 2017), therefore even small changes in low-level lighting can lead to a significant effect. These small changes in radiance may still have a significant impact on biodiversity. Changes in nighttime light at levels as low as 1.6×10^{-6} lux can impact the ability of many owl species to locate prey and an increase of 0.01 lux has been found to alter the circadian rhythm of some small mammals (Gaston et al. 2013). Moreover, urban growth often results in increased light at city peripheries, and as cities expand into the surrounding landscape, previously semi-natural zones can become brighter (Kyba et al. 2017). Additionally, LED bulbs emit less radiance than traditional bulbs, and the recent uptake in their use can lower the intensity of light detected by satellites. However, LED light scatters more in the atmosphere creating more skyglow that can increase radiance over adjacent areas that have little or no direct lighting (Kyba et al. 2017).

More rapidly developing economies and countries with a higher rural population have slightly higher levels of nighttime light within PAs after designation. This pattern likely reflects the ongoing expansion of solar powered LED lights in rural areas, where access to electricity has historically been limited or prohibitively expensive (Kamat et al. 2020). In contrast, higher population growth rates are associated with lower levels of nighttime light within PAs. One possible explanation is that in countries with high population growth, much of the expansion is concentrated in cities, far from PA boundaries.

Similarly to built area, the political context had a stronger effect on light pollution than socioeconomic factors. However, the directionality of the effect was reversed for the same political factors having an opposite effect on built area or nighttime light. For instance, countries with more liberal political institutions tended to have more nighttime light within PAs. Stronger minority rights may facilitate more equitable access to energy infrastructure, including rural electrification. In this sense, liberal and inclusive governance seems to reduce physical encroachment while simultaneously promoting energy access near or even within PA borders, particularly in remote minority communities.

As with any quasi-experimental evaluation, there are inherent limitations, particularly the risk of unobserved confounding variables (Rosenbaum 2002). Notably, although we find a significant effect of most of these heterogeneous variables, the result is not necessarily causal. There may be other factors that determine why and where PAs were designated depending on the national governance (Abman 2018), and motivations behind PA designation are not considered in this study. Furthermore, prior research on the effectiveness of PAs suggests that the inherent bias in PA location often leads to

overestimation of conservation impacts. To address this, we employed rigorous matching methods combined with a panel regression to consider both observed and unobserved confounders. A two-way fixed effects model was not deemed suitable for this study as the treatment effect heterogeneity and the known time-lag after PA designation (Li et al. 2024) would have caused too much bias. These approaches give us confidence that our results reflect the effects of PAs on urbanisation rates during the study period. We also found that without controlling for country-year and biome-year fixed effects our models were overestimating the global impact of PAs in reducing urbanisation within their boundaries, emphasizing the importance of including observable confounding variables.

Our findings demonstrate that the effectiveness of PAs is driven by a combination of economic and political influences. While economic development does influence the pressures on PAs, our analysis shows that the political context plays a bigger role in determining urbanisation rates inside PA boundaries. National-level liberal policy frameworks, capacity, and political stability significantly affect the ability of PAs to prevent human encroachment. In an era marked by increasing political volatility and regime shifts in many parts of the world, understanding how governance structures influence conservation outcomes are more critical than ever. These results highlight that the long-term success of PAs depends not only on their legal designation but also on their integration into stable and supportive political systems.

Chapter 5 – General discussion

5.1 Evaluation of research objectives related to main findings

There is now direct evidence of the impact that geopolitical shifts can have on conservation outcomes. The first objective of this thesis is to assess the influence of stochastic geopolitical events on progress toward international biodiversity goals. Through a literature review and expert consultations, the second chapter discussed the impact of the escalation of the war in Ukraine in early 2022 on the drivers of biodiversity loss. I found that there were immediate and far-reaching impacts of the policies made in response to the war on biodiversity, and that policies that may seem regionally focused, in fact have worldwide implications through global-to-local-to-global linkages. I highlight the importance of re-evaluating the progress made towards goals set in multilateral environmental agreements with more focus on regionalisation scenarios to account for the increased uncertainty in the future storylines. Furthermore, I recommend developing new socioeconomic storylines that reflect the changes made to production and consumption patterns and which focus on a de-globalisation pathway. These would not replace the existing scenarios but would broaden our horizon to ensure that it encapsulates all possible futures, to increase our chances at meeting international biodiversity targets. Finally, I stress the need for mainstreaming biodiversity and that geopolitical policy decisions, even those unrelated to the environment, need to have a long-term vision that considers nature.

The second objective of this thesis is to evaluate the effectiveness of the global network of terrestrial PAs on reducing human pressures within their boundaries. To achieve this objective a large and extensive statistical analysis was undertaken with publicly available data of the main threats contributing to species extinction risk. I found that overall, PAs reduce, but do not eliminate threats to wildlife, and that strict and small PAs tend to be most effective. However, I did find a lot of national heterogeneity in the results with some countries performing much better than others. The results from Chapter 3 can contribute to assessing progress towards achieving the qualitative aspects of GBF target 3, specifically related to an effective PA network, as well as target 4 that calls for “*urgent management actions to halt human induced extinction of known threatened species [...] in situ*” (CBD 2022). With these results, I recommend that countries with low PA coverage should focus on establishing and expanding PAs, while countries with high coverage should instead prioritize enhancing the effectiveness of existing areas, and this is particularly important in countries with high endemic and threatened species richness.

The fourth chapter delved deeper into the observed heterogeneity in PA effectiveness. The third objective of this thesis is to examine the role of economic development and the strength of political systems on the performance of PAs, considering how national governance and institutional capacity shape conservation outcomes. By combining robust impact evaluation methods with the political and socioeconomic context of PAs, Chapter

4 found that the rate of economic development affects PA performance, yet the political context matters more. Stronger protection for minorities through more liberal political institutions, and higher state capacity have the biggest effect on PA effectiveness by significantly reducing built area inside their boundaries. The results from this chapter can contribute to improving conservation policy, offering new insights into how regime change and leadership priorities can affect long-term conservation outcomes.

Taken together, the findings from this thesis can be used to assess how periods of political uncertainty affect conservation outcomes and may impact the achievement of international biodiversity targets. These applications of the results will be discussed in the following two sections where I discuss the conservation relevance of the findings in section 5.2, and the policy implications in section 5.3. I then conclude with section 5.4 on the limitations and the subsequent research questions that this work has inspired.

5.2 Conservation relevance of principal findings

5.2.1. Impact evaluation methods

In this thesis two methods of quasi-experimental impact evaluation were used to assess the effectiveness of PAs. Although other causal analysis methods exist, such as instrumental variables and two-way fixed effects models, they were not suited for the research questions of this thesis. Specifically, the variety of threats compared in Chapter 3, the lack of time-series data for many of the variables used, and the heterogeneous quality of the impact of PAs would have introduced too much bias to these other methods. Therefore, statistical matching and DiD regression were the most robust tools to answer these research questions.

It has historically been difficult to conduct robust impact evaluations of PAs for two main reasons. First, because of limited data and processing power most studies have lacked scope. They have been small-scale (Cisneros et al. 2022), lacked counterfactual comparisons (Spracklen et al. 2015), or have only looked at one threat at a time (Andam et al. 2008). Second, is the empirical challenge to estimate a causal relationship from direct observations of biodiversity. For example, Wauchope et al. (2022) used robust impact evaluation methods at a global scale, however their analysis focused on direct biodiversity measures for which the data is regionally biased due to data limitations. This thesis addresses both of these limitations, using numerous threat maps together with quasi-experimental methods at a global scale.

Due to the known biased location of PAs across the landscape, which are often placed in areas with fewer existing threats or far from human pressures, as stated throughout this thesis, it is of extreme importance to account for this through counterfactual impact evaluation rather than relying on simple inside-outside comparisons. Without a counterfactual the effectiveness of PAs could be under or overestimated in both the terrestrial and marine realms. For example, PAs can displace disturbances to unprotected

areas in the landscape through ‘leakage’ (Ewers & Rodrigues 2008), or conversely the benefits from a PA can enhance biodiversity in nearby unprotected places through ‘spillover’ effects (Brodie et al. 2023).

The analyses of both Chapters 3 & 4 found that the effect of protection is very low. This can be due to the relative effect of individual PAs compared to their controls. The measured effectiveness of individual PAs depends on the context, and two PAs with the same observed pressure can have different effectiveness scores based on the difference in pressure compared to their matched controls. For example, two PAs with identical levels of high threat can have opposite effects, where one PA that has reduced threats relative to controls has a negative ATT, and the other PA has a positive ATT if it is located in a low-pressure area (Nolte et al. 2013). Similarly, a PA can have low effectiveness if it is located in a low-pressure area, even if it has completely eliminated the threat. It is also possible that reducing a low threat pressure by a small amount can have a big impact, or in contrast, that a PA has no measurable effect simply because the pressure from that threat is absent. In sum, the small effect of PAs found in Chapters 3 & 4 is likely due to PAs being located in areas that are under less human pressure where they innately have lower threats, underscoring the importance of using a counterfactual to avoid overestimation.

Statistical matching is being increasingly used in conservation biology, however this approach is lagging behind the advancements in impact evaluation strategies in other fields. Panel regressions are more statistically robust and should be used more widely in conservation when time series data allows for it. Although both methods provide reliable and robust results (Jones & Lewis 2015), panel regressions account for time-invariant unobservable bias that is not possible with matching alone. Additionally, panel regressions can be used on their own without needing to first create a matched dataset. However, when treatment points are very different from controls, matching provides an additional assurance in getting the two groups as similar as possible in terms of observable characteristics before panel regression analysis (Jones & Lewis 2015). If treatment effects can be estimated accurately on observable data alone, estimation with matching or panel regression methods will yield similar results (Jones & Lewis 2015). However, this assumption is difficult to evaluate and therefore using panel regressions will provide a more reliable effect in most cases. Nevertheless, the main limitation with panel regressions is that it requires timeseries data to estimate an effect.

