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Post-2020 biodiversity framework challenged by cropland expansion in protected areas

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Protected areas (PAs) are essential for biodiversity conservation but are threatened by cropland expansion. Recent studies have only reported global cropland expansion in large PAs between 1990 and 2005. However, the amount of cropland expansion in global PAs (including relatively small PAs) since the 2000s is unclear. Using 30-m cropland maps, we find that the cropland expansion in PAs accelerated dramatically from 2000 to 2019, compared with that of global croplands. The areal expansion was mainly in large PAs, less-strict PAs and Afrotropical PAs, which also matches the higher species extinction risks. Such PAs appear to be less effective due to greater threats, such as higher background cropland expansion rate. Notably, some PAs with the highest conservation levels failed to prevent cropland expansion. This new picture of cropland dynamics in PAs illustrates that cropland expansion is an ongoing intractable global conservation challenge that will impinge on the aspirations of the post-2020 global biodiversity framework.

Protected areas (PAs) conserve biological diversity through legal or other effective means[1], and are recognized as a cornerstone for habitat and species conservation[2]. PAs currently encompass 15.72% of the global land surface[3] and are expected to cover 30% by 2030[4]. However, human activities within PAs (for example, land use and land cover change) can undermine the role of PAs in mitigating species extinction[5–7]. Global croplands have expanded dramatically over the past two decades[8], primarily driven by increased demand for food from a growing population[9]. Recent studies predicted that approximately 500 million ha of additional croplands will be required in 2050 to address global food demand[10], which will increase pressure on natural habitats[11]. Cropland expansion can disrupt landscape connectivity[12], cause terrestrial biodiversity loss[13] and reduce the effectiveness of PAs[6,14].

Recent studies found that croplands represent 18% of all human impacts (including human population pressure, land use and infrastructure, and human access[5]) in PAs[14]. Globally, cropland encroached on 6% of the area covered by PAs in 2013[14], and expanded more in global PAs than in unprotected areas from 1990 to 2005[6]. These findings suggested that some PAs have been unable to prevent cropland expansion in the early twenty-first century and have weakened habitat protection and threatened species[14]. A recent study from Potapov et al. showed that global cropland expansion doubled from 2000 to 2019[8], but the

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dynamics, effectiveness and drivers of cropland expansion in PAs during the past 20 years in different regions are still unclear.

Global cropland maps from satellite images have been used to characterize and better understand the dynamics of cropland expansion in global PAs[6,14]. Many previous analyses of cropland encroachment into PAs used the global cropland maps at coarse spatial resolutions (for example, 5 arcmin in ref. [6] and 1 km in ref. [14]), which have inherent and large uncertainties in cropland area estimates due to mixed pixel issues. These coarse spatial resolution global cropland maps cannot adequately capture cropland dynamics (loss or gain) within small PAs (for example, <1 km^2 or 100 ha), which is problematic as many of them provide unique contributions to species conservation[15]. In recent years, various efforts have been made to generate global cropland maps from satellite images at high spatial resolutions (for example, 30-m spatial resolution)[8,16,17]. Potapov et al.[8] released a global cropland dataset from 2000 to 2019 at 30-m spatial resolution in 4-year intervals with an overall classification accuracy of more than 97%. Two other datasets, Annual Global Land Cover (AGLC, 2000–2015)[16] and GlobeLand30 (2000/2010/2020)[17], also provide cropland maps at 30-m spatial resolution.

Here, we mainly used the cropland data layers from Potapov et al.[8] (2000–2019; reasons why we selected this dataset are provided in Supplementary Notes 1 and 2) to characterize cropland dynamics over time at the global scale in PAs grouped by PA sizes, biogeographic realms (Supplementary Fig. 1; Afrotropic, Australasia, Indomalaya, Nearctic, Neotropic and Palaearctic) and the International Union for Conservation of Nature (IUCN) management categories (I–VI). Other cropland datasets from AGLC[16] (2000–2015) and GlobeLand30[17] (2000–2020) were used for sensitivity analyses. Further, we assessed the effectiveness of PAs using the counterfactual matching method, that is, comparing cropland changes inside PAs with outside PAs, to explore what would have happened if PAs had not been established[6,18]. Then, we assessed the potential effects of cropland expansion on biodiversity by overlapping cropland dynamics and species extinction risks in PAs. Finally, we modelled PA cropland expansion rates using a set of predictors through a spatially and non-spatially varying coefficient (SNVC) modelling method[18,19]. The predictors included PA sizes, IUCN categories, biogeographic realms, background cropland expansion rates, government effectiveness, corruption, share of gross domestic product (GDP) from agriculture, levels of human development and population density. Specifically, the background cropland expansion rate represents the cropland expansion rate in the control area in the counterfactual matching method. Government effectiveness reflects perceptions of the quality of public services and credibility of the government's commitment to policies. Detailed sources and meanings of these variables are provided in Supplementary Table 1.

