Article

Mixed effectiveness of global protected areas in resisting habitat loss

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Protected areas are the cornerstones of conservation efforts to mitigate the anthropogenic pressures driving biodiversity loss. Nations aim to protect 30% of Earth's land and water by 2030, yet the effectiveness of protected areas remains unclear. Here we analyze the performance of over 160,000 protected areas in resisting habitat loss at different spatial and temporal scales, using high-resolution data. We find that 1.14 million km^2 of habitat, equivalent to three times the size of Japan, across 73% of protected areas, had been altered between 2003 and 2019. These protected areas experienced habitat loss due to the expansion of built-up land, cropland, pastureland, or deforestation. Larger and stricter protected areas generally had lower rates of habitat loss. While most protected areas effectively halted the expansion of built-up areas, they were less successful in preventing deforestation and agricultural conversion. Protected areas were 33% more effective in reducing habitat loss compared to unprotected areas, though their ability to mitigate nearby human pressures was limited and varied spatially. Our findings indicate that, beyond establishing new protected areas, there is an urgent need to enhance the effectiveness of existing ones to better prevent habitat loss and achieve the post-2020 global biodiversity goals.

The Anthropocene[1,2] has resulted in a dramatic loss of biodiversity and even potentially a sixth mass extinction event[3–5]. Habitat loss, degradation, and fragmentation caused by anthropogenic activities are the critical factors inducing an unprecedented decline in biodiversity[6–8]. Establishing and expanding protected areas (PAs) have been the key instruments used by nations to alleviate and reverse biodiversity loss, as PAs are seen as the backbone of global conservation efforts[9,10]. This has resulted in rapid growth of the global network of PAs, which currently cover about 16.64% of Earth's land surface and 7.74% of the marine realm[11]. The newly adopted Kunming-Montreal Global Biodiversity Framework further calls for 30% of the world's land and water to be PAs[12,13]. This is an ambitious goal, but simply expanding PAs cannot guarantee biodiversity conservation[10]. Given the crucial importance of addressing biodiversity loss for human well-being, biodiversity

conservation efforts in the next decade must be implemented through the most effective conservation strategies and actions.

Some studies have shown that many individual PAs slow habitat loss[14] and stop land clearing[15]. Moreover, it is generally recognized that biodiversity will likely be better protected from human activities after an area has been designated as a PA[16]. There is no doubt that well-managed PAs can conserve biodiversity[17]. However, habitat loss and human encroachment, especially those due to urbanization[18], conversion to cropland[19] and pastureland, and deforestation[20] have been found to occur inside the boundaries of many PAs, and these pressures are still the greatest threat to terrestrial biodiversity loss[21]. A recent comprehensive assessment revealed that one-third of global PAs are under intense human industrial-level pressure[22]. The encroachment of anthropogenic land use on natural habitats, which has caused habitat

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loss, degradation, fragmentation[23], and loss of ecosystem integrity[24] and functional connectivity[25], continues to undermine the functionality and effectiveness of PAs in preventing biodiversity loss. Therefore, doubts about the effectiveness of the overall PA estate are growing[26].

Given the importance of PAs for halting biodiversity loss, it is crucial to continue to generate datasets and methods of quantifying their effectiveness, taking advantage of up-to-date data and advanced analytical techniques[10,22,27]. However, despite the apparent relationship between human activities, habitat loss, and biodiversity decline, assessing the effectiveness of PAs is challenging because biodiversity response to PA conservation efforts is difficult to measure. Recent advances in remote sensing over the past few decades have provided the capacity to monitor the long-term habitat changes in the PAs[27], and assessments of PA effectiveness in resisting human pressure have received increasing attention in recent years[15,28–31]. However, most previous studies have focused on a single type of habitat alteration, such as deforestation[20] or conversion to cropland[19]. There is a lack of comprehensive, multidimensional, and systematic assessments of PA effectiveness, with the few existing comprehensive assessments[10,22] not fully capturing the high-resolution dynamic changes in habitat within PAs. This is largely because these assessments rely on coarse resolution data (e.g., 5 arcmin[10] and 1 km[19,20]), which introduces inherent and large uncertainties in habitat change estimates due to mixed pixel issues[32]. Moreover, coarse spatial resolution data that is often used in PA effectiveness studies cannot adequately capture habitat dynamics within numerous small-scale PAs (such as < 1 km^2) worldwide, and these places are simply ignored despite often being of biodiversity conservation importance. Among the more than 160,000 protected areas involved in this study, sizes range from 900 m^2 to 5 km^2, encompassing ~128,000 individual protected areas.

In addition, most existing effectiveness assessments have focused only on the spatial performance of PAs (comparison of effectiveness between protected and non-protected areas in preventing habitat loss), without examining their temporal effectiveness over the long term[22]. A comprehensive assessment of temporal and spatial effectiveness will better capture their actual effectiveness[33]. This is mainly because the establishment of PAs is not entirely random, and there may be significant differences in the initial habitat loss states within the PAs, which can lead to inherent uncertainty in the evaluation of PA effectiveness. Furthermore, earlier studies have insufficiently explored the distinct heterogeneity of PAs, and have not thoroughly analyzed the determinants of their effectiveness in an integrated and broad framework that considers crucial elements such as the establishment time of the PA, governance type (indigenous and community vs. government), biodiversity importance, the distance from cities, and the human footprint within and beyond the boundaries of the PA. This understanding of why certain PAs are effective and why others are not is critical when considering the global 30 × 30 agenda.

Here we provide a comprehensive, multidimensional (temporal and spatial assessment), and systematic assessment of long-term habitat loss in over 160,000 protected areas using high-resolution satellite data (30-m resolution). Using these data, we estimated the spatiotemporal effectiveness of global PAs in resisting habitat loss. To our knowledge, no other assessment has incorporated such a broad range of habitat loss types in PAs globally at this high spatial resolution. We focused on four types of natural habitat loss: conversion to (i) built-up land, (ii) cropland, (iii) pastureland, and (iv) deforestation, due to their prevalence. Moreover, to reduce double counting and land use classification errors, we also combined these four types of habitat loss between 2003 and 2019. We first investigated the dynamics and pattern of habitat loss in the PAs. To understand the changes in PA effectiveness over time, we used a causal effect model[34] to estimate the performance of designated PAs at resisting habitat loss. Spatially, we compared habitat loss inside and outside the PAs based on different buffer zones crossing the boundaries of PAs. Moreover, we also used a non-experiment matching approach to further quantify the spatial performance of PAs in resisting habitat loss by comparing random sampling sites inside the PAs and matched unprotected sites. We focused on the heterogeneity of spatial effectiveness at the site (PA), ecoregion, and biome scale. We also applied the integrated framework of metacoupling[35] (human-nature interactions within a PA as well as between the PA and other places such as cities near and far) to understand factors influencing the PA effectiveness. The framework provides a theoretical conceptual foundation for our quantitative analysis. It treats a PA as an 'open system' and allows for an assessment of the impacts of human activities both within a PA and in the PA's immediate surroundings and distant regions. In other words, the framework enables us to have a more comprehensive understanding of the effectiveness of PAs beyond those limited to internal factors. Thus, our quantitative analysis integrates both internal factors (e.g., establishment time of the PA, governance type) and external factors such as the PA's distances to different land uses and cities. The results can help develop more effective strategies for PA management than just considering internal factors.

Results
Prevalent habitat loss in global protected areas
The prevalence of global habitat loss from our analyses indicates that PAs have not been effective in curbing habitat loss within their boundaries. We combined four types of habitat loss in PAs between 2003 and 2019 (see Supplementary Figs. 1 and 2a–d) and found that global PAs had experienced a rapid growth of habitat loss. Total habitat loss was 405,930 km^2 in PAs designated before 2003, covering 2.94% of the total PA area and distributing in 46,341 PAs (Supplementary Data 1). However, by 2019, this area increased to 1,142,861 km^2, covering 5.55% of the total PA area, and was scattered in 118,002 PAs (72.78% of the total number of PAs). Even PAs in the core of the Amazonian forests, which are considered to be among the most pristine wilderness areas on the planet[36], were not free from habitat loss (Fig. 1a). Moreover, PAs located in areas that have already experienced a high degree of human pressure underwent a high percentage of habitat loss. Approximately one-third of PAs in Europe and the United States (33.8% and 31.4%, respectively) experienced >10% habitat loss (Fig. 1b).

Moreover, newly established PAs in recent decades have not been effective tools to curb habitat loss compared to longer established ones (the percentage of habitat loss is 6.43% for PAs established after 2010, compared to 5.45% for PAs established before 1990), and some PAs have even been established in areas in the middle of human activities and pressures (Supplementary Fig. 3a–j). We found that PAs with strict biodiversity conservation targets (IUCN categories I and II) had a significantly lower proportion of habitat loss (4.0%) than non-strict PAs (IUCN categories III-VI), which exhibit a habitat loss rate of 8.0% (Kruskal-Wallis test $\chi^2 = 1078.7$, $P < 0.01$). Small PAs (the smallest 25% of all PAs) were much more likely to have lost a high proportion of habitat (16.4%) than large PAs (the largest 25% of all PAs; habitat loss proportion = 5.9%; Kruskal-Wallis test $\chi^2 = 4627.5$, $P < 0.01$).