5.2.2. The role of PAs for species protection in an uncertain world

PAs play a crucial role in safeguarding biodiversity, and serve as essential refuges for species, particularly those with small ranges or restricted distributions (Carroll & Noss 2022). However, a critical issue is that PAs do not exist in solitude; they are linked to larger systems and cannot always shield species from stressors that originate outside their boundaries (Nowakowski et al. 2023), and they often lack adequate resources for enforcement (Coad et al. 2019). More than half of the threats in the IUCN Red List threat

classification scheme, such as pollution run-off, climate change, and invasive species, require additional inputs like active site management or larger-scale landscape management (Pressey et al. 2015; Kearney et al. 2020). Therefore, PAs on their own are not enough to completely safeguard biodiversity and need to be integrated into the wider landscape and conservation strategy.

Not only do PAs need to be considered as part of the wider landscape to have a positive impact on wildlife, but a more integrated approach is also needed within national policy. Chapter 2 discusses how the world order is currently experiencing shifts and turbulence which can have knock-on effects on nature. Additionally, Chapter 4 found that the political context in which a PA is situated has a large effect on threat abatement. Together, these results highlight the need for mainstreaming biodiversity protection into all government policies at a national scale. Integrating biodiversity across all sectors and levels of national policymaking. For example, establishing a national inter-ministerial biodiversity working group to assess proposed policies for their potential impact on biodiversity and to ensure alignment with national environmental commitments. Governments need to recognize that decisions not directly related to nature can still have significant, often overlooked, ecological consequences.

Additionally, as highlighted in Chapter 4, improving minority rights and strengthening state capacity can have a positive impact on PAs in their ability to withstand the pressure of encroaching built area. Inclusive involvement of diverse stakeholders in PA management is essential for achieving improved environmental and social outcomes (Oldekop et al. 2016), yet many PA managers have limited resources and inadequate support that makes stakeholder engagement difficult (Fisher et al. 2023). As suggested from research on Colombia's PAs, investment in staff, equipment, and infrastructure may fail to increase enforcement capacity and yield positive conservation outcomes unless accompanied by clear use rights, land tenure, and improved patrolling strategies (Nolte 2016). Furthermore, a case study from Snuol and Keo Seima Wildlife Sanctuaries in Cambodia highlights how secure Indigenous land tenure supports effective governance, and underscores the need to invest in site-level capacity to avoid PADDD events (Nuttall et al. 2023).

Poorly managed PAs, or those that lack resources for enforcement, are all too common and can lead to species decline even within their boundaries (Geldmann et al. 2013; Gill et al. 2017; Coad et al. 2019). For example, in Sierra Leone, the Gola Rainforest National Park has lower deforestation rates than other less well-resourced PAs (Malan et al. 2024), such as the Kambui Hills Forestry Reserve where exploitation is reducing plant diversity and richness and plant regeneration ability is poor due to weak conservation governance (Fayiah et al. 2020).

Finally, the global political economy determines how conservation and development policies are framed, with global economic and political dynamics significantly influencing biodiversity conservation and PA management (Büscher & Whande 2007). Recognizing

and responding to emerging trends shaped by these forces is therefore essential. In politically volatile contexts, PAs face different pressures that can undermine their effectiveness. For example, in Colombia, where armed conflict has marked much of their recent history, retaliation against PA staff through threats, violence, and equipment damage has weakened law enforcement (Nolte 2016). In this context, the effectiveness of conservation was strongest in large PAs while the presence of FARC guerrillas increased deforestation (Liévano-Latorre et al. 2021). This highlights the need for context-specific conservation strategies that account for both ecological goals and the broader political and security landscape.

5.3 Policy implications

5.3.1. *Improving indicators*

This thesis underscores the need to shift the conservation agenda from simply expanding the global network of PAs to improving the management effectiveness and threat mitigation of existing sites. While increasing PA coverage remains important, especially in regions with low coverage and high endemic biodiversity, it is often impractical if sites are poorly managed or ineffective at withstanding mounting human pressures such as land conversion, urbanisation, and resource extraction.

The current indicators for the GBF identified in the monitoring framework are more focused on the quantitative aspects of the targets largely because these indicators already existed at the time of adoption. However, there is a need to develop new indicators that can efficiently assess the qualitative aspects of the targets uniformly across different habitat types. For example, the contribution of PAs to biodiversity outcomes depends on factors such as their management quality, governance structures, threats, and the condition of the surrounding landscape, therefore global percentage-based protection targets are broad generalisations that overlook these underlying complexities (Geldmann et al. 2021; Carroll & Noss 2022).

This requires moving beyond the current indicators like percentage PA coverage to more nuanced, outcome-oriented measures. Species threat data offer a valuable foundation for developing such indicators, particularly for Target 3 (area-based conservation) and Target 4 (reducing species extinction risk). Tools like the IUCN Red List Index (Butchart et al. 2004) and the STAR metric (Mair et al. 2021) directly link threat reduction actions to changes in extinction risk, providing a clearer picture of conservation effectiveness over time. The STAR metric considers the Red List threats that affect each listed species, however it assumes those threats are evenly distributed across the species range. This is a known limitation of the STAR metric (Mair et al. 2023), and therefore integrating the spatially explicit threat results from Chapter 3 into the STAR metric has the potential to improve its ability to more accurately track extinction risk at a global scale.

Threat-based planning provides a valuable framework for directing conservation investments to where they can have the greatest impact (Mair et al. 2021). By aligning actions with species vulnerability and site-specific pressures, this approach helps prioritize conservation interventions especially in areas where small-scale habitat loss can have a big impact (Carroll & Noss 2022). For instance, the likelihood of a vertebrate being listed as threatened on the IUCN Red List increases with the proportion of its range that is urbanised, and only a small increase in urbanisation for small-ranged species can have a big impact on the probability of it being listed (McDonald et al. 2008). Therefore, understanding the drivers of threats like urbanisation within PAs, as explored in Chapter 4, can support more effective targeting of indirect pressures and improve strategies to reduce species extinction risk.

The methods described in Chapters 3 & 4 can be applied at both global and site-specific scales and repeated periodically to track trends, enabling adaptive management. This approach also provides a more nuanced understanding of how PAs function as a key mechanism for reducing extinction risk. Moreover, a globally improved and harmonized use of SMART (specific, measurable, ambitious, realistic, and time-bound) indicators enhances transparency and accountability across countries (Pillay et al. 2024). Therefore, embedding threat-driven, outcome-oriented indicators into the GBF is important for making conservation targets both actionable and meaningful, and can guide more strategic conservation investments.

The GBF represents a critical opportunity to shift from aspirational conservation targets to measurable outcomes. Doing so requires a rethinking of biodiversity indicators from static, area-based metrics to dynamic, impact-driven assessments that reflect both ecological realities and societal values (Adams et al. 2021). Threat mapping and scenario planning offer promising tools, but their success depends on political will, financial commitment, and inclusive capacity development (Maney et al. 2024).

5.3.2. Beyond 2030

Biodiversity conservation must adapt to an increasingly complex and uncertain geopolitical landscape. Addressing the biodiversity crisis requires collective and coordinated global action, however this may become more difficult with increasing international instability with an increase in conflict, shifting alliances, and nationalism. The recent changes to the geopolitical order, as exemplified with the war in Ukraine, has disrupted global cooperation in place since the Cold War (Mariotti 2022). As some nations and regions reconsider their reliance on globalised systems and move toward greater self-sufficiency, the pathways to successful MEAs and collective biodiversity action are becoming less predictable. With the international focus shifting back to security, conservation policies must reestablish themselves into new national security frameworks to remain politically acceptable (Büscher & Whande 2007). This change may also shift national funding away from environmental protection and towards improved state security.

In this context, the future of conservation must focus on flexible and adaptive strategies that can withstand geopolitical shocks or ecological stochasticity such as pandemics or natural disasters. Adaptive monitoring systems that are guided by scenarios and grounded in principles of justice, equity, and ecological integrity, will be vital (Obura 2023). These systems must integrate both local and global economic dynamics that are likely to guide behaviour with regards to conservation and PA management going forward (Büscher & Whande 2007).

In the face of this complexity, the role of national and subnational implementation becomes even more critical. The GBF emerged from a four-year negotiation process, and it is unlikely that the targets will be fully achieved within the remaining five years therefore pushing for rapid implementation risks ineffective or even harmful solutions (Reed et al. 2025). MEAs like the GBF rely on national pledges, but their impact depends on the actions taken at local and regional levels (Reed et al. 2025). Therefore, capacity-building commitments outlined in the GBF must be prioritized to ensure equitable participation in global biodiversity governance (Zhang et al. 2025).

History offers both caution and hope. During the Cold War, the environment became a subject of competition, which fuelled a surge in MEAs as superpowers sought to appear green (Brain 2016). A potential second Cold War scenario (Buzan 2024) could reawaken political will and pave the way for the transformational change needed to bend the curve on biodiversity loss. Ultimately, the future of biodiversity conservation after 2030 will depend not just on meeting fixed targets, but on the ability of global and national actors to adapt to shifting politics while remaining committed to the GBF 2050 vision of a world of living in harmony with nature.

5.4 Limitations and further research

Although the methods developed in this thesis can be applied to improving indicators for the GBF, it is not a silver bullet. The average PA effectiveness on its own is not enough to derive good policy recommendations. These need to be grounded in the site-specific context and considered as part of wider PA systems. Furthermore, indicators developed from threat data only represent the status of pressure on biodiversity and must be integrated into a wider state–pressure–response–benefits model (Burgess et al. 2024). Currently, there are many existing metrics and indicators which can cause confusion and hinders effective decision-making (Burgess et al. 2024). Therefore, I do not propose that this become a new indicator on its own, rather that it be used to improve existing indicators or metrics such as STAR.

One of the main limitations of this thesis is the large amount of uncertainty in the political world. Firstly, there is a known limitation with the political data used in Chapter 4 such as rule of law and state capacity which contain a lot of uncertainty and can be subjective. This uncertainty has been found to affect size and statistical significance of estimated parameters in other econometrics studies (Desbordes & Koop 2016). Secondly,

there is a lot of uncertainty in the future direction of the geopolitical world and political agendas. This thesis tries to take a first step to address this uncertainty and the impact it may have on biodiversity policy.