Results

Accelerated cropland expansion in PAs of all categories

Potapov et al.'s cropland data showed that one-third of PAs established in or before 2000 experienced a pervasive expansion of croplands within their boundaries during 2000–2019 (Fig. 1). This expansion was a net absolute area increase of almost 40,000 km^2 (Fig. 2a) and the expansion rate increased 58-fold from 74 $km^2\,yr^{-1}$ (2003–2007) to 4,265 $km^2\,yr^{-1}$ (2015–2019; Fig. 2d). Using a counterfactual approach, we found that global PAs reduced cropland expansion within their boundaries compared with outside PAs (Supplementary Fig. 2).

The effectiveness of PAs differed with levels of protection (Kruskal–Wallis test χ^2 = 2,095.7, d.f. = 7, P < 0.01; Fig. 3). Most PA cropland expansion was clustered in less-strict PAs that allow for some human activities (IUCN categories III, IV, V and VI)[5], especially in IUCN V (absolute area has increased by 4,856 km^2) and in PAs with no IUCN classification (35,217 km^2; Fig. 2b,e). Notably, although PAs under strict management regulations (IUCN categories I and II) showed less pressure from cropland expansion in 2019 (Supplementary Fig. 3), the relative increase compared with the 2000 initial cropland areas was higher in IUCN category Ib (Fig. 2h), which are the world's last wilderness areas where human activities should be absent or minimal[20]. The drastic change in PAs in the IUCN category Ib may arise from the low cropland baseline in this category. Similarly, counterfactual analyses-based results also showed that PAs underwent higher cropland increases during 2000–2019 than matched counterfactuals in the IUCN Ib (Dunn's test, P < 0.05; Fig. 3b) and unclassified categories (Dunn's test, P < 0.05; Fig. 3b). In other IUCN categories, PAs were relatively effective at stemming pressure from cropland expansion over the past 20 years (Fig. 3b).

Large and Afrotropic PAs more affected by cropland expansion

We also found the effectiveness of PAs differed with their size (Kruskal–Wallis test χ^2 = 1,139.1, d.f. = 8, P < 0.01; Fig. 3). Our results in small PAs (<1 km^2), which comprise 58% of global PAs (Fig. 2o), underscore the importance of using fine-scale datasets (for example, 30 m) to monitor cropland dynamics in PAs (Fig. 1). Despite covering a smaller area, small PAs play a key role in biodiversity protection, as they provide habitat and improve landscape connectivity or quality to support large PAs[5,6]. We found that 98% of the absolute cropland expansion area occurred in relatively large PAs (>100 km^2; Fig. 2c). PAs with an area smaller than 20 km^2 (which accounted for 86% of all PAs but only 1.3% of the global PA area) had less cropland expansion within their boundaries (Fig. 2c,f,i,l,o), especially during 2000–2011 (Supplementary Fig. 4). The magnitude of changes in the cropland area in these smaller PAs was small, and even decreased somewhat, while large PAs had a substantial absolute increase in cropland area (0.9% versus 98%; Fig. 2c). The counterfactual analyses also showed that PAs of small sizes were more effective than relatively large PAs (Dunn's test, P < 0.05; Fig. 3c). This difference suggested that smaller PAs may better prevent cropland expansion and help maintain regional and exotic species diversity[15].