Deforestation and conversion to cropland, pastureland, and built-up land accounted for 42, 32, 24, and 2%, respectively, of all habitat loss areas in PAs between 2003 and 2019. The highest percentage (53%, $n = 85,637$) of the total number of PAs were affected by deforestation, followed by cropland (38%, $n = 60,577$), built-up land (24%, $n = 38,630$), and pastureland (14%, $n = 22,921$). A small portion of PAs (6% and $n = 9,050$) have four types, 17,782 PAs (11%) have three types, 31,325 PAs (19%) have two types, and 59,955 PAs (37%) have one type, respectively (see Fig. 1c). Moreover, we found a "linkage effect" in habitat loss, that is, the habitat loss of two types sometimes occurs synchronously. Four types of habitat loss areas in PAs were moderately correlated (Pearson's r ranged from 0.39 to 0.52, $P < 0.01$, see Supplementary Data 2).
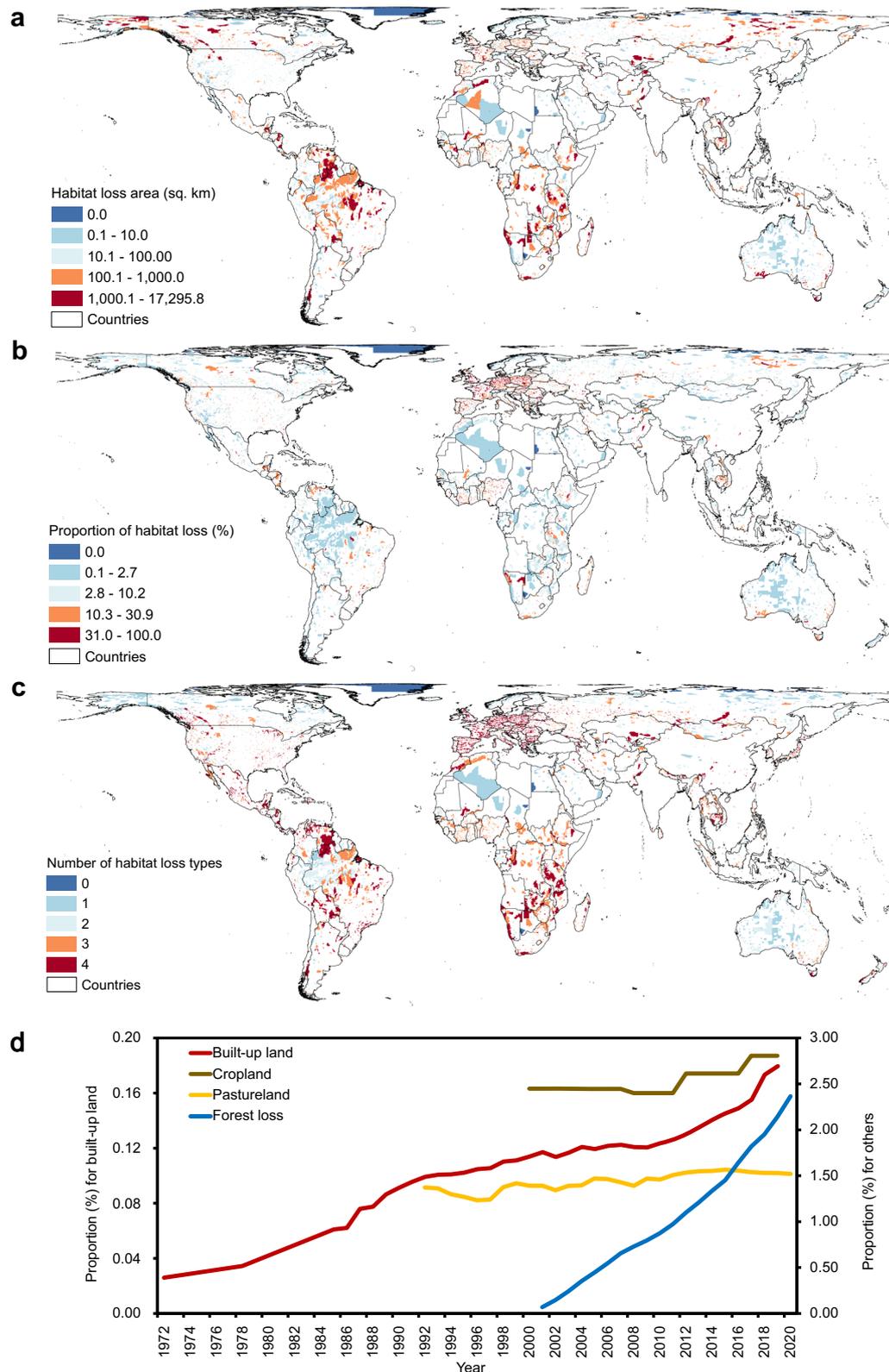
Fig. 1 | Habitat loss in protected areas. a Combined habitat loss area of the world's terrestrial PAs, due to four types of habitat loss (built-up land, cropland, pasture-land, and deforestation) between 2003 and 2019. **b** Proportion of habitat loss within each PA. **c** Number of types of habitat loss in PAs. **d** Long-term changes in the proportion of habitat loss within PAs. The global maps were created using ArcGIS Pro v3.2 software, and the country boundary data is sourced from https://www.naturalearthdata.com/. Source data are provided as a Source Data file.

In addition, we found that the four individual habitat loss types in PAs show high heterogeneity. The proportion of built-up land in PAs has increased from 0.03% to 0.18% between 1972 and 2019 (Fig. 1d; Supplementary Data 1). Surprisingly, the annual growth rate of the built-up land in PAs between 1972 and 2019 was 4.34%, which was substantially higher than the global average growth rate outside PAs (3.40%). Similarly, the proportion of cropland in the PAs increased from 1.35% to 1.74% between 2003 and 2019 (Fig. 1d and Supplementary Data 1). In addition, between 2003 and 2019, cropland area within 29,545 PAs established before 2003 expanded by 19.05%, considerably higher than the global level of 9%[37]. Likewise, we found that pastureland in PAs established before 1992 covered 1.21% of the total PA, but by 2020, this had increased to 1.38% of the total PA (Fig. 1d and Supplementary Data 1). From 1992 to 2020, the proportion of pastureland area in PAs to the global total area of pastureland increased from 3.64% to 9.81%. The accelerating global forest loss in PAs is even more alarming. We found that the cumulative forest loss area in the PAs was 558,142 km^2 between 2001 and 2020, which accounted for 13.57% of the total area of global forest loss.

Temporal effectiveness of protected areas

Based on the synthetic difference-in-differences (SDID) model (Methods), we found that the effect of PA establishment on the annual growth of built-up land in PAs (in terms of both area and proportion) was significantly negative for almost all PA groups (11 groups, see Fig. 2), which implied that most PAs have been effective in halting built-up land expansion in PAs. Across the total sample of PAs with designated status information in 2019 ($n = 26,361$), we estimated an average reduction in the area (1.72 ha) and proportion (0.21%) of built-up land in PAs after their designation (Fig. 2a, b, k and Supplementary Data 3). Surprisingly, we found no significant difference in the expansion of built-up land between strict PAs and non-strict PAs, even though strict PAs do not perform as well as non-strict PAs in preventing the proportion growth of built-up land in the PAs. Larger PAs are more effective than smaller PAs in restraining the growth of the built-up land area in PAs, whereas smaller PAs are clearly more effective than larger PAs in curbing the proportion of built-up land growth. Because small PAs have a smaller total area than large PAs, a relatively small expansion of built-up land in smaller PAs could trigger a rapid increase in the proportion of built-up land. Thus, it appears that small PAs are effective in restraining human disturbance. Across different continents, the PAs in South America and Asia have the best performance in preventing the growth of built-up land area and proportion, respectively. However, PAs in North America and Oceania are not successful in halting built-up land area expansion, and PAs in Oceania are not effective in reducing the proportion of growth. This also implies that the effectiveness of PAs is not constant throughout the world and that it is important to restore the functionality of these ineffective PAs. At the country level, we found that several European countries (e.g., Austria, Italy, Finland, and France) have PAs that show good performance (see Supplementary Data 4). In traditional understanding, Europe is considered to have high human activity levels. This suggests that human governance can play an important role in the effectiveness of PAs. This type of governance can be a useful reference and promotion value for developing countries.

Most PAs exhibited poor performance in halting cropland expansion (Fig. 2c, d, k), but there are a few exceptions. We found that smaller PAs are effective in limiting the area growth of cropland. However, larger PAs show good performance in restricting the proportion growth of cropland in PAs, resulting in an average decrease of 0.43%. The PAs in North America, especially in the United States, showed excellent performance in preventing cropland expansion. On average, we observed a reduction of 12.8 ha in area and 3.04% in the proportion of cropland per PA in North America after the designation of the PAs (Supplementary Data 3). However, the overall effectiveness of PAs in curbing cropland expansion is not encouraging. Increasing

demand and pressure on land for food production may result in the penetration of PAs and the degradation of their internal natural habitat. Consequently, PAs will experience more pervasive trade-offs between biodiversity conservation and food security. As with cropland, PAs are generally ineffective in limiting pastureland expansion (Fig. 2e, f, k), and most designated PAs have even accelerated pastureland growth across many groups and regions. However, a notable exception is Asia, where the establishment of PAs has significantly contributed to a reduction in the area and proportion of pastureland within PAs (average ATT = − 323 ha and − 1.82% per PA). At the country level, Denmark and Chile have shown outstanding performance, while Estonia has experienced rapid growth of pastureland in PAs (average ATT = 24.7 ha and 10.67% per PA, Supplementary Data 4). Importantly, PAs have not been an effective policy tool for the restriction of forest loss, especially in limiting area expansion of forest loss. Our results suggest that all groups of PAs experienced a significant increase in forest loss area (except for four non-significant groups with $P > 0.1$, Fig. 2g, h, k), and some PAs have even acted as a catalyst for the exacerbation of forest loss (Supplementary Fig. 4a–d). Regarding the proportion of forest loss, PAs in IUCN categories III-VI (ATT = − 0.52%, $P = 0.03$) and PAs in North America (ATT = − 0.12%, $P < 0.01$) and Oceania (ATT = − 3.88%, $P < 0.01$) have been effective at inhibiting accelerated forest loss within PAs. However, at the country level, few countries have shown good performance (except for Ghana and Japan). PAs are also ineffective for stopping the expansion of combined total habitat loss in terms of absolute area (Fig. 2i, j, k), and small PAs (the bottom 25% in size) are only marginally effective. In some cases, the establishment of PAs has even exacerbated overall habitat loss areas, especially in Africa (average ATT = 16.89 ha) and South America (average ATT = 7.40 ha). However, PAs have had a significant effect on curbing increases in the proportion of total habitat loss, especially for PAs in Europe and North America and for small PAs.

Our findings reveal that PAs exhibit time lags of 1–6 years in persistently restraining habitat loss. Furthermore, we found that this time-lag effect varies across different types of human disturbance (Supplementary Data 5). Assuming a one-year lag in the establishment of PAs, we found that PAs are significantly effective in restricting built-up land expansion. We consistently observed six-year temporal lags in the effectiveness of PAs in curbing the rise in cropland proportions within their boundaries. We found that PAs exhibited a similar lag effect in their limitation of the growth of combined total habitat loss as a proportion, lasting up to 5 years after the establishment of PAs. This suggests that the performance of PAs may not be immediately apparent. A similar temporal delay in the effect of PAs was also found in the proportion (but not the absolute area) of pastureland expansion 3–6 years after PA establishment. Nevertheless, the time-lag effect of PAs on restricting growth in the proportion of forest loss occurred more rapidly (1–2 years after the PAs were established). Overall, our results indicate a pervasive time-lag effect of PA establishment, a process that has been often overlooked in previous assessments of PA effectiveness. This suggests that the establishment of PAs does not necessarily produce timely effects and that well-functioning PAs may require long-term operation and management.