This thesis highlights the need to use a counterfactual to avoid overestimating the impact of PAs in threat reduction. Although the use of a counterfactual provides a more realistic effect of the impact of PAs on threat reduction, the nuance of site-specific effectiveness can be missed at the global scale. Therefore, although this thesis highlights the importance of using state of the art statistical techniques of impact evaluation, I stress the caution needed when interpreting the global level results at a smaller scale. However, since the matched dataset is spatially explicit it can be reanalysed at any resolution from the site scale upwards, using a subset of the global dataset depending on future research questions that may arise. For example, the global dataset was subset to include only Italian PAs and will be used for a national gap analysis on PA prioritization. Future research on PAs should aim to improve on the quasi-experimental design of statistical matching and better account for the dynamic nature of wildlife threats. Additionally, improving the availability of time series data on global pressures could significantly improve the accuracy and reliability of impact assessments and help guide more targeted conservation efforts.

There is also a limitation with the PA data with some sites being underreported in the WDPA and the WD-OECM. For example, private PAs are playing a growing role in complementing government-managed PAs. They contribute to ecological representativeness, improve connectivity, and help reduce deforestation, particularly in areas facing intense human disturbance (Palfrey et al. 2021). However, they remain underreported at an international level, often causing them to be overlooked in global PA research (Palfrey et al. 2022). Additionally, as stated in Section 3.4.4, the threats assessed in this thesis, although numerous, are not comprehensive due to a lack of standardised open-access datasets.

The possibilities of reusing the global high resolution matched dataset developed in Chapter 3 are nearly endless. One application is presented in Chapter 4, however there is potential to investigate additional national complexities and heterogeneity. Future research could also examine the impacts of local armed conflicts on PA effectiveness or the influence of differential investments on biodiversity outcomes. Furthermore, the nature of the dataset makes it relatively simple to add more data when new global threat maps are released. The next research question I hope to answer building on this thesis is to directly relate the threat abatement capacity of PAs to species extinction risk. Combining data on species' Area of Habitat (Lumbierres et al. 2022), the individual threats that affect each species, and the threat abatement potential of individual PAs, I hope to analyse the "effective" PA coverage of mammal ranges. This type of analysis can contribute to the expand vs enforce debate and look at which strategy would have a bigger effect at the species- and site-specific levels.

This thesis has highlighted the interdisciplinary nature of biodiversity conservation. Building on a strong foundation of ecology and conservation and integrating political science theory and econometrics methods, this thesis provides a policy relevant and scientifically robust assessment of PAs in a changing geopolitical world.

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Scientific output and contributions

Conference contributions

May 2025, Biodiversity and Global Changes: A Conservation Perspective. Society for Conservation Biology, Italy Chapter, L'Aquila, Italy. **Assessing the IUCN Red List threats inside the global network of protected areas.** *Finalist, and first runner up, best student oral presentation.*

July 2023, 31st International Congress for Conservation Biology (ICCB) Kigali, Rwanda. **Are Global Biodiversity Metrics Enough? Integrating environmental DNA data with the STAR Metric.** Part of the symposium *Environmental DNA from theory to practice: case studies from global practitioners.*

July 2023, 31st International Congress for Conservation Biology (ICCB) Kigali, Rwanda. **Assessing the impact of terrestrial protected areas in abating threats to mammals.** *Poster.*

April 2023, Challenging conservation: adattarsi al cambiamento. Society for Conservation Biology, Italy Chapter, Rome, Italy. **Assessing the impact of terrestrial protected areas in abating threats to mammals.** *Oral presentation.*

Scientific articles

Vincent, C., A. Cristiano, I. Cuadros-Casanova, M. Pacifici, C.D. Soria, L. Tedeschi, M. Beekmann, A. D'alessio, P.M. Lucas, D. Nania & C. Rondinini. (2023). The war in Ukraine is changing plausible future socioeconomic scenarios leading to an unexplored outlook for biodiversity. *Conservation Science and Practice*: e13056.

Pacifici, M., M. Beekmann, A. Bissattini, V. Buono, A. Cristiano, C. Fornarini, A. D'alessio, M. Davoli, A. Lauti, C. Vincent & C. Rondinini. (*In prep*). The cost of development for biodiversity in the Mexican Interoceanic Corridor.

Santostasi, N., M. Beekmann, A. Bissattini, V. Buono, A. Cristiano, M. Fernando, C. Fornarini, A. D'alessio, M. Davoli, A. Lauti, M. Pacifici, C. Vincent, C. Zhang & C. Rondinini. (*In prep*). A comparative assessment of methods for monitoring threats to terrestrial and marine mammals: knowledge transfer across realms.

Student projects supervised

Emanuela Maiocchetti, MSc. An analysis of the effectiveness of protected areas in reducing the threat of Invasive Alien Species.

Nicola Alessandro Orsi, BSc. Efficacia delle aree protette nel ridurre la minaccia del cambiamento climatico sui mammiferi terrestri. Effectiveness of protected areas in reducing the threat of climate change to terrestrial mammals.

Research secondments

November 2022 – April 2023 **Enel Green Power S.p.A**

Research objective: To fill gaps in the global STAR metric with site-specific data from Environmental DNA (eDNA) technology to improve business reporting towards their biodiversity impacts.

Output: Presented the results at the International Congress for Conservation Biology in Kigali, Rwanda and wrote a report of the results for Enel.

November 2023 – April 2024 **University of Texas at Dallas**

Research objective: To receive mentorship from prof. Elías Cisneros on impact evaluation methods and econometrics techniques to improve my analysis.

Output: Collaboration on two of my PhD chapters that are being prepared to submit to scientific journals for publication.

Appendix 1.

Supplementary figures and tables for Chapter 3

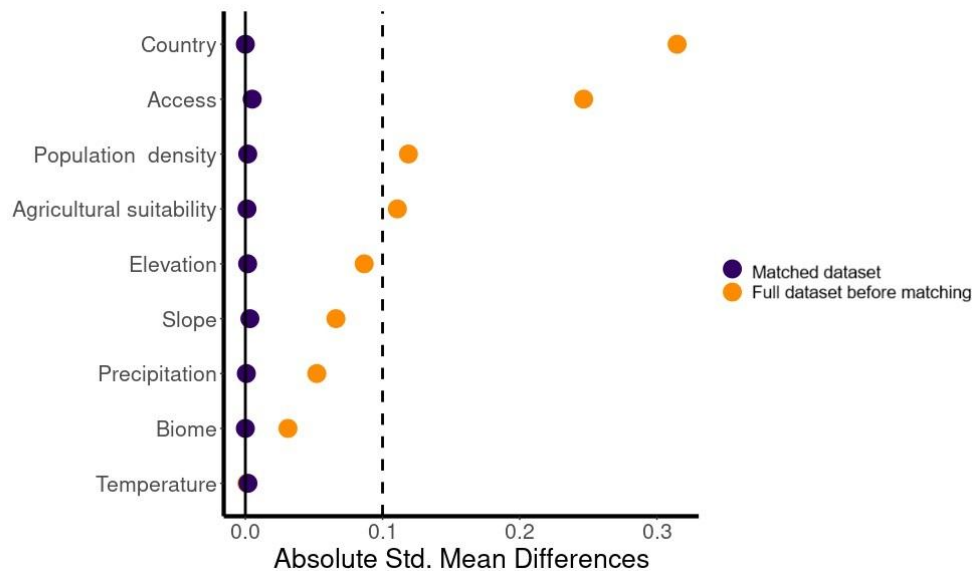


Figure A1.1 | Assessing matching quality. Covariate balance showing differences in the absolute standard mean differences of covariates before (orange) and after (purple) coarsened exact matching with the final model. For determining imbalance, we used a threshold of > 0.1 (dashed line).

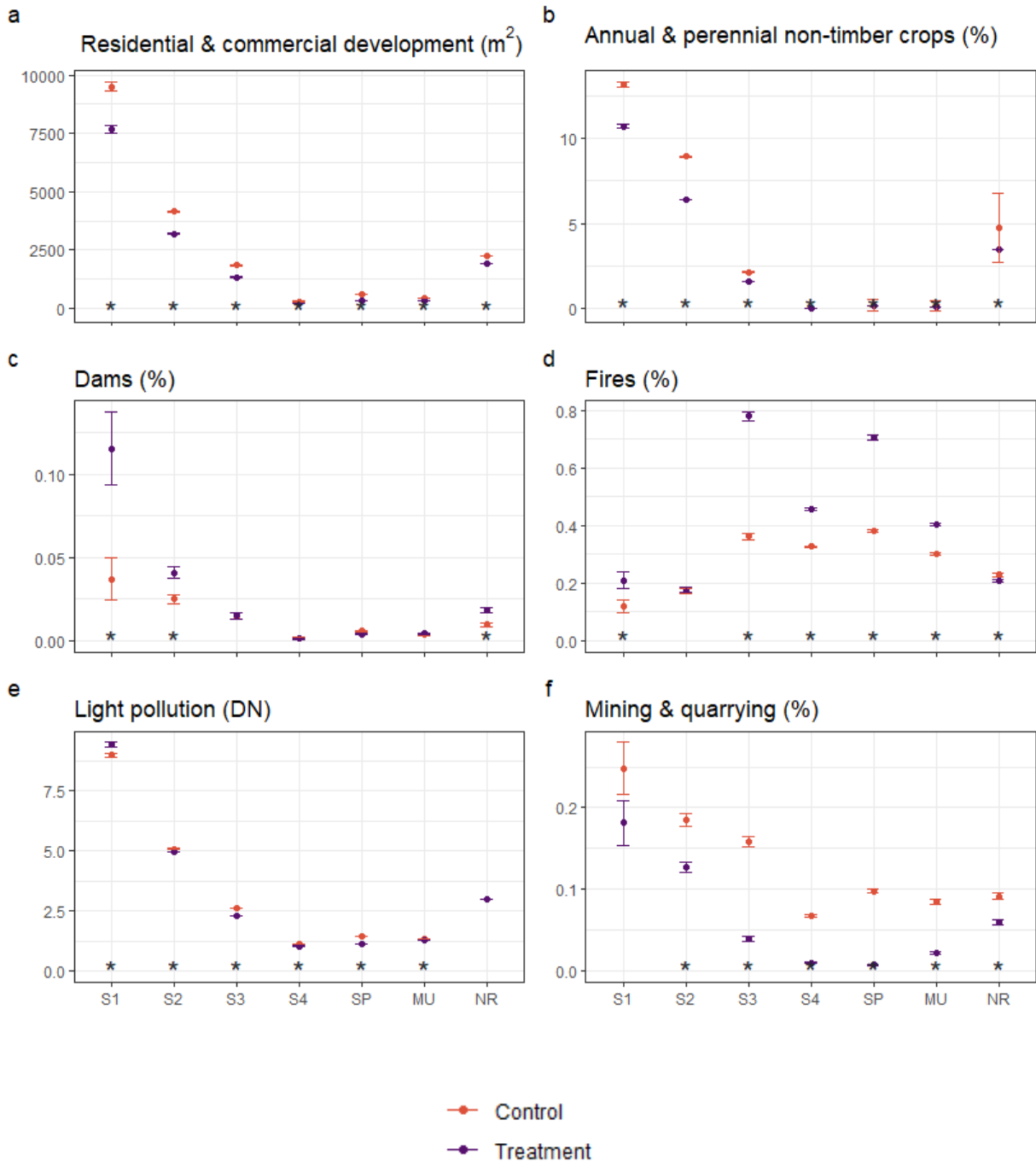


Figure A1.2 | Protected area characteristics. The mean values and the standard error across 1 km² pixels of PAs (treatment) and their matched controls for each threat (**a-f** and **g-m** on the following page). PAs are grouped by their size (S1: <10 km², S2: 10-500 km², S3: 500-2000 km², S4 >2000 km²) and management categories (SP: Strict protection IUCN categories Ia-IV, MU: Multi-use IUCN categories V-VI, NR: IUCN category is not reported). Note that the y-axes change depending on the threat. Asterisks indicate significant differences between treatment and controls (p < 0.05).