The performance of PAs also differed among the realm (Kruskal–Wallis test χ^2 = 4,142.5, d.f. = 5, P < 0.01; Fig. 3). PAs in the Afrotropics were the most impacted (79% of cropland expansion was within these areas), with a 31,430 km^2 absolute increase in cropland area (Fig. 2a) and a nearly 5-fold relative increase in the annual expansion rate (Fig. 2d). The cropland expansion in the Afrotropics PAs accounted for 98% relative increase compared with the 2000 cropland area in those PAs (Fig. 2g), and a 1.03% relative increase compared with its PA size (Fig. 2j). Considering the performance of PAs, we also found that croplands in the Afrotropics PAs increased more than matched counterfactuals (Dunn's test, P < 0.05; Fig. 3a). The second largest expansion of cropland into PAs was in the Neotropics, with an absolute cropland expansion area of 6,880 km^2, or a 66% relative increase compared with the 2000 cropland area in those PAs, and a 0.21% relative increase compared with its PA size. Respectively, these same increases were 3,914 km^2, or 31%, and 1.06% in Indomalaya and 303 km^2, or 0.3%, and 0.008% for the Palaearctic. The Nearctic region had a reduction in cropland area of 2,618 km^2, or 21% within its PAs, which was a 0.10% reduction relative to the PA size (Fig. 2a,g,j). All the Neotropics, Indomalaya, Palaearctic and Nearctic PAs showed lower cropland expansions inside PAs than the matched counterfactuals.

We also used the 30-m AGLC (2000–2015)[16] and GlobeLand30 (2000–2020)[17] datasets for sensitivity analyses (Supplementary Figs. 5 and 6). Both datasets agree with the total increase in croplands in PAs, but with a considerable difference (Supplementary Note 3): 7,559 km^2 according to AGLC from 2000 to 2015; 53,383 km^2 according to GlobeLand30 from 2000 to 2020; and 40,000 km^2 according to Potapov et al. from 2000 to 2019 (Supplementary Fig. 7c). These datasets also concur in that cropland expansion rates in PAs have increased during the study period but showed differences in magnitudes of cropland dynamics in PAs (Supplementary Fig. 7d). Specifically, the increase in cropland change rates was 1.5-fold (GlobeLand30 based on cropland expansion rates from 2000 to 2010 and 2010 to 2020) and 2-fold (AGLC based on cropland expansion rates from 2003 to 2007 and 2011 to

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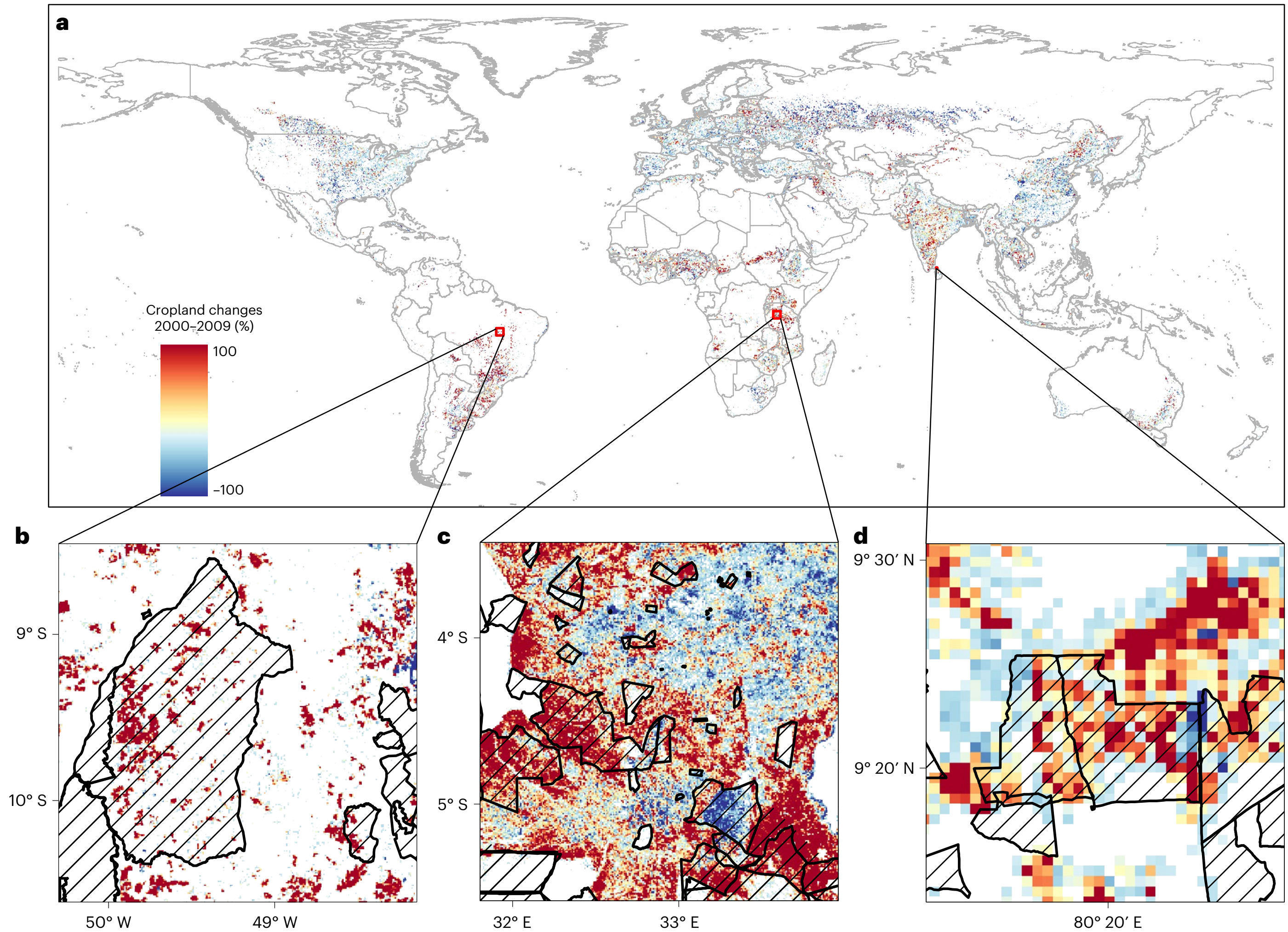