We delved further into the investigation of the heterogeneity of this lag effect across different continents and between strict and non-strict PAs (Supplementary Data 6). Our findings reveal that PAs in North America, Europe, and under non-strict protection exhibit a more pronounced time-lagged effect in relation to the total habitat loss. Surprisingly, PAs in North America demonstrate significant efficacy in curbing the growth of built-up areas and cropland within their bounds, even with a lag of six years. In addition, PAs in Asia and those under non-strict protection also manifest this effect in curbing the increase in cropland within their boundaries. However, this lag effect is less observed for pastureland and forest loss. Notably, PAs under strict protection do not exhibit this effect. The observed lag effect in global
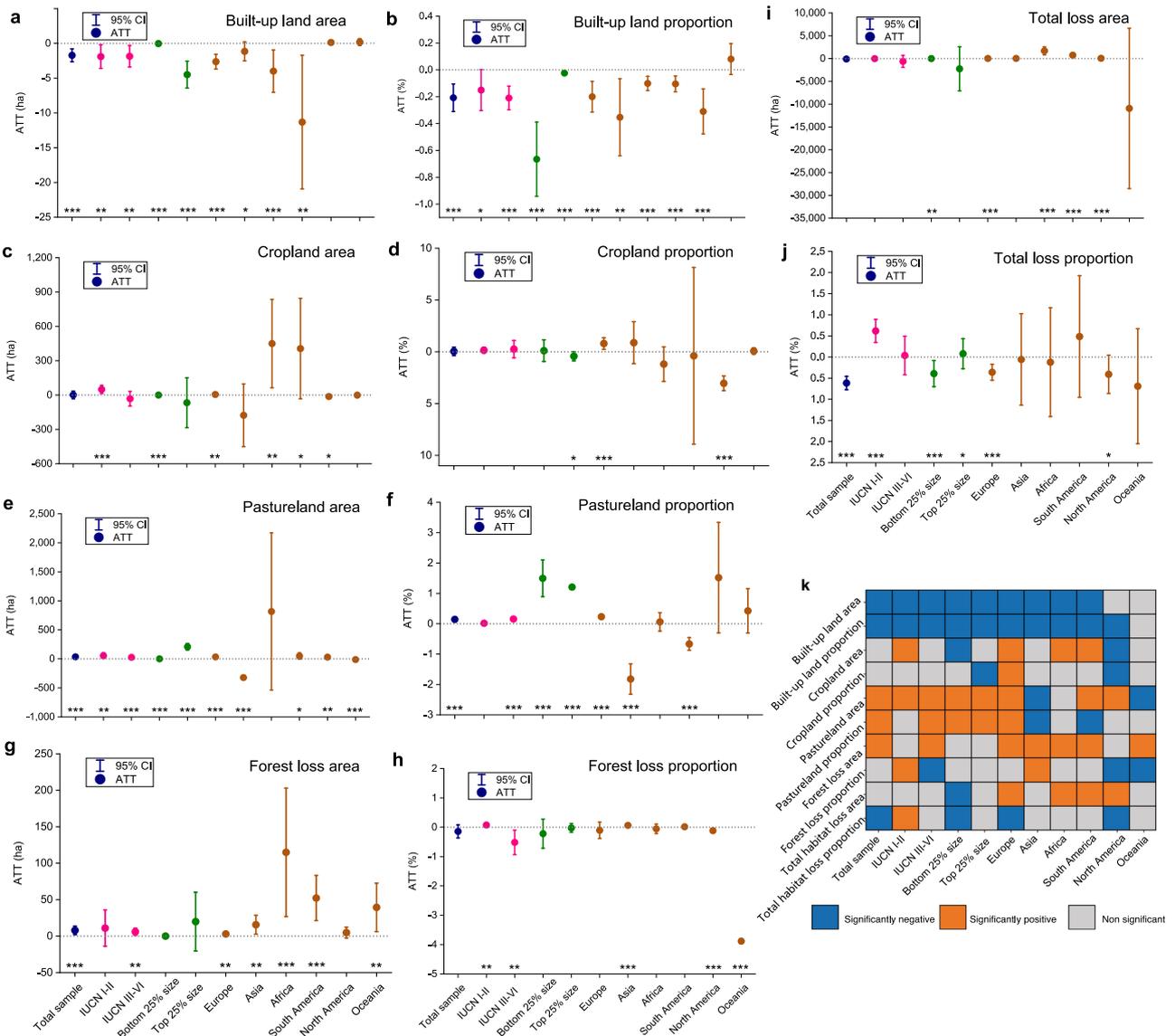
Fig. 2 | Effects of designated PAs on retarding habitat loss. ATT is the "average treatment effect on the treated" of PAs, namely the estimated annual average effect of established PAs on retarding the area and proportion of habitat loss in PAs, including the area and proportion of built-up land (**a** and **b** n = 26,361), cropland (**c** and **d** n = 19,221), pastureland (**e** and **f** n = 52,507), forest loss (**g** and **h** n = 38,692), and combined total habitat loss (**i** and **j** n = 63,394). The total sample encompasses all the PAs examined in the study. PAs designated as IUCN I-II are those strictly protected according to the IUCN categories. Conversely, PAs classified as IUCN III-VI are not under strict protection. The term "Bottom 25% size" refers to PAs within the smallest 25% in terms of size, representing small-scale PAs. Meanwhile, "Top 25% size" pertains to the largest 25% of PAs, indicative of large-scale PAs. A summary of influence direction and significance level were shown in (**k**). Error bars indicate 95% confidence intervals. For all ATT coefficients of area (**a**, **c**, **e**, **g**, **i**), the unit of measurement has been changed from m^2 to ha. Asterisks represent significance levels: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$. Exact P-values can be found in Supplementary Data 3. The absence of an asterisk indicates statistical non-significance. Significant negative values indicate that the establishment of the PA can significantly reduce habitat loss, while positive values indicate the opposite. Source data are provided as a Source Data file.

PAs' effectiveness in curbing habitat loss provides several policy implications. Establishing PAs proactively and promptly is vital to effectively mitigate habitat loss before it becomes severe. Tailoring strategies to regional specifics, such as climate, biodiversity, and socio-economic factors, enhances the effectiveness of these areas. The balance between strict and non-strict conservation measures should be carefully considered, recognizing that flexible approaches can sometimes yield significant benefits, especially in regions where strict conservation might be impractical. Long-term monitoring and adaptive management are crucial, as the impacts of conservation efforts on habitat loss may not be immediately apparent. This involves regular assessment and the willingness to adjust strategies based on ecological changes and evolving scientific understanding.

We, therefore, examined the variation in the temporal effectiveness of existing PAs against five criteria: the establishment time of the PA, governance type (indigenous and community vs. government), the importance of biodiversity, the distance to cities, and human footprint (Fig. 3). We used proportion changes in combined total habitat loss in PAs to represent habitat alteration.

We found that earlier established PAs are more effective in curbing the overall loss proportion of habitat over the time period assessed (Fig. 3a). The ATT values for PAs established before and after 2010 were −0.67% and −0.48%, respectively. This implies that to achieve the 30 × 30 agenda, it is crucial to act promptly, and the longer the establishment time, the more likely the PA will become effective. This is potential because only after the establishment of PAs can there
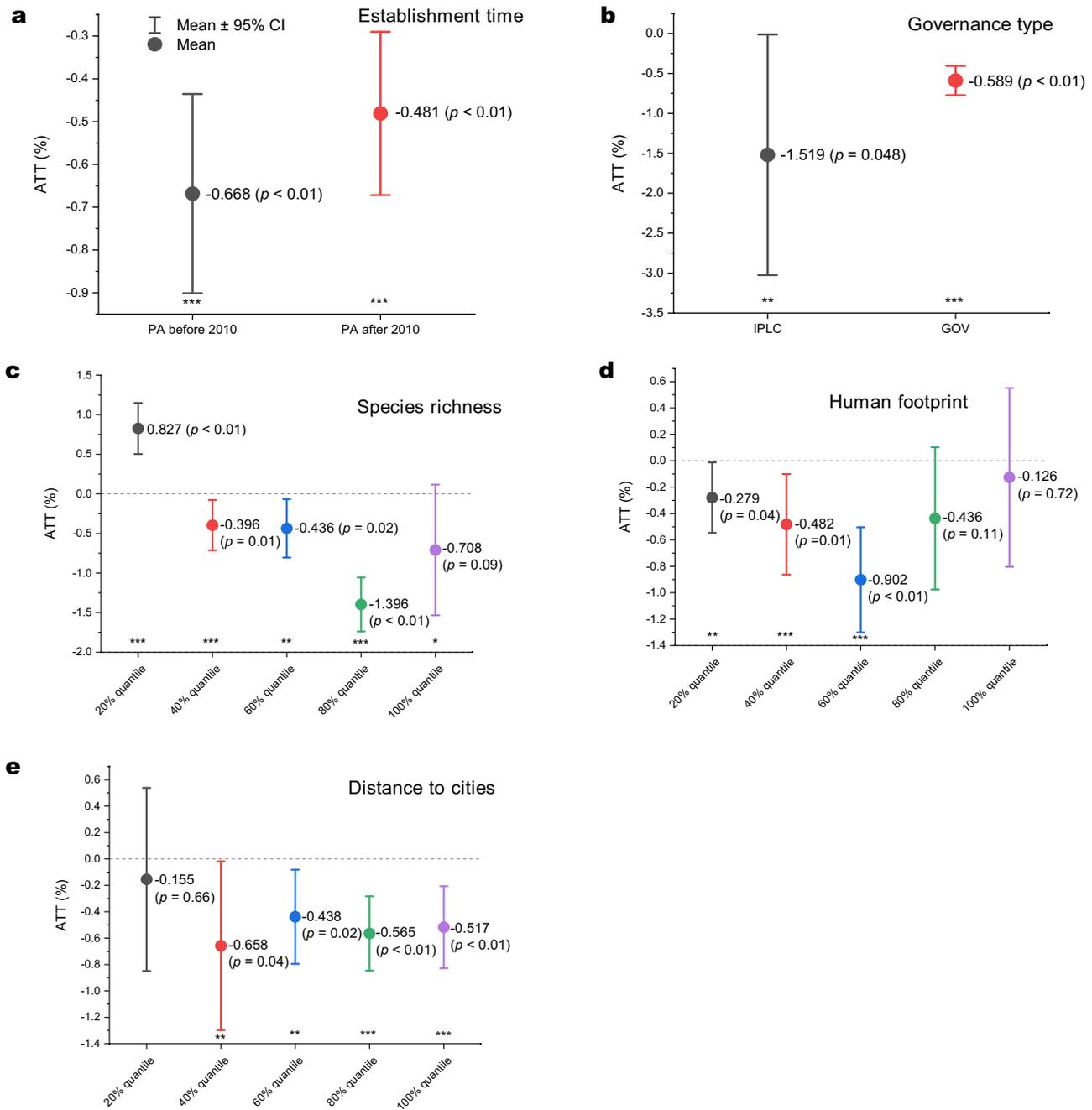
Fig. 3 | Differentiated effects of designated PAs on retarding habitat loss. ATT is the "average treatment effect on the treated" of PAs, namely the estimated annual average effect of established PAs on retarding the proportion of total habitat loss in PAs between 2003 and 2019. Error bars indicate 95% confidence intervals. Asterisks represent significance levels: *$P < 0.1$, **$P < 0.05$, ***$P < 0.01$. The absence of an asterisk indicates statistical non-significance. If AAT is significantly negative, it indicates that PA establishment has a significant effect on reducing habitat loss. Here we consider the multiple heterogeneity of PAs, including the establishment time of PAs, before 2010 ($n = 25,551$) and after 2010 ($n = 33,448$) (**a**), governance type: indigenous peoples and local communities' lands (IPLC, $n = 4,210$) and government (GOV, $n = 51,250$) (**b**), species richness (**c**), human footprint (**d**), distance to cities (**e**). To further examine the heterogeneity of PAs, we divided the sample PAs into quintiles (e.g., 20% quantile in (**c**) represents PAs with the lowest 20% species richness, $n = 59,625$). The exact results can be found in Supplementary Data 7. Source data are provided as a Source Data file.