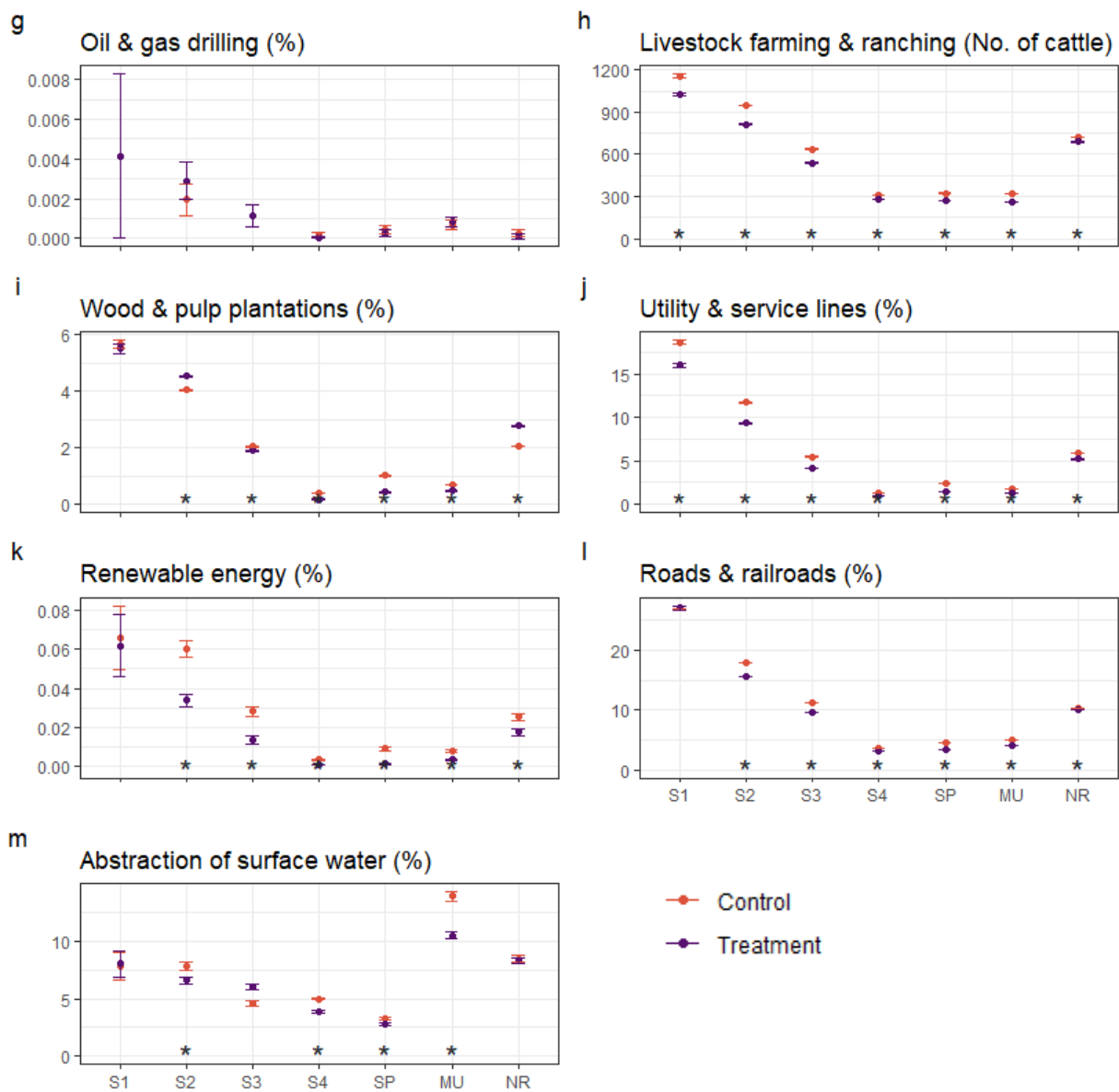


Figure A1.2 continued.

Table A1.1 | Sensitivity test results. The E-value represents the minimum strength of association that an unmeasured confounder would need to have with both the treatment and the outcome to fully explain away the observed treatment-outcome relationship.

	Normalized mean difference	Risk ratio (RR)	E-value
Residential & commercial development	-0.020	0.98	1.15
Annual & perennial non-timber crops	-0.098	0.91	1.41
Wood & pulp plantations	-0.022	0.98	1.16
Livestock farming & ranching	-0.027	0.98	1.18
Oil & gas drilling	0.000085	1.00	1.01
Mining & quarrying	-0.018	0.98	1.15
Renewable energy	-0.0063	0.99	1.08
Roads & railroads	-0.029	0.97	1.19
Utility & service lines	-0.034	0.97	1.21
Fire	0.017	1.02	1.14
Dams	0.000029	1.00	1.01
Light pollution	-0.020	0.98	1.16

Table A1.2 | The nine covariates used in the coarsened exact matching algorithm to improve balance on treatment and control points.

Predictor variable	Description	Justification for inclusion	Source
Agricultural suitability	The highest agro-climatic potential yield (estimated from historical climatic conditions 1971-2000) per pixel of 16 crops that are most important for the global economy, food security and biofuels (Zabel et al. 2014); <i>Hordeum vulgare</i> , <i>Manihot esculenta</i> , <i>Arachis hypogaea</i> , <i>Zea mays</i> , <i>Pennisetum americanum</i> , <i>Elaeis guineensis</i> , <i>Solanum tuberosum</i> , <i>Brassica napus</i> , <i>Oryza sativa</i> , <i>Secale cereale</i> , <i>Sorghum bicolor</i> , <i>Glycine maximum</i> , <i>Saccharum officinarum</i> , <i>Helianthus annuus</i> , <i>Triticum aestivum</i> , and <i>Triticum gestivum</i> . Resolution of 5 arcminutes (about 9x9 km at the equator).	Previous studies have found that the establishment of PAs coincided with low-productivity lands unsuitable for agriculture (Scott et al. 2001; Pressey et al. 2002). Both old and new PAs do not target places with high concentrations of threatened vertebrate species but instead were established in locations that minimize conflict with agriculturally suitable lands (Venter et al. 2018).	Fischer, G., Nachtergaele, F.O., van Velthuisen, H.T., Chiozza, F., Franceschini, G., Henry, M., Muchoney, D. and Tramberend, S. 2021. Global Agro-Ecological Zones v4 – Model documentation. Rome, FAO. https://doi.org/10.4060/cb4744en
Precipitation	Total annual precipitation calculated with the sum of 12 months precipitation data. Each month was derived from the average monthly precipitation data for 1970-2000. From WorldClim version 2.1 released in January 2020 with a resolution of 30 arcseconds (about 1x1 km at the equator).	Precipitation has a very strong link to agricultural suitability. Additionally, temperature and precipitation are the most critical factors that control the distribution of species in terrestrial ecosystems (Pearce-Higgins et al. 2015; Gutierrez et al. 2021).	Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37 (12): 4302-4315.
Temperature	Average annual temperature calculated from monthly mean temperature data for 1970-2000. From WorldClim version 2.1 released in January 2020 with a resolution of 30 arcseconds.	Temperature has a very strong link to agricultural suitability. Additionally, temperature and precipitation are the most critical factors that control the distribution of species in terrestrial ecosystems (Pearce-Higgins et al. 2015; Gutierrez et al. 2021).	Fick, S.E. and R.J. Hijmans, 2017. WorldClim 2: new 1km spatial resolution climate surfaces for global land areas. International Journal of Climatology 37 (12): 4302-4315.

Human population density	The Gridded Population of the World, Version 4 (GPWv4), for the year 2000 with a resolution of 30 arcseconds.	Human population density is a key cause of species becoming threatened with extinction and continued increase in human population densities increases species biodiversity threats (McKee et al. 2013). The establishment of PAs coincided with wild and scenic areas far from human activity (Scott et al. 2001).	Center for International Earth Science Information Network (CIESIN), Columbia University. 2018. Documentation for the Gridded Population of the World, Version 4(GPWv4), Revision 11 Data Sets. Palisades NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H45Q4T5F
Travel time	Estimated travel time to the nearest city of 50,000 or more people in the year 2000, with pixel values representing minutes of travel time with a resolution of 30 arcseconds.	Remoteness is an underlying characteristic of highly threatened PAs, and the number of threats was lower in more remote PAs (Schulze et al. 2018). Most PAs are biased to places with greater distances to roads and cities (Joppa & Pfaff 2009), and the establishment of PAs coincided with wild and scenic areas far from human activity (Scott et al. 2001; Pressey et al. 2002).	Nelson, A. (2008) Estimated travel time to the nearest city of 50,000 or more people in year 2000. Global Environment Monitoring Unit - Joint Research Centre of the European Commission, Ispra Italy.
Biome	We included all 14 terrestrial biomes. This vector data was rasterized to 1x1 km grid cells and included in the matching algorithm as an exact match.	The global pattern of PA coverage is influenced by vertebrate biodiversity, human activities and agricultural suitability, however the relative importance of these factors varies among biogeographical realms (Loucks et al. 2008). There is also a difference between forested and non-forested PAs in their ability to mitigate anthropogenic threats (Geldmann et al. 2019).	Olson, D. M., Dinerstein, E., Wikramanayake, E. D., Burgess, N. D., Powell, G. V. N., Underwood, E. C., D'Amico, J. A., Itoua, I., Strand, H. E., Morrison, J. C., Loucks, C. J., Allnutt, T. F., Ricketts, T. H., Kura, Y., Lamoreux, J. F., Wettengel, W. W., Hedao, P., Kassem, K. R. 2001. Terrestrial ecoregions of the world: a new map of life on Earth. <i>Bioscience</i> 51(11):933-938.