Fig. 1 | Percentage of cropland area change in PAs from 2000 to 2019. a, Global distribution of the proportion of cropland changes within 0.00825° × 0.00825° grid cells based on Potapov et al.'s 30-m cropland dataset[8]. **b**–**d**, Zoom-in of cropland changes (marked in red in **a**) in PAs (shown with slash lines) for three examples by different PA sizes (**b**, large PA, 15,800 km^2), biogeographic realms (**c**, part of Afrotropic) and IUCN categories (**d**, IUCN category Ib).

2015), which was much smaller than that of Potapov et al.'s estimates using cropland expansion rates from 2003 to 2007 and 2015 to 2019. GlobeLand30 confirmed the highest share of cropland was in the Afrotropics. Despite the different estimates in magnitudes due to different cropland definitions adopted, data inputs and classification methods (more details are provided in Supplementary Note 1), all three datasets agree well with the accelerated cropland expansion in PAs.

Species extinction risks and cropland expansion in PAs

Human activities can cause a large number of species to be threatened with extinction[14,21]. Here, we used the spatial overlap between croplands in PAs (Potapov et al.'s, 2000–2019) and species extinction risks to explore whether areas with faster rates of cropland expansion also experience higher rates of species extinction. We focused on four vertebrates (birds, mammals, amphibians and reptiles) that were imperilled by agricultural activities. The species extinction risks were represented by two metrics: the species mean extinction risk value in a PA (aMER) and the percentage of threatened species (aPTS)[21]. We investigated the spatial covariation distributions of species extinction risks and cropland changes in PAs (Potapov et al.'s, 2000–2019) grouped by biogeographic realms, IUCN management categories and different PA sizes (Methods and Fig. 4). The bivariate results highlight the regions where the expansion of cropland areas within PAs were likely to have the greatest potential impacts on biodiversity[14].

We found that the proportion of the consistently high values (≥66% of the distribution; class 9 in Fig. 4) for both cropland expansion in PAs and aMER (or aPTS) were highest in the Afrotropics, IUCN category II and large PAs. Specifically, the proportions of 'Acrop and aMER', 'Acrop and aPTS', 'Rcrop and aMER' and 'Rcrop and aPTS' for class 9 in the Afrotropics were 74%, 74%, 55% and 55%, respectively. These same proportions were 50%, 50%, 34% and 33% in IUCN category II and 90%, 85%, 57% and 54% in the relatively large PAs (for example, >10,000 km^2), respectively. In addition, class 9 was also the highest relative to the proportion of these 9 classes in PAs in Indomalaya (70%, 69%, 40%, 39%) and the IUCN Ia (19%, 18%, 24%, 21%) and Ib (20%, 20%, 25%, 22%) categories. However, the proportions of classes 2 and 3 were lower, which indicated that cropland expansion in PAs had a negligible impact on biodiversity extinction risk. The reduction of cropland encroachment in PAs was consistent with lower values of aMER or aPTS (Supplementary Fig. 8).