be corresponding resource support, and the effectiveness of PAs is not immediately apparent but requires a long-term process. Moreover, it is essential to recognize that newly established PAs tend to become "paper parks", as nations try and achieve numbers of PAs in terms of area and not outcomes. Moreover, the government type of PAs is an important factor that affects their effectiveness. Indigenous peoples and local communities lands are more effective in controlling habitat loss in PAs compared to government and other entities (ATT were

−1.52% vs. −0.59%, Fig. 3b). This is potentially because of their deep understanding of the local environment and traditional knowledge and practices for sustainable resource use and management[38]. Their participation in the management of PAs can help to improve the effectiveness of conservation efforts and promote the sustainable use of natural resources[38].

We also found PAs currently distributed in regions of high biodiversity richness and importance have stronger effectiveness in
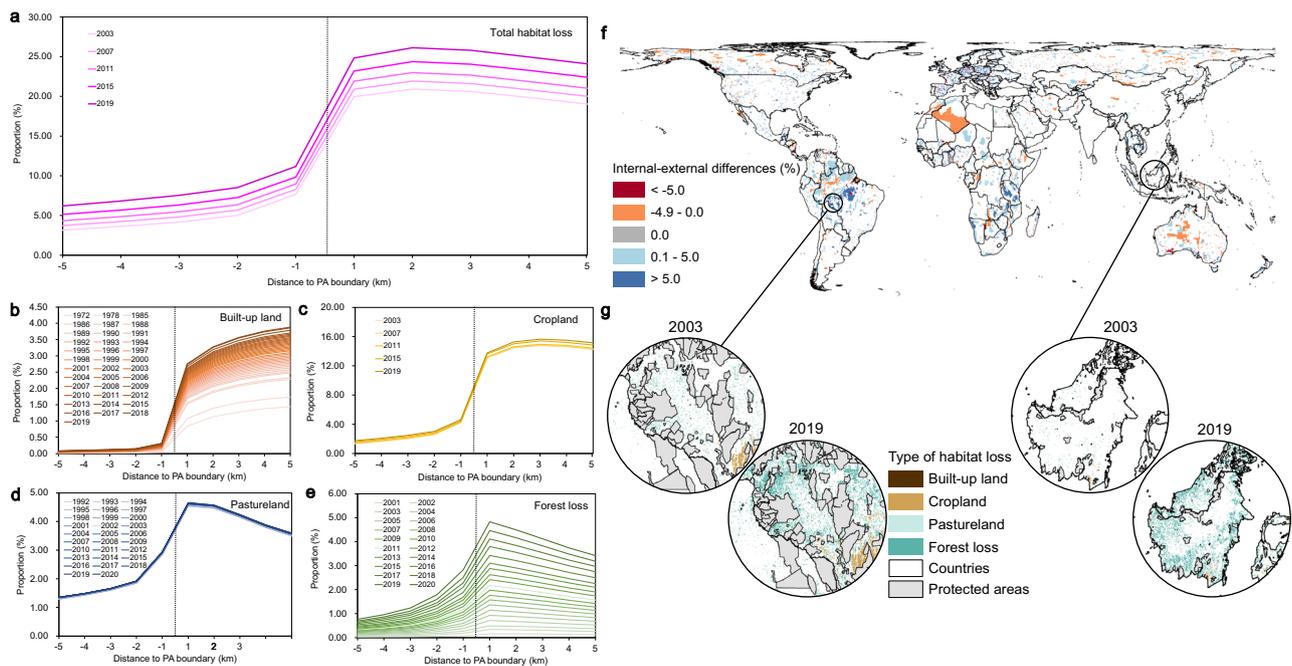
Fig. 4 | Habitat loss across the boundaries of PAs. a Proportion changes in combined total habitat loss. **b** Proportion changes in built-up land. **c** Proportion changes in cropland. **d** Proportion changes in pastureland. **e** Proportion changes in forest loss. **f** Internal-exterior differences of habitat loss proportion with 1 km buffer of PA boundaries in 2019. **g** PAs in Rondônia, Brazil, and Kalimantan Island have experienced lower levels of habitat loss than their surrounding areas. The geographic maps were created using ArcGIS Pro v3.2 software, and the country boundary data is sourced from https://www.naturalearthdata.com/. Source data are provided as a Source Data file.

preventing habitat loss (Fig. 3c and Supplementary Data 7). One potential reason for this is that these areas with high species richness are often far from human activity areas, and the probability of human disturbance is, therefore, relatively low compared to other regions. This has been further supported by human footprint data, which shows that PAs distributed in the top 40% of human footprint areas do not significantly inhibit habitat loss (Fig. 3d and Supplementary Data 7). In addition, the distance of PAs to cities can provide a reference for the establishment of future PAs. PAs that are farther from cities were more effective in significantly curbing habitat loss, while the effectiveness of PAs near cities is not significant (Fig. 3e and Supplementary Data 7). This is potentially because areas near cities are more likely to be affected by intense human activities, such as infrastructure construction, urbanization, industrialization, and tourism, which can lead to habitat loss. Therefore, it is important to consider the distance from cities when establishing PAs to maximize their effectiveness in protecting biodiversity and habitats.

Effectiveness within and beyond protected area boundaries

To examine the spatial effectiveness of PAs at resisting habitat loss, we compared the proportion of habitat loss inside and outside each PA across buffer zones of different sizes inside and outside the PA's boundaries. Overall, although most PAs have experienced extensive habitat loss within their boundaries, they are still more effective at resisting habitat loss than their surrounding areas, which indicates that PAs have a substantial inhibitory effect on human pressure. We found that there was an average of 12.30% difference in the proportion of habitat loss within the 1 km buffer zone inside and outside the PA boundary in 2003 (Fig. 4a). Moreover, this difference increased over time to 13.67% by 2019. Interestingly, the proportion of total habitat loss peaked in the 2-km buffer zone outside the PA boundary and then gradually decreased with increasing distance to PA. This suggests that the 2 km buffer zone outside the PA boundary is an area of potentially

dramatic anthropogenic land use change. This zone faces the most severe conflict between development and conservation.

We also found that there was substantial variability in the spatial effectiveness of PAs and different spatial patterns among the four habitat loss types. From 1972 to 2019, the built-up land proportion inside the PAs remained less than 0.11%. However, in all 5 km buffers outside of the PAs, this proportion rapidly increased to a high level, ranging from 0.84% to 3.88%, especially in areas close to the PA boundaries (Fig. 4b). Moreover, we found the proportion of built-up land increased across the buffer zones from the core PAs to surrounding areas, suggesting a "gradient effect".

The proportion of cropland exhibited a similar spatial distribution pattern (Fig. 4c). The spatial compression process (rapid growth of human activities has resulted in the effective area of PAs being smaller than their geographical extent, resulting in spatial compression)[39] near the boundaries of PAs was apparent in our data. Specifically, the external buffer zones of PAs are fiercely contested between conservation and agricultural development. Cropland proportion showed stronger growth (by > 10%) in the 1 km buffers outside the PAs than inside the PAs and continued to steadily increase within the 3 km buffers outside the PAs, clearly demonstrating the ability of PAs to prevent the expansion of cropland. However, our data also reveal that cropland was moving closer to PAs. Such habitat compression will inevitably affect the connectivity and integrity of ecosystems and, consequently, further undermine the overall functioning and stability of PAs.

From 1992 to 2020, the changes in pastureland proportion showed an even more pronounced pattern. We found that pastureland proportion was highest in the 1-km buffer outside PAs and then gradually decreased with increasing distance outside the boundary (Fig. 4d). This suggests that the pressure for pastureland expansion is stronger in areas closest to PA boundaries. Although PAs are effective, using PAs to curb human pressures in areas immediately adjacent to them is ineffective.

Changes in the proportion of forest loss across PA borders further confirmed the findings outlined above. We also found that the proportion of forest loss peaked in the 1 km buffer zone outside the PAs (Fig. 4e). Moreover, differences in the proportion of forest loss between buffer zones inside and outside the PAs increased annually. By 2020, these differences exceeded 2%; however, the cumulative percentage of global forest loss in PAs was only 2.68%. This provides further evidence for the spatial effectiveness of PAs. Nevertheless, the areas closest to PA boundaries were hotspots of forest loss.

Globally, within 81.11% of the PAs, the total habitat loss proportion within the 1 km buffer zone was less than that outside the buffer zone in 2019 (Fig. 4f). If it were not for the rigid spatial constraints imposed by PAs, the loss of habitats could be greater and more widespread, especially in regions where there is a serious conflict between development and conservation (Fig. 4g). However, 15.69% of the PAs showed ineffectiveness, with a higher habitat loss proportion within the 1 km buffer zone than outside. The remaining 3.20% showed no substantial difference between the inside and outside of the buffer zone. This indicates that there is still a certain number of PAs that are not as effective as we anticipated.

Differentiated spatial effectiveness of protected areas and its implications for 30 × 30 agenda

Nations that have committed to the Kunming-Montreal Global Biodiversity Framework aim to designate 30% of Earth's land and water areas for protection by 2030. Given this ambition, an urgent need is to identify where setting up PAs will be most effective[38]. The current effectiveness assessment of PAs may provide a reference for this purpose. We therefore examined the heterogeneity of the spatial effectiveness of existing PAs at the PA scale, the ecoregion scale, and the biome scale, using a large-scale spatial sampling (~1.05 million grids in PAs) and the Propensity Score Matching (PSM) method. We used proportion changes in combined total habitat loss, built-up land, cropland, pastureland, and forest loss in PAs to represent habitat alteration.