Country	Country boundaries. This vector data was rasterized to 1x1 km grid cells and included in the matching algorithm as an exact match.	The number of reported threats is lower in PAs with higher control of corruption and lower human development scores (Schulze et al. 2018), which can vary greatly between countries.	Natural Earth v5.1.1
Elevation	Global digital elevation model (GTOPO30) from USGS with a resolution of 30 arcseconds.	PAs are preferentially placed in higher elevations (Scott et al. 2001; Joppa & Pfaff 2009). Additionally, PAs at higher elevations have fewer reported threats (Schulze et al. 2018).	Gesch, D. B., Verdin, K. L., & Greenlee, S. K. (1999). New land surface digital elevation model covers the Earth. <i>Eos, Transactions American Geophysical Union</i> , 80, 69–70.
Slope	Slope was calculated from the above digital elevation model in GRASS GIS using the r.slope.aspect function.	PAs are biased to areas with steeper slopes (Pressey et al. 2002; Joppa & Pfaff 2009).	Own analysis

Table A1.3 | Testing for multicollinearity. The Variance inflation factors (VIF) of the nine covariates used in the coarsened exact matching algorithm to test for multicollinearity, calculated from a random 10% sample of the dataset. A VIF value under 5 is interpreted as having a low probability of being highly correlated.

Predictor variable	VIF
Human population density	1.05
Slope	1.43
Biome	1.44
Elevation	1.52
Precipitation	1.68
Travel time	1.69
Agricultural suitability	4.04
Temperature	4.39

Table A1.4 | Assessing matching quality. The variance ratio (Var. Ratio) and the standard mean difference (SMD) between each predictor variable from the treatment and control groups before and after matching.

Predictor variable	SMD unmatched	SMD matched	Var. Ratio unmatched	Var. Ratio matched	Var. Ratio % improvement
Agricultural suitability	-0.1108	0.0012	1.1629	1.0018	99
Population density	-0.1189	0.0017	0.4641	1.1050	87
Biome	-0.0310	0.0000	0.6398	1.0000	100
Country	-0.3147	0.0000	0.8274	1.0000	100
Elevation	-0.0866	-0.0017	0.9348	1.0012	98
Slope	0.0660	-0.0033	1.4445	1.0058	98
Precipitation	0.0521	0.0007	1.2798	0.9987	99
Temperature	-0.0012	-0.0019	1.1625	1.0007	100
Access	0.2466	0.0050	0.4495	0.9964	100

Table A1.5: Threat presence in PAs and matched control sites. The threat category follows the IUCN Red List threat classification scheme version 3.3 as defined by Salafsky et al (2008). The difference between treatment (PAs) and controls is calculated as the average treatment effect on the treated (ATT). Standard errors are shown in round brackets.

Threat category	Mean control	Mean treatment	ATT	p-value
1 Residential & commercial development [m ²]				
1.1 Housing & urban areas	940.76	716.62	-224.15	<0.001
1.2 Commercial & industrial areas	(5.34)	(4.50)	(3.49)	
2 Agriculture & aquaculture				
2.1 Annual & perennial non-timber crops [%]	1.36 (0.005)	0.99 (0.004)	-0.37 (0.003)	<0.001
2.2 Wood & pulp plantations [%]	1.13 (0.01)	1.02 (0.01)	-0.11 (0.01)	<0.001
2.3 Livestock farming & ranching [No. of cattle]	418 (0.7)	367 (0.7)	-50 (0.5)	<0.001
3 Energy production & mining [%]				
3.1 Oil & gas drilling	0.00050 (0.00013)	0.00047 (0.00012)	-0.00003 (0.00009)	0.87
3.2 Mining & quarrying	0.09 (0.002)	0.03 (0.001)	-0.06 (0.001)	<0.001
3.3 Renewable energy	0.013 (0.0006)	0.006 (0.0004)	-0.007 (0.0004)	<0.001
4 Transportation & service corridors [%]				
4.1 Roads & railroads	6.2 (0.01)	5.4 (0.01)	-0.8 (0.01)	<0.001
4.2 Utility & service lines	3.0 (0.01)	2.3 (0.01)	-0.7 (0.01)	<0.001
5 Biological resource use				
5.1 Hunting & collecting terrestrial animals	Defaunation was 18.3% lower inside PAs than in unprotected landscapes across the Neotropics (Bogoni et al. 2020).			
5.2 Gathering terrestrial plants	Not considered since no global pressure map exists, and previous studies are only at the site level.			
5.3 Logging & wood harvesting	Globally, another study found forest loss to be lower inside PAs with an ATT of -1.20% $\pm$ 0.03 p < 0.01 (Li et al. 2024).			
6 Human intrusions & disturbance	Not considered, since this is likely only mitigated in well managed PAs (Kearney et al. 2020).			
7 Natural system modifications [%]				
7.1 Fire & fire suppression	0.31 (0.003)	0.46 (0.004)	0.15 (0.002)	<0.001
7.2.1 - 7.2.4 Abstraction of surface water	5.23 (0.09)	4.48 (0.08)	-0.75 (0.06)	<0.001
7.2.9 - 7.2.11 Dams	0.006 (0.0004)	0.008 (0.0005)	0.002 (0.0003)	0.003
8 Invasive & other problematic species, genes & diseases	Not considered, since this is likely only mitigated in well managed PAs or through landscape management and species control (Kearney et al. 2020).			
9 Pollution				
9.6.1 Light pollution [DN]	1.79 (0.003)	1.66 (0.003)	-0.126 (0.002)	<0.001
10 Geological events	Not considered, since this is likely only mitigated in well-managed PAs, but only through restoration (Kearney et al. 2020).			
11 Climate change & severe weather	Not considered, since this is likely only mitigated in well-managed PAs, but only through restoration (Kearney et al. 2020). However, PAs can facilitate species to adjust to rapidly changing climatic conditions (Lehikoinen et al. 2019) and can slow locally rising temperatures (Xu et al. 2022).			
12 Other options	Not considered			

Table A1.6 | Threat differences based on protected area characteristics. The IUCN Red List threats with the difference in their occurrence between PAs and matched control sites (ATT in bold) for different size and protection classes of PAs. N represents the number of paired 1km² pixels compared between matched pairs of treatment and control pixels. Note that % in this table refers to percentage points.

	IUCN class			Size class			
	Strict protection	Multi-use	Not Reported	Class 1	Class 2	Class 3	Class 4
	(Ia-IV)	(V-VI)		(<10 km ²)	(10-500 km ²)	(500-2000 km ²)	(>2000 km ²)
Residential & commercial development [m²]	-277.3	-134.8	-320.8	-1818.6	-972.5	-524.2	-77.9
std. error	4.4	3.5	11.4	135.9	23.0	14.3	2.1
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
N	1125710	1302161	747240	24225	309510	360963	2480413
Annual & perennial non-timber crops [%]	-0.068	-0.071	-1.273	-2.446	-2.543	-0.562	-0.03
std. error	0.002	0.002	0.013	0.113	0.027	0.013	0.000
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
N	1087551	1224241	746613	24194	309386	360402	2364423
Wood & pulp plantations [%]	-0.58	-0.21	0.71	-0.15	0.49	-0.17	-0.20
std. error	0.01	0.01	0.02	0.11	0.03	0.02	0.00
p-value	<0.01	<0.01	<0.01	0.46	<0.01	<0.01	<0.01
N	627807	935602	479447	22001	256699	261284	1502872
Livestock farming & ranching [No. of cattle]	-51	-59	-34	-128	-135	-98	-32
std. error	1	1	1	10	2	2	1
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
N	1110331	1284333	732540	23996	304743	354626	2443839
Oil & gas drilling [%]	-0.0002	0.0002	-0.0001	0.0000	0.0010	0.0000	-0.0002
std. error	0.0001	0.0002	0.0001	0.0029	0.0006	0.0004	0.0001
p-value	0.53	0.67	0.77	1	0.46	1	0.13
N	1125710	1302161	747240	24225	309510	360963	2480413
Mining & quarrying [%]	-0.09	-0.06	-0.03	-0.07	-0.06	-0.12	-0.06
std. error	0.002	0.001	0.002	0.02	0.01	0.004	0.001
p-value	<0.01	<0.01	<0.01	0.12	<0.01	<0.01	<0.01
N	1117190	1299854	747054	24210	308879	358650	2472359
Renewable energy [%]	-0.008	-0.004	-0.008	-0.004	-0.026	-0.014	-0.003
std. error	0.0005	0.0005	0.0012	0.011	0.003	0.002	0.000
p-value	<0.01	<0.01	<0.01	0.87	<0.01	<0.01	<0.01
N	1125710	1302161	747240	24225	309510	360963	2480413
Roads & railroads[%]	-1.28	-0.81	-0.19	-0.10	-2.30	-1.53	-0.55
std. error	0.01	0.01	0.02	0.20	0.05	0.04	0.01
p-value	<0.01	<0.01	<0.01	0.78	<0.01	<0.01	<0.01
N	1125710	1302161	747240	24225	309510	360963	2480413

Table A1.6 continued.