Predictors of cropland expansion in PAs

The SNVC model can account for geographical regional scale variability and allow testing whether the effects of predictors vary spatially or can be treated as constant[18,19]. Based on the SNVC model, we found background (control area) cropland expansion rates (estimate = 0.60, s.e.m. = 0.10, $P < 0.05$; Fig. 5) and shares of GDP on agriculture (estimate = 0.0002, s.e.m. = 8.9×10^{-5}, $P < 0.05$) were both positively associated with the cropland expansion rates in PAs. The effects of background

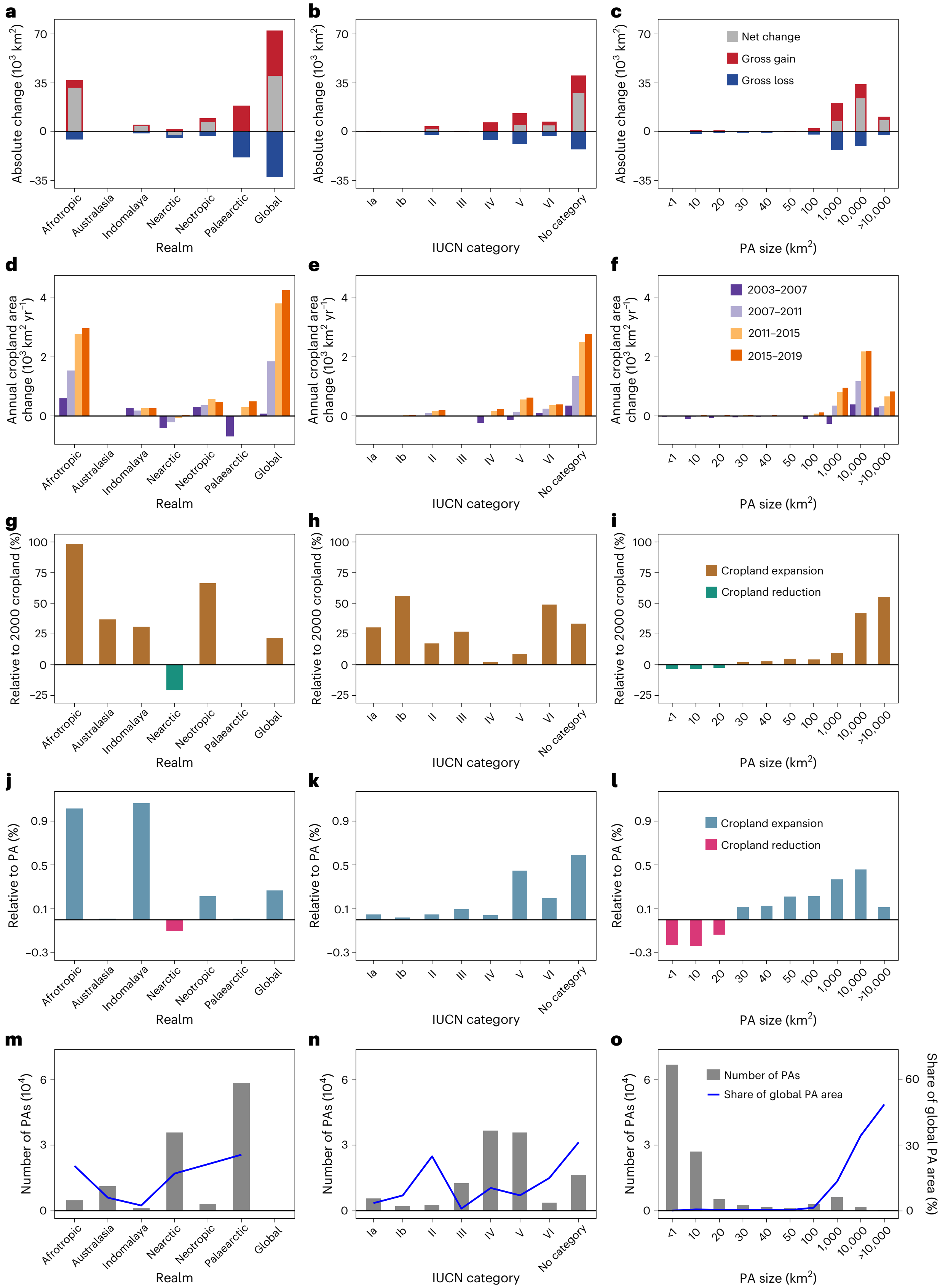

Fig. 2 | Cropland changes in PAs from 2000 to 2019. a–o, Absolute cropland area changes (**a**–**c**), annual cropland area change rates (**d**–**f**), fraction of cropland changes relative to the 2000 initial cropland areas in PAs (**g**–**i**), fraction of cropland changes relative to PA size (**j**–**l**), and number of PAs and their share of the global PA area (**m**–**o**) based on biogeographic realm (**a**,**d**,**g**,**j**,**m**), IUCN category (**b**,**e**,**h**,**k**,**n**) and PA size (**c**,**f**,**i**,**l**,**o**). Typically, in the second row, the initial cropland expansion rate (2003–2007) in PAs was calculated by subtracting the 2003 value from the 2007 value and dividing by four. Similarly, the last cropland expansion rate (2015–2019) in PAs was calculated by subtracting the 2015 value from the 2019 value and dividing by four.