We found significant habitat loss rate differences between PAs and matched unprotected areas (Fig. 5a–e), with 71.45% sampling grids (749,879 / 1,049,468) in PAs having less habitat loss rate than matched unprotected grids. Estimated average habitat loss rates in PAs were 4.20, 0.08, 2.54, 0.38, and 1.20% lower than in similar unprotected areas for total habitat loss, built-up land, cropland, pastureland, and forest loss, respectively (all $P < 0.01$, see Supplementary Data 8). It suggests that global PAs have the potential to reduce habitat loss rates by approximately 33.08, 27.69, 52.57, 9.49, and 33.55% for total habitat loss, built-up land, cropland, pastureland, and forest loss, respectively. PAs are particularly effective in curbing cropland expansion and deforestation. However, this effectiveness hides considerable type and spatial variation.

Indeed, PA type is closely related to its conservation effectiveness. Our analysis revealed that the Strict Nature Reserves (IUCN Ia category) have performed the best, followed by the Natural Monuments (III) and the National Parks (II), whereas the Wilderness Areas (Ib) did not show the expected effectiveness (Fig. 5f). This is likely due to significant losses of wilderness that have occurred in the past two decades, primarily driven by increasingly severe human disturbances[40]. Other types of PAs (IV, V, and VI) do perform worse. Yet in terms of curbing cropland expansion in PAs, non-strict PAs perform better. We also found the indigenous territories PAs have the best effect in curbing habitat loss, followed by strict protected PAs (Ia, Ib, and II), sustainable use PAs (III, IV, V, and VI), and local communities conserved areas (Fig. 5g).

Spatially, PAs in southern Saharan Africa, the Amazon Basin, Europe, Central America, the central and southeastern United States, Central Asia, and Southeast Asia have lower effectiveness. Yet PAs in the Amazon Basin, North Africa, West Asia, central and

northwestern Australia, China, and the Far East have higher effectiveness. In Africa, PAs along the Gulf of Guinea, Eastern, and Southern Africa, and Madagascar do not show effectiveness compared to unprotected samples (Fig. 5a). This is mainly because these PAs have experienced the highest proportion of threats from cropland expansion, followed by forest loss and pastureland (Figs. 5c–e, 6). With the future population of Africa expected to further increase, there may be apparent trade-offs between food security and ecological conservation[41]. Moreover, sustainable use PAs and areas conserved by local communities were the predominant types of PAs with low effectiveness in these regions (Supplementary Fig. 5). At the same time, the surrounding areas of the Amazon Basin are also globally noteworthy as low-efficiency PAs. The expansion of pastureland and rapid loss of forests are the main threats to the effectiveness of PAs in this region (Fig. 6). However, Indigenous territories and strict PAs in the Amazon Basin have indeed shown excellent conservation performances, especially Indigenous territories in curbing forest loss (see Fig. 5 and Supplementary Fig. 6). The effectiveness of PAs faces the greatest challenges in Europe, which has the most widespread distribution of low-efficiency PAs globally, and also the widest range of threats (Supplementary Fig. 7). PAs in this region have experienced extensive expansion of forest loss and cropland (Fig. 6), which largely due to Europe that faces the greatest pressure of habitat loss globally (the total habitat loss rate for the matched unprotected grids is as high as 21.67%, habitat loss pressure is defined as the rate of habitat loss that would have been expected within the boundaries of a PA had it not been protected [counterfactual]). Similarly, PAs in North America have also not been as effective as expected, with poor performance in Central America and the Central and Southeastern United States. These regions are widely threatened by the expansion of cropland and forest loss (Fig. 6), especially for sustainable use PAs (Supplementary Fig. 8). It is worth noting that the proportion of PAs in North America affected by built-up land expansion is the highest in the world (15%). Furthermore, some PAs in Central Asia and Southeast Asia also exhibited low conservation effectiveness. Yet PAs in Central Asia are more affected by the expansion of pastureland, whereas those in Southeast Asia encounter more substantial challenges related to forest loss (Fig. 5 and Supplementary Figs. 9, 10). Indeed, the analysis of the spatial effectiveness of global PAs holds significant implications for achieving the 30 × 30 targets outlined in the Global Biodiversity Framework by 2030. It offers insights into the strengths and weaknesses of ongoing conservation efforts, highlights areas where conservation strategies are effective, and pinpoints areas in need of improvement.

We aggregated estimates of PA effectiveness at the ecoregion and biome scales (Fig. 7). Several ecoregions distributed in Asia and South America exhibited excellent effectiveness of PAs, such as the Mongolian-Manchurian grassland, Montane Grasslands & Shrublands, Kazakh semi-desert, Khathiar-Gir dry deciduous forests, Low Monte, and Humid Chaco (Fig. 7a). However, several ecoregions located in Southern Africa, Central Asia, and North America do not show good performance, such as the Kalahari Acacia woodlands, Madagascar succulent woodlands, Central Asian northern desert, and the Isthmian-Atlantic moist forests. Low-effectiveness ecoregions in Africa and Central Asia are mainly attributed to the expansion of pastureland, while PAs in South America, Europe, and Southeast Asia are more threatened by forest loss (Fig. 7d, e). Yet PAs in North America are more affected by the expansion of built-up land and cropland (Fig. 7b, c). At the biome scale, Temperate grasslands, savannas, and shrublands, Tundra, Montane grasslands and shrublands, and Deserts and xeric shrublands have shown excellent performance. However, tropical biomes have exhibited slightly worse performance. Moreover, Mediterranean forests, woodlands, and scrub are the only biome
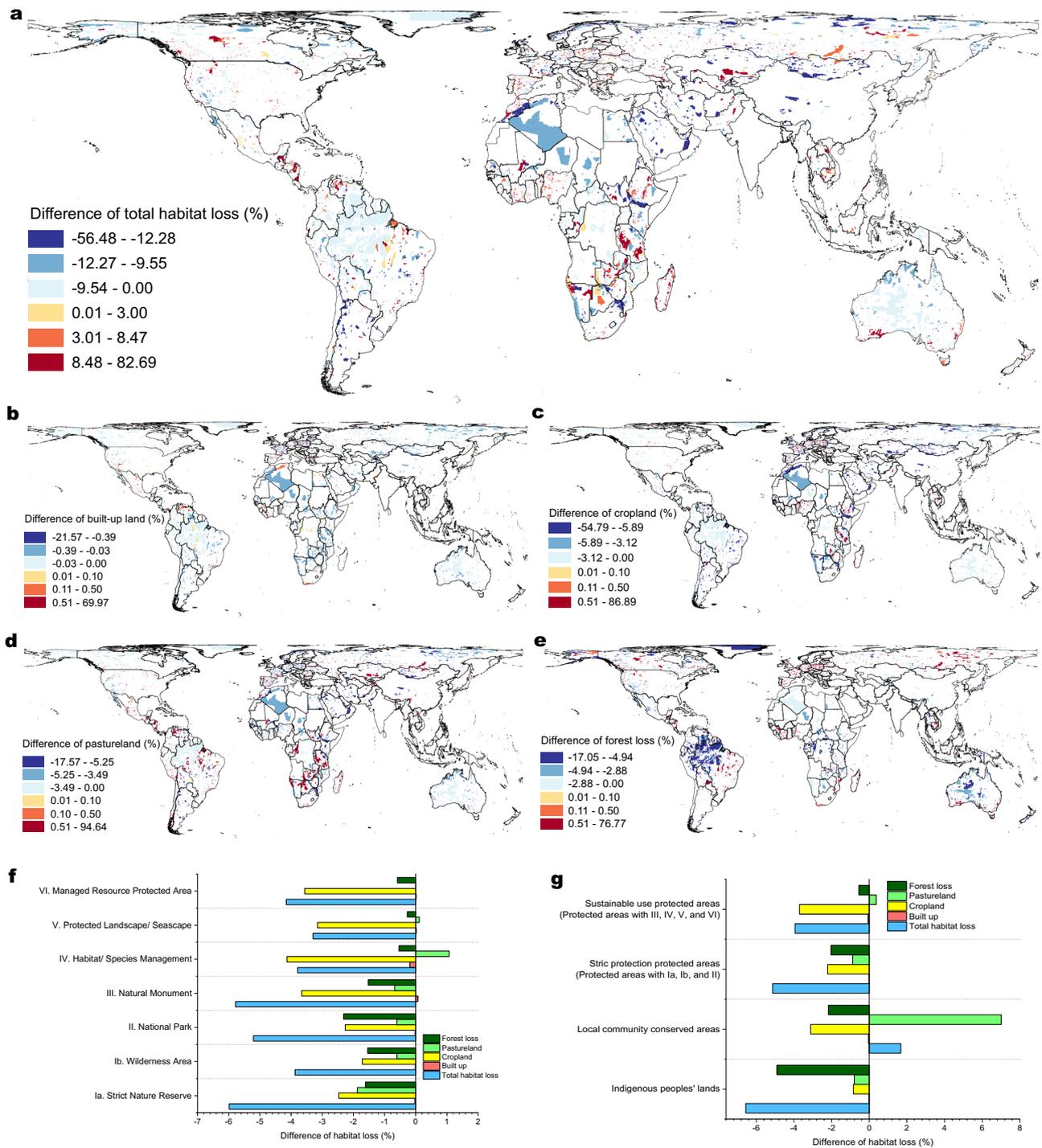
Fig. 5 | Habitat loss rate comparison with PAs and matched unprotected areas at the PA scale. a Rate difference in combined total habitat loss with PAs and matched unprotected areas. **b** Rate difference in built-up land. **c** Rate difference in cropland. **d** Rate difference in pastureland. **e** Rate difference in forest loss. **f** Rate differences in IUCN's protected areas management categories. **g** Rate differences in aggregated four types of protected areas. The global maps were created using ArcGIS Pro v3.2 software, and the country boundary data is sourced from https://www.naturalearthdata.com/. Source data are provided as a Source Data file.