	IUCN class			Size class			
	Strict protection	Multi-use	Not Reported	Class 1	Class 2	Class 3	Class 4
	(Ia-IV)	(V-VI)		(<10 km ²)	(10-500 km ²)	(500-2000 km ²)	(>2000 km ²)
Utility & service lines [%]	-1.02	-0.41	-0.67	-2.67	-2.39	-1.33	-0.36
std. error	0.01	0.01	0.02	0.17	0.04	0.03	0.01
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
N	1125710	1302161	747240	24225	309510	360963	2480413
Fire & fire suppression [%]	0.324	0.101	-0.020	0.091	0.005	0.416	0.132
std. error	0.005	0.004	0.004	0.018	0.005	0.009	0.003
p-value	<0.01	<0.01	0.01	0.01	0.67	<0.01	<0.01
N	1125710	1302161	747240	24225	309510	360963	2480413
Abstraction of surface water [%]	-0.48	-3.37	-0.14	0.14	-1.21	1.43	-1.10
std. error	0.06	0.26	0.19	0.82	0.23	0.16	0.07
p-value	<0.01	<0.01	0.36	0.60	0.02	0.13	<0.01
N	111734	16589	22486	1068	13486	21340	114915
Dams [%]	-0.0016	0.0005	0.0086	0.0784	0.0158	0.0003	-0.0006
std. error	0.0005	0.0004	0.0010	0.0126	0.0023	0.0015	0.0002
p-value	0.09	0.5	<0.01	<0.01	<0.01	0.93	0.07
N	1125710	1302161	747240	24225	309510	360963	2480413
Light pollution [DN]	-0.296	-0.049	-0.008	0.438	-0.125	-0.335	-0.101
std. error	0.003	0.002	0.005	0.061	0.011	0.006	0.001
p-value	<0.01	<0.01	0.63	<0.01	<0.01	<0.01	<0.01
N	1109536	1300418	747182	24225	309451	360963	2462497

Table A1.7 | Average treatment effect on the treated (ATT) for each threat by country. Values in bold indicate significance at $p < 0.05$. Green text indicates significantly lower threat inside PAs and red text indicates significantly higher threat inside PAs compared to matched controls.

	Abstraction of surface water [%]	Built area [m ²]	Cropland [%]	Dams [%]	Fire [%]	Light [DN]	Mining [%]	Oil & gas [%]	Livestock [#cattle]	Tree plantation [%]	Power- lines [%]	Renew- ables [%]	Roads [%]
Afghanistan	65.47	-62	-0.01	0.00	0.00	0.47	0.00	0.000	-29	0.00	0.57	0.00	2.03
Albania	-69.00	-538	-2.73	0.38	0.00	0.40	-0.29	0.000	113	0.00	-0.29	0.00	-1.33
Algeria	NA	104	-0.01	0.00	0.00	0.29	0.00	0.000	0	0.00	-0.14	0.00	0.21
Angola	NA	30	0.03	0.00	0.00	0.00	0.00	0.000	14	0.00	0.00	0.00	50.00
Argentina	-3.29	-551	-0.02	-0.01	0.27	-0.03	0.03	-0.003	-237	-0.04	-0.65	0.00	-2.42
Armenia	NA	-494	-0.05	0.00	0.00	0.76	-0.24	0.000	-788	0.00	5.83	0.00	1.46
Australia	-6.81	-50	-0.02	0.00	0.27	0.21	-0.07	0.000	-61	-0.09	-0.18	0.00	-0.69
Austria	30.50	-1630	-3.68	0.07	0.00	0.28	0.00	0.000	-24	1.37	-3.83	0.14	-5.27
Azerbaijan	21.34	-7603	-0.15	0.09	0.00	-2.24	-0.18	0.000	-1172	0.00	-10.42	0.00	-3.56
Bahamas	3.08	-125	0.00	0.00	0.00	-0.24	0.00	0.000	-2	0.00	-3.25	0.00	0.00
Bangladesh	-2.39	-10373	-0.14	0.00	0.00	-0.91	0.00	0.000	-1371	0.00	-8.76	0.00	-34.14
Belize	9.00	-623	-0.09	0.00	0.00	-5.18	0.00	0.000	-285	0.00	-5.00	0.00	-30.00
Benin	32.59	-11064	0.00	0.00	-1.47	-1.04	0.00	0.000	809	1.05	3.53	0.00	0.59
Bhutan	NA	-95	0.00	0.00	0.00	0.05	0.00	0.000	14	0.00	-1.35	0.00	-1.08
Bolivia	-24.19	-3	-0.01	0.00	0.10	-0.15	-0.04	0.000	100	0.00	-0.24	0.00	0.07
Bosnia and Herzegovina	-8.40	-2134	-2.43	0.00	0.08	-0.26	0.00	0.000	-94	1.49	-2.04	0.00	10.75
Botswana	NA	9	0.00	0.00	0.00	0.00	0.00	0.000	-133	0.00	-1.51	0.00	13.07
Brazil	-6.70	48	0.00	0.00	-0.01	-0.20	0.01	0.000	-260	-0.17	-0.61	-0.03	-0.64
Bulgaria	-45.36	-1799	-14.20	0.03	0.01	-0.82	-0.48	0.000	-88	4.34	-2.04	-0.02	1.68
Burkina Faso	NA	-1480	-0.08	-0.08	3.50	0.64	0.00	0.000	-170	0.00	0.23	0.00	-3.95
Burundi	-0.10	-632	-0.03	0.00	0.00	-0.40	0.00	0.000	41	0.00	-15.88	0.00	-0.28
Cambodia	10.37	-2646	-0.26	-0.04	17.42	0.55	-0.01	0.000	-749	-10.44	-2.88	-0.01	-18.45
Cameroon	-34.20	-1274	-0.01	-0.01	0.42	0.09	0.00	0.000	-238	-0.55	-1.25	0.00	-6.61
Canada	-0.89	-55	-0.01	0.00	0.00	-0.28	-0.07	0.002	-7	0.00	-0.63	0.00	-0.60
Central African Republic	NA	-121	0.01	0.00	-1.17	-0.90	0.00	0.000	-85	0.00	-1.29	0.00	-4.81
Chad	7.09	-264	-0.04	0.00	-0.38	0.18	0.00	0.000	-140	0.00	0.06	0.00	0.37
Chile	9.73	-28	0.00	0.00	0.00	0.29	-0.02	0.000	-54	0.00	0.29	-0.02	0.46
China	1.07	-537	0.00	0.00	0.00	-0.23	0.02	0.000	-10	0.33	-0.97	0.00	-1.96

Colombia	0.51	-244	0.00	0.01	-0.18	0.29	0.04	0.000	392	-0.90	-0.35	0.00	-1.21
Costa Rica	NA	-2434	0.03	0.00	0.00	-0.24	0.00	0.000	-532	-2.59	-9.48	0.00	-12.07
Cote d'Ivoire	-4.80	-1318	0.02	0.00	1.41	0.51	0.00	0.000	72	-0.18	-2.64	0.00	-10.72
Croatia	-26.17	-2860	-14.62	0.03	0.00	-1.77	-0.11	0.000	-34	8.66	-7.09	0.03	-11.16
Cuba	-0.50	-751	-0.05	-0.03	-0.03	-2.00	-0.49	0.000	-758	0.00	-3.31	-0.05	-9.86
Cyprus	-17.00	3379	-0.12	0.00	0.00	3.39	0.93	0.000	62	0.47	-2.34	0.00	4.67
Czechia	-4.00	-2501	-22.30	-0.19	0.00	-0.02	-0.19	0.000	-390	0.39	-5.64	-0.19	-17.51
Democratic Republic of Congo	2.70	390	0.01	0.00	5.08	-0.68	-0.02	0.000	59	0.00	0.63	0.00	-0.34
Djibouti	NA	279131	0.00	0.00	0.00	52.25	0.00	0.000	143	0.00	50.00	0.00	0.00
Dominican Republic	11.50	-2781	-0.14	0.08	0.00	-0.33	0.04	0.000	-2332	0.13	-5.10	-0.04	-6.03
Ecuador	-29.86	-48	-0.01	0.02	0.00	0.23	0.00	0.000	-1002	-1.06	-4.62	0.00	-11.78
Egypt	NA	-92	-0.01	0.00	0.00	-2.24	0.00	0.000	-29	NA	-1.61	0.00	2.90
El Salvador	NA	-4918	0.00	0.00	0.00	-0.09	0.00	0.000	-715	0.00	-14.71	0.00	-23.53
Equatorial Guinea	NA	-783	0.00	0.00	0.00	-3.32	0.00	0.000	-10	0.00	-6.73	0.00	2.69
eSwatini	NA	-4948	0.02	2.50	0.00	0.75	0.00	0.000	-151	0.00	-15.00	0.00	-27.50
Ethiopia	56.67	-117	0.03	0.00	0.19	-0.20	0.00	0.000	909	0.00	-1.52	0.00	-0.27
Fiji	NA	-514	0.00	0.00	0.00	-0.27	0.00	0.000	208	NA	0.00	0.00	1.35
France	-3.44	-1842	-7.94	0.05	0.00	0.39	-0.03	0.000	-372	8.81	-0.47	-0.29	-0.70
French Guiana	59.86	3	0.00	0.00	0.00	0.02	-1.11	0.000	-7	0.00	-0.84	0.00	-0.46
French Polynesia	NA	-30674	0.00	0.00	0.00	-7.22	NA	0.000	0	NA	0.00	0.00	0.00
Gabon	-1.00	-17	0.00	0.00	0.01	0.35	0.00	0.000	-1	0.00	-0.28	0.00	-0.06
Georgia	NA	-5124	-0.01	0.00	0.00	0.39	-0.11	0.000	-337	0.00	-3.24	-0.11	-0.67
Germany	NA	5581	-25.20	0.00	0.00	2.68	0.00	0.000	385	0.34	0.00	-0.17	13.80
Ghana	NA	1706	-0.12	0.00	32.20	4.03	0.00	0.000	-57	0.00	16.95	0.00	20.34
Greece	-27.09	-1114	-0.39	0.02	0.00	-0.63	0.00	0.000	43	-0.06	-0.76	-0.32	0.56
Greenland	3.02	0	0.00	0.00	0.00	0.01	0.00	0.000	NA	NA	0.00	0.00	0.00
Guatemala	7.00	-1387	-0.01	0.00	0.00	0.61	0.00	0.000	-359	-3.14	-3.27	0.00	-14.95
Guinea	1.00	611	0.00	0.00	1.02	0.08	0.05	0.000	180	0.00	-1.26	0.00	2.81
Guinea-Bissau	NA	281	0.00	0.00	0.00	-0.67	0.00	0.000	1077	0.00	0.00	0.00	55.56
Guyana	-16.22	-6	0.00	0.00	-0.03	-0.14	-0.04	0.000	1	0.00	-0.27	0.00	-0.52
Haiti	-35.00	-2915	-0.04	0.00	0.00	-0.29	0.00	0.000	-110	0.00	0.86	0.00	-0.34
Honduras	93.50	-223	0.00	0.00	0.00	-0.29	0.00	0.000	-805	-4.91	-4.53	0.00	-1.72
Hungary	-26.80	-2142	-19.62	0.02	0.00	0.66	0.12	0.000	-74	4.50	-0.46	0.00	4.67