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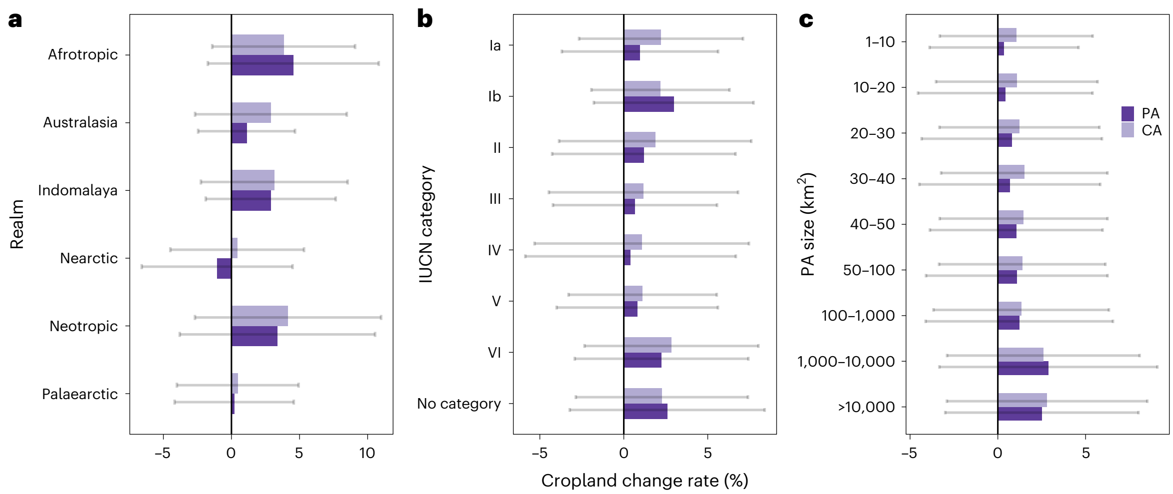

Fig. 3 | Mean values in cropland change rate between 2000 and 2019 by biogeographic realms, IUCN management categories and PA sizes, for PAs and associated matched counterfactuals. a–c, Mean values in cropland change rate between 2000 and 2019 by biogeographic realm (**a**), IUCN management category (**b**) and PA size (**c**), for PAs and associated matched counterfactuals (CA). Positive values indicate that cropland has increased during 2000–2019. Error bars are the standard deviation of the differences of each 1 km × 1 km observation from the mean. N = 147,191 (Afrotropic), 2,766 (Australasia), 39,991 (Indomalaya), 30,881 (Nearctic), 21,416 (Neotropic) and 250,646 (Palaearctic) in **a**; N = 3,544 (Ia), 1,558 (Ib), 25,620 (II), 3,021 (III), 59,193 (IV), 118,360 (V), 31,466 (VI) and 250,851 (No category) in **b**; N = 21,562 (~1–10 km^2), 13,131 (~10–20 km^2), 10,084 (~20–30 km^2), 8,093 (~30–40 km^2), 7,016 (~40–50 km^2), 30,662 (~50–100 km^2), 200,297 (~100–1,000 km^2), 155,727 (~1,000–10,000 km^2) and 47,041 (>10,000 km^2) in **c**.