globally that is ineffective in PA preventing total habitat loss (Fig. 7f). Forest loss is the primary threat affecting the effectiveness of PAs in Boreal forests or taiga, Tundra, Mangroves, Temperate conifer forests, Temperate broadleaf and mixed forests, Tropical and subtropical moist broadleaf forests, as well as Montane grasslands and shrublands. However, for Tropical and subtropical dry broadleaf forests and Tropical and subtropical coniferous forests, the primary threat is pastureland expansion. Tropical and subtropical grasslands, savannas,

and shrublands, Temperate grasslands, savannas, and shrublands, Mediterranean forests, woodlands, and scrub, and Deserts and xeric shrublands are primarily threatened by cropland expansion. Only PAs in the Flooded grasslands and savannas are primarily threatened by the expansion of built-up land. Strict PAs perform well in most biomes, while most sustainable use PAs are less effective. PAs located in indigenous territories have superb performance in most biomes except for Tropical and subtropical coniferous forests and Temperate broadleaf
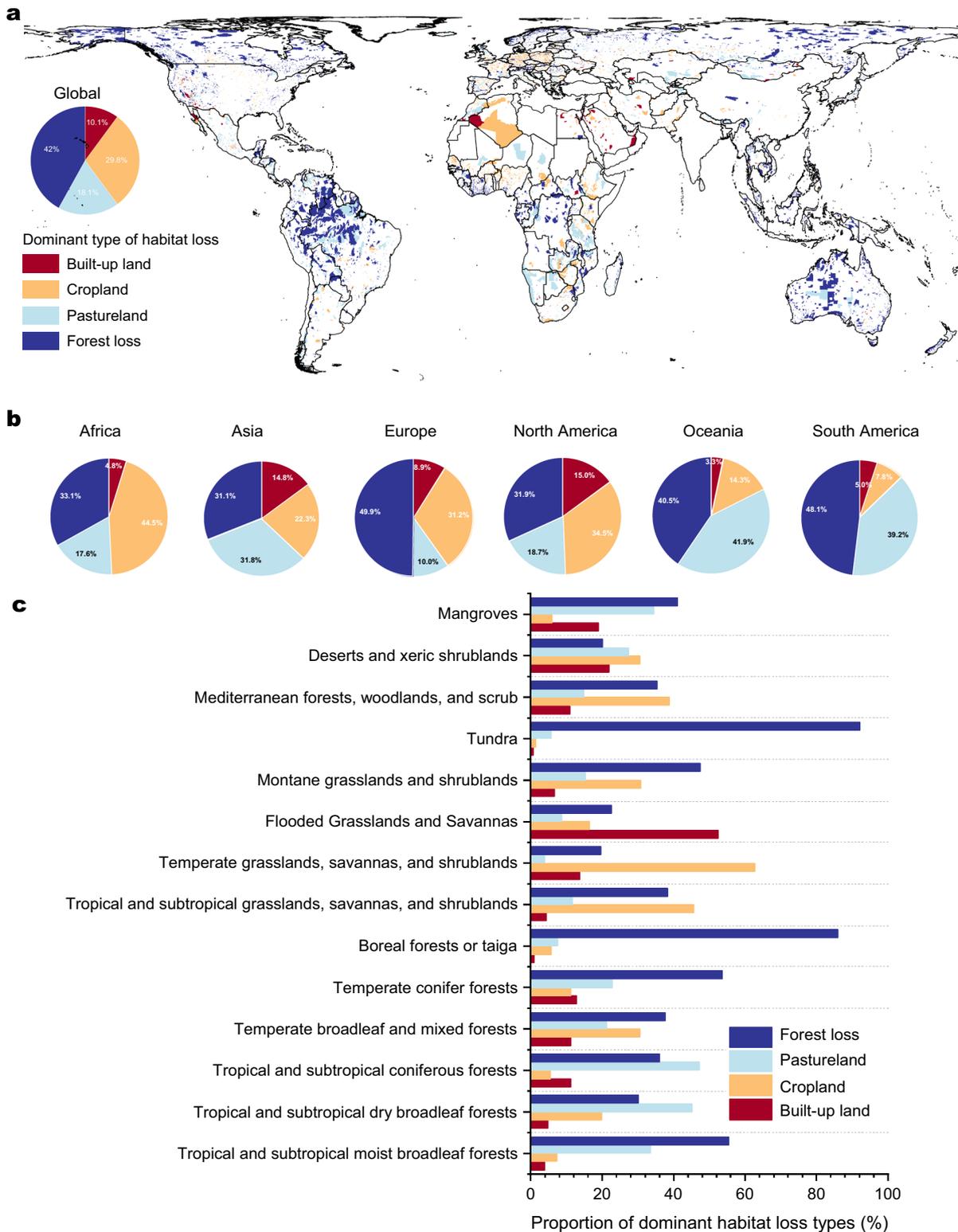
Fig. 6 | Primary types of threats to habitat loss for PAs. a Four dominant types of habitat loss or threats in PAs are characterized by the largest proportion of habitat loss types within a PA. The pie chart shows the proportion of PAs under different primary threats. **b** The proportion of PAs under different primary threats for six continents. **c** The proportion difference between the biomes. The global map was created using ArcGIS Pro v3.2 software, and the country boundary data is sourced from https://www.naturalearthdata.com/. Source data are provided as a Source Data file.

and mixed forests. However, local communities' conserved areas do not perform well, even worse than sustainable use PAs.

To further unravel the roots and influencing factors of heterogeneous PA spatial effectiveness, we constructed five machine-

learning models to quantify the impact of different influencing factors on PA effectiveness, including total habitat loss and four specific types (Supplementary Fig. 11a–e). These final five machine learning models had R^2 values ranging from 0.60 and 0.80 on our independent
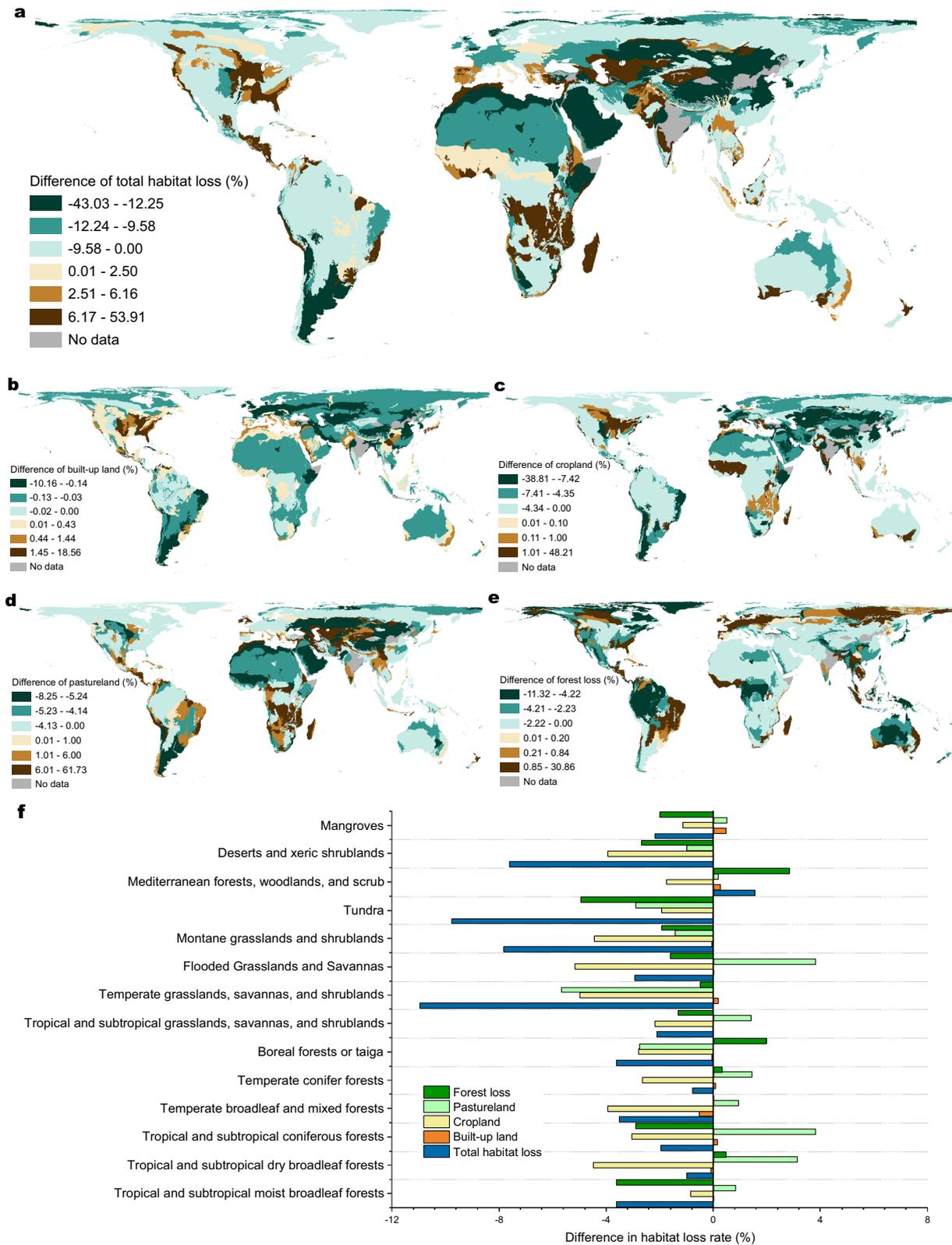
Fig. 7 | Habitat loss rate comparison with PAs and matched unprotected areas at the ecoregion scale and biome scale. a Rate difference in combined total habitat loss with PAs and matched unprotected areas. **b** Rate difference in built-up land. **c** Rate difference in cropland. **d** Rate difference in pastureland. **e** Rate difference in forest loss. **f** Rate differences in biomes. The global maps were created using ArcGIS Pro v3.2 software, and the country boundary data is sourced from https://www.naturalearthdata.com/. Source data are provided as a Source Data file.

test set, indicating moderate to high explanatory power (see Supplementary Data 9). We found path dependence is an important factor influencing the spatial effectiveness of PAs, regardless of the overall habitat loss rate or the four specific types, as the rate of current habitat loss in PA has consistently been the most important explanatory variable. This implies that to increase the effectiveness of PAs, the priority is to curb the proportion of habitat loss within the PAs themselves. Subsequently, the main influencing factor is the distance to habitat loss events within PAs (see Supplementary Fig. 12), indicating the presence of potential spatial spillover effects of habitat loss within PAs. Areas that have experienced habitat loss are more likely to trigger chain reactions in surrounding areas. Moreover, the baseline human footprint and forest cover are also important factors, indicating that the intensity of early human activities and differences in natural endowments often affect the current effectiveness of PAs. We also found that the management categories of PAs did not have the expected level of importance, ranking in the middle in terms of importance. Population count within PAs has a significant impact on the built-up land expansion within PAs, but it does not have an evident influence on other types. For forest loss, travel time to cities is an important influencing factor. This is because the accessibility to cities can indicate the distance to markets, and the convenience to markets is crucial for logging in forests.

Discussion

Our analyses have considerable implications for post-2020 global PA targets[42] and biodiversity conservation in PAs. In terms of spatial effectiveness, PAs are highly effective in curbing human pressures compared to surrounding areas and unprotected areas. The majority of PAs are not "paper parks"[15]. It is undeniable that PAs are still the backbone of global biodiversity conservation efforts[43]. However, we found that the existing PAs have undergone substantial habitat loss within their borders. Prevalent habitat loss may undermine the ecological conservation value and cornerstone status of PAs. Over 100,000 new PAs have been established since the beginning of the 21st century, but these new protected areas still exhibit low levels of effectiveness (as determined by comparing the ratio of built-up land and pastureland expansion in PAs before 2001 vs. after 2001). The presence of human activities and habitat loss in many PAs does not necessarily suggest that these PAs need to be downgraded, downsized, degazetted[44], or defunded[22]. Instead, as anthropogenic land expansion in the PAs accelerates, it is critical to reinforce—not roll back—protection efforts[44,45] by upgrading and restoring PAs to increase their resistance to all threats and disturbances. Prioritizing areas of PAs for restoration may be one of the most important proactive efforts to mitigate various types of pressures, such as the conversion of undisturbed areas to built-up land, cropland, pastureland, and deforested areas. In addition, it is necessary to design targeted restoration and resilience methods for different risks.