India	3.47	-897	-0.09	0.06	0.00	-0.37	-0.10	0.000	-773	-2.04	-2.25	0.00	-0.13
Indonesia	21.18	-667	0.00	0.00	0.01	-0.99	-0.10	0.000	-400	-5.65	-1.59	-0.01	-6.63
Iran	38.17	-613	-0.03	-0.01	-0.03	-5.99	0.00	-0.013	-51	0.00	-3.48	0.00	0.07
Iraq	50.55	-1734	-0.22	0.00	-0.32	-5.12	0.00	-0.032	-51	0.00	-9.72	0.00	-18.75
Israel	NA	11132	0.05	0.00	0.00	5.50	0.00	0.000	-369	0.00	0.00	0.00	0.00
Italy	-44.67	-5301	-6.49	0.14	0.00	-2.45	-0.02	0.000	-452	2.93	-4.60	-0.15	-4.77
Jamaica	NA	41577	0.15	0.00	0.00	12.75	0.00	0.000	-177	0.00	100.00	0.00	25.00
Japan	NA	-6536	-0.03	0.61	0.00	1.57	0.06	0.000	-112	-2.20	-1.90	0.24	-2.63
Jordan	NA	-707	0.00	0.00	0.00	-0.93	-0.82	0.000	1	0.00	-2.46	0.00	-6.96
Kazakhstan	1.52	-239	-0.04	0.00	-0.66	-0.44	-0.13	-0.001	12	0.00	-0.83	0.00	-0.86
Kenya	-14.13	114	-0.01	-0.18	0.00	-0.10	0.00	0.000	-1040	0.00	2.35	0.00	-0.27
Kuwait	50.00	-790	0.00	0.00	0.00	-2.95	0.00	0.000	-4	NA	0.30	0.00	11.14
Kyrgyzstan	-38.31	-38	0.00	0.00	0.00	0.10	0.00	0.000	-35	0.00	-1.56	0.00	-4.40
Laos	5.86	-227	-0.02	-0.01	0.17	-0.61	-0.04	0.000	-259	0.00	-2.32	0.00	-3.92
Lebanon	NA	-12941	-0.02	0.00	0.00	-6.74	0.00	0.000	-118	0.00	-26.32	0.00	-36.84
Lesotho	NA	-540	-0.07	0.00	0.00	0.00	0.00	0.000	-152	0.00	0.00	0.00	33.33
Liberia	NA	-2348	0.00	0.00	0.00	2.27	0.00	0.000	12	0.00	-1.82	0.00	-3.64
Madagascar	-7.59	-16	0.01	0.00	-0.11	-0.35	0.00	0.000	24	NA	0.04	0.00	-0.14
Malawi	NA	-286	0.03	-0.07	0.00	-0.47	0.00	0.000	553	-0.07	0.60	0.07	-3.22
Malaysia	-22.25	-1092	0.00	0.01	0.00	-1.27	-0.15	0.000	-29	-15.91	-4.75	0.00	-3.20
Mali	NA	-364	-0.03	0.00	0.20	0.13	0.00	0.000	-134	0.00	-0.16	0.00	-0.15
Mauritania	85.00	-76	0.10	0.00	0.00	0.00	0.00	0.000	1	0.00	0.00	0.00	0.00
Mauritius	NA	-10217	0.00	0.00	0.00	-2.00	0.00	0.000	-49	NA	0.00	0.00	0.00
Mexico	21.97	-312	-0.01	0.00	0.00	-0.60	-0.18	0.000	-166	-0.21	-0.88	0.00	-3.28
Moldova	76.90	4676	-14.19	0.00	0.00	1.14	0.00	0.000	62	0.49	4.56	0.00	1.97
Mongolia	-21.32	-11	0.00	0.00	0.00	-0.02	-0.06	0.000	-37	-0.01	-0.83	0.00	-0.93
Montenegro	NA	-686	0.55	0.30	0.00	-0.42	0.00	0.000	-138	0.00	8.58	0.00	0.59
Morocco	-36.00	2586	-0.03	0.01	0.00	2.40	0.39	0.000	29	0.00	-1.19	-0.01	0.71
Mozambique	-0.68	-949	-0.03	0.00	-0.42	-0.32	0.00	0.000	-86	0.00	-0.27	0.00	0.27
Myanmar	-4.92	-255	-0.01	0.00	-0.06	-0.28	0.00	0.000	31	-0.21	-0.27	0.00	-0.86
Namibia	95.80	-241	-0.03	0.00	0.32	-0.27	-0.02	0.000	-448	-0.02	0.70	0.00	2.08
Nepal	-23.13	-2676	-0.08	0.00	0.00	-0.92	0.00	0.000	-820	0.04	-1.78	0.00	-0.52
New Caledonia	-100.00	-404	0.00	0.00	0.00	-1.38	-1.40	0.000	164	0.00	-2.71	-0.09	-2.80
New Zealand	NA	-81	0.00	0.00	0.00	-0.45	0.00	0.000	-168	0.00	-1.69	0.00	-6.44
Nicaragua	-49.23	-418	0.00	0.00	0.00	-1.22	0.00	0.000	-4501	0.00	-2.69	0.00	-13.76
Niger	-22.45	155	-0.01	0.00	-0.01	-0.09	0.00	0.000	251	0.00	-0.04	0.00	0.36
Nigeria	NA	738	-0.20	0.00	0.69	0.46	0.00	0.000	234	0.00	0.17	0.00	4.90

North Korea	NA	-783	-0.08	0.00	0.00	13.73	0.00	0.000	691	0.00	0.00	0.00	-16.67
North Macedonia	NA	-29	-0.22	0.00	0.00	1.32	0.20	0.000	-64	0.00	-7.81	0.00	-2.93
Norway	-3.60	-39	0.00	-0.02	0.00	-0.87	-0.01	0.000	-30	0.00	-4.80	-0.02	-2.82
Oman	31.67	-527	0.00	0.00	0.00	-2.48	0.00	0.000	-35	NA	-4.05	0.00	-4.83
Pakistan	1.59	1281	-0.04	-0.03	0.00	0.10	0.00	0.000	-743	0.00	2.34	0.00	3.33
Panama	20.30	-1040	-0.01	-0.05	0.00	-1.03	0.56	0.000	-579	-0.05	-4.32	0.00	-6.71
Papua New Guinea	NA	-154	0.00	0.00	0.92	0.06	0.00	0.000	94	0.00	0.62	0.00	-3.69
Paraguay	-18.86	-515	-0.02	0.00	-0.06	-0.14	0.00	0.000	-157	0.00	-1.25	0.00	-2.73
Peru	-5.06	-60	0.00	0.00	0.00	-0.06	-0.08	0.000	-32	-0.03	-0.22	0.00	-0.34
Philippines	-6.97	-28	-0.02	0.00	0.17	-0.68	-0.07	0.000	-26	-4.73	-1.05	0.03	-0.04
Puerto Rico	NA	0	0.00	0.00	0.00	-14.00	0.00	0.000	NA	0.00	-100.00	0.00	0.00
Republic of Congo	NA	-155	0.00	0.00	-0.91	0.14	0.00	0.000	19	0.00	0.12	0.00	1.05
Romania	-14.71	-2536	-11.00	0.12	-0.09	-0.94	-0.06	0.000	-9	4.44	-2.30	0.01	0.72
Russia	3.16	-76	-0.01	0.00	0.03	-0.09	-0.14	0.000	-6	-0.01	-0.47	0.00	-0.35
Rwanda	NA	-49423	-0.38	0.00	0.00	-5.92	0.00	0.000	-148	-16.67	-25.00	0.00	-75.00
Samoa	NA	286	0.00	0.00	0.00	0.75	NA	0.000	0	NA	0.00	0.00	-25.00
Sao Tome and Principe	NA	-1296	0.00	0.00	0.00	-4.00	0.00	0.000	11	0.00	100.00	0.00	-100.00
Saudi Arabia	NA	-1942	0.00	0.00	0.00	-1.86	0.00	0.000	-25	0.00	4.64	0.00	-3.10
Senegal	9.51	-52	0.00	0.00	-2.34	-0.88	0.00	0.000	-128	0.00	2.59	0.00	-3.26
Serbia	-35.78	-805	-12.26	0.00	0.00	-0.04	-0.35	0.000	-51	5.30	-1.55	0.00	2.37
Sierra Leone	NA	-183	0.00	0.00	6.18	-0.40	0.00	0.000	-351	0.00	5.88	0.00	3.68
Slovakia	-17.00	-5757	-4.37	0.05	0.00	-1.76	0.05	0.000	-69	0.40	-3.42	0.00	-9.56
Slovenia	NA	2727	0.25	-1.92	0.00	1.44	1.92	0.000	-473	1.92	17.31	0.00	9.62
Solomon Islands	NA	-22	0.00	0.00	0.00	-0.80	0.00	0.000	2	0.00	0.00	0.00	0.00
South Africa	-26.00	-448	-0.03	0.06	0.52	-0.88	0.19	0.000	53	-1.56	-2.34	0.00	-0.97
South Korea	74.00	-5568	-0.13	0.84	0.00	-1.37	0.00	0.000	-654	-1.12	-5.03	0.00	-9.78
Spain	NA	-17761	-10.10	0.00	0.00	-8.74	-1.00	0.000	105	-17.33	-1.33	0.33	-7.67
Sri Lanka	0.55	-16660	-0.13	-0.76	0.00	-4.30	0.00	0.000	-272	-0.08	-16.99	0.00	-46.47
Sudan	7.00	-1495	-0.11	-0.01	0.66	-0.46	0.00	0.000	-659	0.00	-1.94	0.00	-0.03
Suriname	NA	16	0.00	0.00	0.00	0.11	-5.49	0.000	-7	0.00	-1.10	0.00	0.00
Switzerland	2.50	-3990	-7.42	0.00	0.00	2.10	0.00	0.000	-997	0.94	-0.47	-0.47	7.04
Syria	NA	-34	0.00	0.00	-0.74	-5.96	0.00	0.000	45	0.00	-2.78	0.00	3.53
Taiwan	NA	-6781	-0.02	0.00	0.00	-4.68	0.00	0.000	-20	2.13	-12.77	0.00	-13.12
Tajikistan	-6.54	-7767	-0.08	-0.04	0.00	-1.18	-0.13	0.000	-252	0.00	-6.30	0.00	-1.36