Our findings also have important implications for the design and establishment of new protected areas through initiatives such as '30 by 30'[46] or 'Half Earth'[47] to sustain global biodiversity conservation[48]. Protected areas should be designed to play more practical and critical roles in minimizing or halting the loss of habitats and species. Ever-expanding area-based targets must be accompanied by equally ambitious targets to ensure PA effectiveness[33]. Moreover, our results indicate that spatially, it is no longer possible to rely solely on PAs to resist rapid habitat loss because the areas surrounding PAs have suffered higher rates of habitat loss. There is an urgent need to improve the performance of existing PAs and their surrounding areas and to sustain the connectivity and integrity of the overall network of PA ecosystems by establishing safeguard buffer zones around PAs and by conserving and restoring critical connectivity areas[25]. We found wide variability in the temporal and spatial effectiveness of PAs, which implies that different regions need to implement specific improvement and

enhancement measures to address deficiencies in the effectiveness of PAs, depending on their location and attributes. In addition, given the temporal lags in PA effectiveness, our results suggest that the long-term stability and durability of PAs[49] should be guaranteed by long-term investment, management, and proactive land use plans[39].

The conflict between conservation and development is a crucial factor affecting the spatio-temporal effectiveness of global PAs in resisting habitat loss. We found that more than 200 million people (including Indigenous peoples and Afro-descendants) live in PAs, and many of these people are living in poverty (Supplementary Fig. 13). These people and their socio-economic activities are directly related to habitat loss in PAs and their surrounding areas. For such a large population group, displacing and relocating all these people and their households would be not only unfair and unethical but also impossible[13]. Households are basic units of production and consumption, and the number of households has increased faster than the population[50,51] due to factors such as divorce[52], resulting in higher demand for resources. From an equity and human rights perspective, local people need to be able to pursue their traditional livelihoods. However, land resources form the basis of their socioeconomic development, supporting settlements, food production, forestry, livestock, and other important functions. PAs urgently need to establish sustainable development and harmonious coexistence between humans and nature to reduce the trade-off between conservation and development. In practice, nature-based solutions are essential to protect and sustainably manage biodiversity and natural ecosystems by promoting lower-impact land uses and strategically reducing the risk of biodiversity loss within and near PAs[53]. It is even more critical to design a coordinated plan to reduce human demand for settlements, croplands, pasturelands, forest lands, and other resources in PAs[49] through land use displacement, compensation funds, and global assistance. We should ensure that these measures and solutions are also beneficial for Indigenous peoples and local communities and help to improve their economic and social well-being[13,22]. Paying for ecosystem services is one example of such a solution[54].

Our findings also indicate that the effectiveness of PAs in resisting habitat loss differs considerably for different types of habitat loss. Among the four types of habitat loss examined in this study, PAs are less effective in halting the expansion of cropland, pastureland, and forest loss over time than the expansion of built-up land. Each PA may have specific weaknesses. Thus, given these multiple pressures, it is also urgently necessary to enhance the comprehensive effectiveness of PAs. Moreover, the IUCN PAs category system should be updated to focus on characterizing actual human activities, human pressures, and their impacts within PAs rather than simply focusing on management needs[22]. It is important to routinely treat each PA as a coupled human and natural system, with attention to human-nature interactions within a PA, between a PA and adjacent areas (PAs and non-PAs), and between a PA and distant areas[55] under the meta-coupling framework. The application of this framework effectively highlights its value in offering a comprehensive understanding of the multi-scale interactions that shape PA conservation effectiveness. In addition, reducing human activities in PAs is closely linked to sustainable development. The world urgently needs a collaborative solution to address these challenges, which should have comprehensive benefits for biodiversity conservation, climate change mitigation, economic development, and human welfare.

Methods

Research design
We comprehensively assessed the effectiveness of PAs in resisting habitat loss across the globe by focusing on the four most common types of habitat loss—built-up land, cropland, pastureland, and forest loss. To avoid double counting, we further combined the four types of habitat loss based on a global 30-m resolution habitat loss dataset for

2003–2019. First, we calculated the total area and proportion of combined total habitat loss and their spatial and temporal patterns in PAs around the world based on the high-resolution multi-source satellite data available. Second, to evaluate the effectiveness of PAs over time, we used a causal inference method (synthetic difference-in-differences, SDID) to investigate the effects of PA designation time on retarding habitat loss. Third, to assess the spatial effectiveness of protected areas at resisting habitat loss, we used the proportion of habitat loss across different size buffers inside and outside the boundaries of PAs to compare their differences. Moreover, to reduce the non-randomness of PA establishment on the spatial effectiveness of conservation, we also used the Propensity Score Matching (PSM) model to further evaluate the spatial effectiveness of PAs in inhibiting habitat loss.

Protected areas data

Data on terrestrial protected areas were obtained from the February 2022 version of the World Database on Protected Areas (WDPA)[56]. We excluded point data and used only polygon data in our analysis to reduce errors. Following the recommended practice guide of the WDPA (https://www.protectedplanet.net/en/resources/calculating-protected-area-coverage), we eliminated the PAs that were smaller than $900\,m^2$. To reduce the overestimation of PA coverage, we resolved overlapping PAs into a single polygon and assigned the strictest International Union for the Conservation of Nature (IUCN) category. Thus, we obtained, to our knowledge, the most comprehensive coverage of PAs (162,146 PAs) ever compiled (accounting for 67% of all global PAs), including many small-size PAs that are often overlooked. Our final dataset included more than 82% of the total area of terrestrial PAs. We also acquired the spatial extent of Indigenous people's and local communities' lands globally from the Landmark (https://www.landmarkmap.org/) while identifying the PAs covered by these areas (see Supplementary Fig. 14).

Land use data

We used four datasets to characterize habitat loss (including four types: conversion to built-up land, cropland and pastureland, and forest loss) in PAs. These datasets have high spatial resolution and spatial consistency, which facilitate long-term and fine-scale evaluation. However, overlaying these datasets can lead to double counting of habitat loss in PAs, particularly since forest loss may lead to conversion into any of the other three types of habitat loss. To address this issue, we combined the four types of habitat loss to produce a global 30-m resolution habitat loss dataset for 2003–2019. We used the 2003–2019 time period mainly because the cropland dataset covered only that period, which was further divided into five shorter time periods that were not interannual (2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019). We used the ArcGIS spatial overlay method to address potential double-counting among these four datasets. We first decomposed forest loss into different types for each pixel that overlapped with the other three types of habitat loss. Then, if there was an overlapping pixel, we determined the final type of this pixel in order of priority, i.e., built-up land, cropland, pastureland, and forest loss. This approach effectively prevents the double counting of forest loss and land cover conversions. Finally, we produced a global 30-m resolution habitat loss dataset for five time periods within the 2003–2019 timeframe (see Supplementary Figs. 1, 2). We found that the combined total habitat loss was lower (6% in 2019) than the simple summation of four separate types of habitat loss. This implies that calculating the area of different habitat loss types separately in PAs would result in the double counting of about 6% of the habitat loss area in 2019 compared to the total habitat loss after combining the four types.

We used the recently updated 30-m global impervious surface area data (GISA v2.0)[57] to estimate global built-up area distribution inside and outside the borders of PAs. Impervious surface areas (ISAs) are mainly artificial structures, including urban and rural buildings, roads, parking lots, and other affiliated anthropogenic structures. Impervious surface area is an indicator of the intensity of human activities and socioeconomic development. Built-up areas do not support high levels of ecosystem services or provide sustainable habitats for many species of conservation concern. Urban area expansion has a profound and intensive impact on habitat and species loss[18,58]. The updated GISA v2.0 (https://zenodo.org/records/6476661) achieves an overall accuracy of 97.89% and captures long-term dynamics covering the period between 1972 and 2019. It also has high temporal consistency and high spatial and temporal resolution, which helps facilitate the detection of subtle changes in built-up areas within PAs, especially for many small PAs.

To examine habitat loss due to cropland expansion in PAs, we used a global high-resolution cropland dataset[37]. The cropland data was obtained from https://glad.umd.edu/dataset/croplands. At a spatial resolution of 30 m, this dataset provides a time series that consistently characterizes the extent of cropland across the globe. Cropland, as it applies to this dataset, is defined as land used solely for annual or perennial herbaceous crops. Any land used for woody crops, permanent pasture, or shifting cultivation was not considered to be cropland. The cropland mapping was completed by analyzing Landsat satellite data from 2000 to 2019, which was continuously processed. Machine learning classification was utilized to map the global extent of cropland, and the classification models were locally calibrated using training data collected from high spatial resolution remotely sensed data that was freely available and collected through visual interpretation. To improve the accuracy of cropland detection, the mapping was carried out using 4-year intervals (2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019), rather than annual intervals. During each 4-year period, an area was considered to be cropland if a growing crop was observed at any point in the period. Sample validation showed that this dataset has high accuracy, with an overall accuracy of 97.5% for global mapping. High accuracy and consistency are beneficial for detecting cropland changes in PAs around the world.

We created a pastureland dataset using data from the European Space Agency Climate Change Initiative (ESA CCI) for land cover and land use from 1992 and 2020. The original ESA CCI class (class 130) was used to identify and classify pastureland. However, the ESA CCI map does not differentiate between pastureland and natural grassland. To address this, we followed the approach recommended by Strassburg et al.[59] by incorporating data from the Terrestrial Ecoregions of the World[60] and Gridded Livestock of the World v2.0[61] datasets to determine whether each pixel represented natural grassland or pastureland. If a pixel was classified as grassland in the ESA CCI map but was located within an ecoregion of non-grassland ecosystems and had a cattle density of 1 head per km^2 or greater, it was reclassified as pastureland. To reduce inconsistency with other datasets, we resampled the reclassified pastureland data to 30-m spatial resolution. The overall accuracy of this dataset is 75%.

Forest loss data was obtained from the Hansen Global Forest Change v1.8 (2000-2020) dataset (https://storage.googleapis.com/earthenginepartners-hansen/GFC-2020-v1.8/download.html)[62]. According to this dataset, vegetation that exceeds a height of 5 m is classified as tree cover. Forest loss refers to a disturbance that results in the complete replacement of a forest or a transition from a forested area to a non-forested one, within the timeframe of 2000 to 2020[62]. Annual forest loss is a disaggregation of the total amount of forest loss into yearly increments.

Synthetic difference-in-differences model

We used a causal effect method, the synthetic difference-in-differences (SDID) model, to estimate the temporal effectiveness of PAs. This model was used to estimate the "average treatment effect on the

treated" (ATT) in panel data, as proposed in Arkhangelsky et al.[34], which complemented the widely used difference-in-differences (DID) and synthetic control (SC) methods. In nature, SDID is based on a panel (group by time) set-up, in which certain units are treated and the remaining units are untreated. The SDID approach estimates the effect of the treatment by comparing the difference in pre- and post-treatment outcomes between the treated units and synthetic control units. The synthetic control units are selected based on a weighted function of untreated units (with weights specific to each unit) and pre-treatment time period (with time-specific weights). Compared with the DID and SC models, the SDID model has higher robustness and avoids overestimation and underestimation of ATT. Moreover, due to the advantage of the SC model, this model does not need to satisfy the parallel trend test. Detailed SDID configurations and procedures are described in Arkhangelsky et al.[34].

SDID estimation requires several variables. For dependent variables, we used annual proportion and area for four separate types of habitat loss (conversion to built-up land, cropland and pastureland, and forest loss) and combined total habitat loss in PAs. Then we selected a treatment group variable (in this analysis, groups are PAs), a time variable (different for each of the four habitat loss types and combined total habitat loss: 1972–2019 for built-up land, 2003–2019 for cropland, 1992–2020 for pastureland, 2001–2020 for forest loss, and 2003–2019 for combined total habitat loss), and a binary indicator of treatment (set at 0 before the PA was designated and 1 after the PA was designated). The panel based on groups and time must be strongly balanced, as optimal weights are calculated based on full coverage in the pre-treatment periods. Inference in SDID is based on bootstrap, jackknife, or placebo procedures. In this analysis, 50 iterations of bootstrapping were used. We implemented our analysis in Stata 17, employing the SDID package[63]. As SDID is based on a balanced panel of observations, we first make sure there are no missing values. If there is a missing value, we will delete this observation. In this analysis SDID handles a staggered adoption configuration, given that in the period under study, PA designation occurred in different yearly periods. We implement the SDID estimator using the bootstrap procedure to calculate standard errors (default 50 iterations).

To ensure the reliability of the model we chose, we followed the recommendation of Arkhangelsky et al.[34] and compared the performance of the SDID and DID models. For the DID estimator, we estimated the average effect of PA designation time on built-up land (we used the annual proportion and area of built-up land in PAs as an example, see Supplementary Data 10) based on a csdid model[64] (Difference-in-Differences with multiple time periods). The results show that the DID model does not pass the parallel trend test (using the command of the pre-trend test in csdid). This means that if the DID model is used to analyze data here, it will be biased.

To validate the robustness of our findings, we conducted a placebo test. We randomly manipulated the establishment time of the PA to create another treatment group time. Through the placebo test, we found that our results are robust, as the ATT of both models (we also used the annual proportion and area of built-up land in PAs as example) are not statistically significant, which is significantly different from our analysis results, indicating that our results are not random (see Supplementary Data 11).

To examine heterogeneity, we estimated the individual effectiveness of PAs in different groups, including IUCN category (strict I-II vs. non-strict III-VI), PA size (bottom 25% size vs. top 25%), continents (six continents with PAs), and countries (countries with more than 100 PAs).

To investigate potential temporal lags, we further examined the performance of PAs with a lag of several years after their establishment. In practice, we assumed that the performance of a PA lags by 1–6 years after its designation. Based on this assumption, we created

binary indicators of treatment to estimate the effectiveness of each PA in restricting habitat loss.

Assessing effectiveness within and beyond protected area boundaries
In order to investigate the relationship between distances to PA boundaries and changes in habitat loss over several decades, we employed a systematic approach. We created buffers at 1 km intervals inside and outside the PA boundaries, extending up to 5 km inward and outward. Within each buffer interval, we calculated the proportion change in habitat loss, including five types—total habitat loss (2003–2019), conversion to built-up land (1972–2019), cropland (2003–2019), pastureland (1992–2020), and forest loss (2001–2020). Our analysis aimed to determine the spatial effectiveness of PAs in mitigating habitat loss and to assess whether changes in effectiveness were influenced by the proximity to PA boundaries.

Counterfactual matching model
The counterfactual matching method is primarily used to address causal inference problems by matching the covariates of the treatment and control groups to reduce confounding and obtain reliable estimates of treatment effects. Here, we employed a site-level matching approach to mitigate non-random effects arising from the location bias of PAs and further estimate a more accurate spatial effectiveness of PAs. We identified the control pixel (1 km² grid) outside the PAs matching each treatment pixel (1 km² grid) within the PAs, using the most commonly used non-experimental matching method, propensity score matching (PSM) using the Stata 'teffects psmatch' command[65]. The matching was based on five covariates potentially related to habitat loss within the PAs: elevation, slope, initial human footprint (1993), travel time to cities, and tree cover in 2000. We used one-to-four nearest neighbor matching with calipers of width equal to 0.05 of the standard deviation of the logit of the propensity score to implement PSM, as this approach produces good matching results (Supplementary Fig. 15a–c), reduces confounding between treatment and control groups, and allows for a relatively large sample size. We randomly selected 1,049,468 sample points representing ~5% of the area of PA as a treatment group and obtained a 1 km² grid for each sample point (Supplementary Fig. 16a–d). To avoid potential spatial autocorrelation, we set a minimum distance of 3 km between each sample point. Similarly, we randomly selected corresponding double sample points (2,098,936) outside the PA as the control group. Then, we resampled the five covariate data to a 1 km² resolution and extracted the corresponding data for each sample point. The performance of each sample site was simply averaged to characterize the performance of the PAs, ecoregions, and biomes.

Identify dominant threats in protected areas
We use the Tabulate Area tool in ArcGIS Pro v3.2 to identify the dominant threats or habitat loss types in PAs. We defined the largest proportion of habitat loss types within each PA in 2019 as the dominant threat. At the same time, we report on the second threat to PAs in the Supplementary information (Supplementary Fig. 17). Using this simple method, we also aggregated these threats to characterize broader heterogeneity at the continent and biome levels.

Determinants of success or failure in protected areas
To analyze the factors influencing the effectiveness of PAs, we utilized the integrated metacoupling framework (e.g., considering influencing factors both within and outside PAs) and two methods to evaluate temporal effectiveness and spatial effectiveness. First, we evaluated changes in total habitat loss within PAs as a measure of integrated habitat alteration. Subsequently, we investigated the variability in the effectiveness of existing PAs using the SDID method, focusing on five

criteria: the PA's establishment time, governance type (Indigenous and community vs. government), biodiversity importance, distance to cities, and human footprint. The establishment time of PAs, sourced from the WDPA database[54], was categorized into two periods: before and after 2010. In terms of governance, we differentiated between indigenous peoples and local community-managed PAs and those managed by governments. Species richness within PAs was calculated using the Area of Habitat method at a 1 km resolution, taking into account habitats' land cover and elevation. This calculation included 8676 amphibians, 11,406 birds, 12,188 mammals, and 12,494 reptile species, with spatial range maps derived from the IUCN Red List and BirdLife Data Zone. Human footprint data for the year 1993, a metric for human activity intensity, was sourced from https://datadryad.org/stash/dataset/doi:10.5061/dryad.052q5. Additionally, a global map of travel time to cities was obtained from https://doi.org/10.6084/m9.figshare.7638134.v3. To further explore the heterogeneity of PAs, we segmented our sample PAs into quintiles. This categorization was based on species richness, human footprint, and their distance to cities, allowing a more nuanced understanding of their varied characteristics. We also separately applied an ordinary least squares (OLS) model to validate the relationship between the effectiveness of PAs and factors such as species richness, human footprint, and their distance to cities (see Supplementary Data 7).

Second, we also used machine learning models to examine the importance of selected variables affecting PA effectiveness. We trained five machine learning models to quantify the impact of different influencing factors on PA effectiveness, including total habitat loss and four specific types (built-up land, cropland, pastureland, and forest loss). The proportion difference of total habitat loss and four types of habitat loss in sampling grids between treated groups and matched control groups (the results of counterfactual matching analysis) were used as the dependent variables. The sampling grid is the unit of our analysis. We selected explanatory variables most relevant to the effectiveness of PAs, including current habitat loss proportion (in 2019), distance to habitat loss events, human footprint in 1993, tree cover in 2000, ecoregion, elevation, slope, PA IUCN categories, travel time to cities, PA establishment time, population count, and land use suitability (for the total habitat loss model, we considered four specific types of land use suitability). Four land use suitability maps were calculated using the Future Land Use Simulation Model (FLUS)[66]. We then divided the total sample data into a training set and a test set using a 75/25 random split for each type of habitat loss. To enhance the accuracy of the model, we trained five machine learning approaches, including the Generalized Linear Model (GLM), Distributed Random Forest (DRF), Gradient Boosting Machine (GBM), Deep Learning (Neural Networks), and Xtreme Gradient Boosting (XGBoost). Through model training, the GBM model demonstrates superior performance compared to the other four algorithms. All models were run in the R interface linked to the H2O Flow machine learning environment (http://www.h2o.ai, version 3.46.0.1), with the default AutoML, model, parameter, and grid search settings.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability
The datasets for conducting the analysis presented here are all publicly available, including: the updated 30-m global impervious surface area data (GISA v2.0) (https://zenodo.org/records/6476661); the high-resolution cropland dataset (https://glad.umd.edu/dataset/croplands); the ESA CCI land cover data (https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-land-cover?tab=form); and

the Hansen Global Forest Change v1.8 (2000-2020) dataset (https://storage.googleapis.com/earthenginepartners-hansen/GFC-2020-v1.8/download.html). The elevation data are available at https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/. Slope data were calculated on the basis of elevation data using ArcGIS pro v3.2 software. The initial human footprint (1993) data are available at https://datadryad.org/stash/dataset/doi:10.5061/dryad.052q5. The country boundaries data are available at https://www.naturalearthdata.com/downloads/10m-cultural-vectors/. The ecoregion boundaries data are available at https://ecoregions.appspot.com/. The population data are available at https://ghsl.jrc.ec.europa.eu/ghs_pop2023.php. Source data are provided with this paper.

Code availability
The code used for this analysis can be found at: https://osf.io/pbjvf/ (https://doi.org/10.17605/OSF.IO/PBJVF).

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Author contributions
G.D.L. conceived the idea; G.D.L. designed the study; G.D.L. collected data; G.D.L., C.L.F., J.G.L., J.E.M.W., S.S., Q.W., and Z.B.W. analyzed and interpreted data; and all authors wrote and edited the manuscript.

Competing interests
The authors declare no competing interests.

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