Tanzania	-0.50	-2112	-0.04	0.00	0.24	0.11	0.00	0.000	-920	0.00	-1.12	0.00	-0.80
Thailand	13.78	-2560	-0.12	0.00	-1.34	-0.83	0.00	0.000	-499	-1.55	-5.78	-0.11	-8.14
The Gambia	-20.00	-712	-0.01	0.00	2.44	-1.24	0.00	0.000	1248	0.00	-2.44	0.00	-14.63
Togo	27.50	1323	0.09	-0.06	-2.06	0.68	0.00	0.000	170	0.00	-0.17	0.00	2.95
Trinidad and Tobago	NA	-31276	0.00	0.00	0.00	-2.10	0.00	0.000	-691	0.00	-10.00	0.00	-10.00
Tunisia	NA	-294	-0.02	0.00	0.00	-1.79	0.00	0.000	-14	0.00	0.90	0.00	2.57
Turkey	NA	-343	0.11	0.00	0.00	-2.50	0.00	0.000	-674	0.00	0.00	0.00	12.50
Turkmenistan	-17.48	-2270	0.00	0.00	0.00	-0.26	0.00	0.000	0	NA	-7.86	0.00	-9.31
Uganda	-7.72	-1801	-0.14	0.00	0.07	0.30	0.00	0.000	-1419	0.00	-3.26	0.00	-4.37
Ukraine	4.33	-3799	-43.99	0.00	0.00	0.43	0.00	0.000	-1	0.58	-12.88	0.00	-16.35
United Arab Emirates	8.90	-1066	0.00	0.00	0.00	-2.81	0.02	-0.010	-15	NA	-1.90	0.00	-0.80
United States	3.14	-369	-0.03	0.00	-0.02	-0.47	-0.40	-0.002	-55	-1.52	-3.55	-0.03	-1.99
Uruguay	-15.39	-3752	-0.10	-0.06	0.00	-3.86	0.00	0.000	-278	-2.43	-1.80	-0.12	-9.44
Uzbekistan	21.15	-1801	-0.01	0.00	0.00	-0.33	-0.01	0.000	-122	0.00	-0.38	0.00	1.80
Venezuela	12.32	-89	0.00	0.00	0.35	-1.19	0.00	0.000	-759	-0.35	-3.33	0.00	-2.78
Vietnam	-8.15	-2113	-0.07	-0.03	5.48	-0.09	0.05	0.000	-256	-4.19	-2.13	-0.02	-9.20
Yemen	NA	0	0.00	0.00	0.00	-0.30	0.00	0.000	-42	NA	-1.42	0.00	-2.23
Zambia	-27.80	-652	-0.04	0.00	0.09	-1.02	0.00	0.000	10	0.00	-1.16	0.00	1.53
Zimbabwe	20.75	955	-0.09	-0.91	-1.37	-0.02	8.22	0.000	-240	0.00	-1.37	0.00	-16.44

Appendix 2.

Supplementary figures and tables for Chapter 4

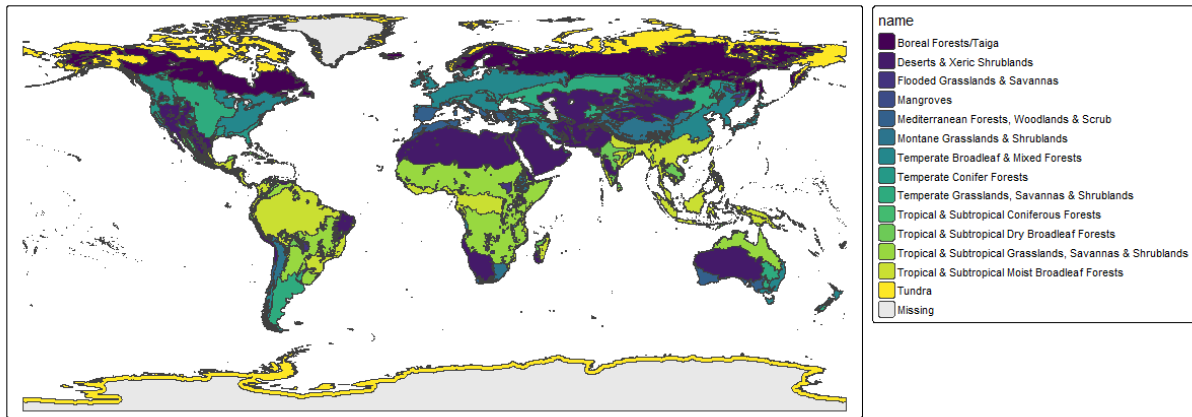


Figure A2.1 | Terrestrial biomes of the world.

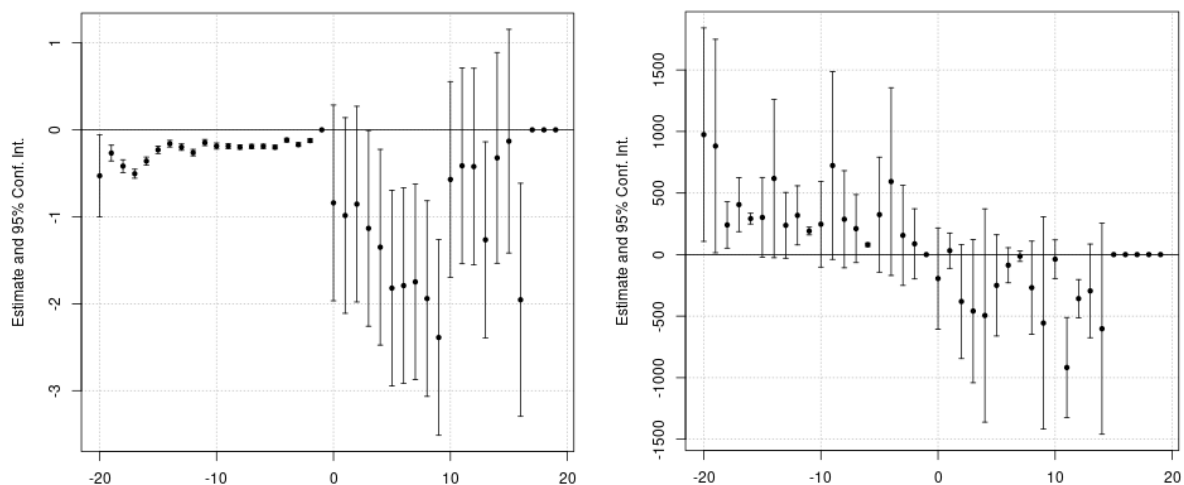


Figure A2.2 | **Dynamic protected area effects.** Event study analysis done with a subset of the panel dataset consisting of the full data from a random selection of 6 countries: Italy, Liberia, Oman, Botswana, Cambodia, and Colombia. The x-axis is time, in years, before (negative) and after (positive) the year of PA designation at year 0.

Table A2.1 | IUCN protected area management categories. All PAs can be classified into one of seven categories depending on their management objectives. Generally, lower categories have stricter rules, and higher categories (i.e. V and VI) allow multi-use activities inside their boundaries. Table derived from (Kalamandeen & Gillson 2007).

Category	Type and description
I (a)	<i>Strict nature reserve</i> : protected area managed mainly for science
I (b)	<i>Wilderness area</i> : protected area managed mainly for wilderness protection
II	<i>National park</i> : protected area managed mainly for ecosystem protection and recreation
III	<i>Natural monument</i> : protected area managed mainly for conservation of specific natural features
IV	<i>Habitat/species management area</i> : protected area managed mainly for conservation through management intervention
V	<i>Protected landscape/seascape</i> : protected area managed mainly for landscape/seascape protection and recreation.
VI	<i>Managed resource protected area</i> : protected area managed mainly for the sustainable use of natural ecosystems.

Table A2.2 | Variance inflation factors. The Variance inflation factors (VIF) of the nine covariates used in the coarsened exact matching algorithm to multicollinearity calculated from a random 10% sample of the dataset. A VIF value under 5 is interpreted as having a low probability of being highly correlated.

Predictor variable	VIF
Human population density	1.05
Slope	1.43
Biome	1.44
Elevation	1.52
Precipitation	1.68
Travel time	1.69
Agricultural suitability	4.04
Temperature	4.39

Table A2.3 | Covariate balance. The variance ratio (Var. Ratio) and the standard mean difference (SMD) between the treatment (PAs) and control groups for each predictor variable used for matching. The difference in covariate balance before and after matching is presented.

Predictor variable	SMD unmatched	SMD matched	Var. Ratio unmatched	Var. Ratio matched	Var. Ratio % improvement
Agricultural suitability	-0.1108	0.0012	1.1629	1.0018	99
Population density	-0.1189	0.0017	0.4641	1.1050	87
Biome	-0.0310	0.0000	0.6398	1.0000	100
Country	-0.3147	0.0000	0.8274	1.0000	100
Elevation	-0.0866	-0.0017	0.9348	1.0012	98
Slope	0.0660	-0.0033	1.4445	1.0058	98
Precipitation	0.0521	0.0007	1.2798	0.9987	99
Temperature	-0.0012	-0.0019	1.1625	1.0007	100
Access	0.2466	0.0050	0.4495	0.9964	100

Table A2.4 | Placebo test. Dependent variable is built area and nighttime light. Placebo test run with the basic model that includes only cell and year fixed effects. Placebo assigned treatment randomly to the dataset. Clustered standard errors at the cell level are reported in round brackets.

	Built area [m ²]	Nighttime light [DN]
Placebo	-0.461 (0.524)	0.0001 (0.0004)
No. observations	30,336,495	114,804,840
No. cells	6,002,791	5,978,060
No. years	5	19
Adj. R ² (full model)	0.972	0.732
p-value	0.38	0.73
Cell & year FE	Yes	Yes