cropland expansion rate varied spatially. Specifically, the expansion rate appeared to be stronger in Europe and central North America, and weaker in the tropical regions. However, the effect of agricultural share of GDP was found to be spatially constant. The category of PAs also showed weak relevance with the cropland expansion rates in PAs, especially IUCN category II (estimate = −0.003, s.e.m. = 0.001, $P < 0.05$), which showed negative effects and was also found to be spatially constant. All other predictors were found to be relatively weak and there was no spatial variability (Supplementary Table 2). It is worth noting that the different results of PA size effects between the SNVC model and counterfactual analyses may be due to the different number of PAs involved in the two analyses. Specifically, some PAs were not considered in the SNVC model due to the lack of values for some indicators in those PAs (for example, government effectiveness, corruption, Human Development Index and share of GDP on agriculture).

Discussion

Cropland expansion threatens post-2020 biodiversity agenda

The relatively higher rate of cropland expansion in PAs after 2000 is alarming, for example, the expansion rate in PAs increased 58-fold compared with the general 2-fold increase globally based on Potapov et al.'s dataset. This expansion poses a great potential threat to biodiversity conservation[22–24]. Major improvements in the governance of PAs in biodiversity hotspots (especially the Afrotropics) and at the highest protection level (IUCN category Ib) are urgently needed as these PAs have been relatively less effective in avoiding cropland expansion. Without such improvements, the conservation targets set by the post-2020 global biodiversity framework will not be reached.

Currently, there are 223,161 km^2 croplands in global PAs established in or before 2000 based on Potapov et al.'s cropland dataset. If the current 58-fold cropland expansion rate change continues, the cropland area in the studied PAs is going to reach 314,214 km^2 by 2030, equivalent to 2.1% of the PA area that we documented. To achieve the target of 30% coverage in 2030, additional lands need to be designed as PAs to fill the gaps from cropland occupancy. Notably, this number (314,214 km^2 or 2.1% of current global PA area documented in this study) may be conservative, as croplands in the PAs established after 2000 have not been considered in the current study (Methods). In light of our findings, the goal of protecting 30% by 2030 might be challenged if croplands in PAs continue to expand at such a high rate.

Potential correlated factors

To inform governance improvements to existing PAs, more attention needs to be placed on why some PAs have been less effective in halting cropland expansion. Analyses of the specific underlying causes of cropland expansion, including counterfactual analysis of effectiveness of specific enforcement measures and governance structures, could help improve PA effectiveness. Without improving the enforcement of existing PAs, current efforts to expand global PAs areas will have limited utility.

Current work suggests that the establishment of PAs in the Afrotropics has too often occurred through top-down and non-participatory approaches, which may weaken the tenure rights of Indigenous and local communities, and undermine existing communal management structures[6,25]. A focus on strengthening governance, improving efficacy of financial support, decentralization of PA management and on measures to alleviate poverty in these contexts may thus lead to stronger improvements in PA efficacy than more forceful PA regulations.

Our finding that the largest expansion of croplands has occurred in Afrotropical PAs supports previous studies investigating PAs and macroscale cropland expansion globally[6,8,26,27]. Severe and persistent funding shortages, poor governance, poverty and illegal wildlife trade hinder the effectiveness of conservation management in these regions. In particular, the COVID-19 disease could amplify Africa's conservation crisis to a catastrophic level, largely due to the continued dwindling funding, which would further restrict the capacity of conservation practitioners to manage PAs[28].

Although cropland expansion in PAs poses severe threats to biodiversity, it is crucial to acknowledge the trade-offs that biodiversity protection entails, especially in the context of high poverty levels and the strong dependence of human subsistence on agricultural land use. In tropical regions, cropland expansion is largely driven by local people in vulnerable communities that are dependent on these landscapes to meet basic human needs[29]. Imposing stricter regulations to halt cropland expansion into PAs can thus pose severe threats to global justice and harm people who are already marginalized[30]. Greater study

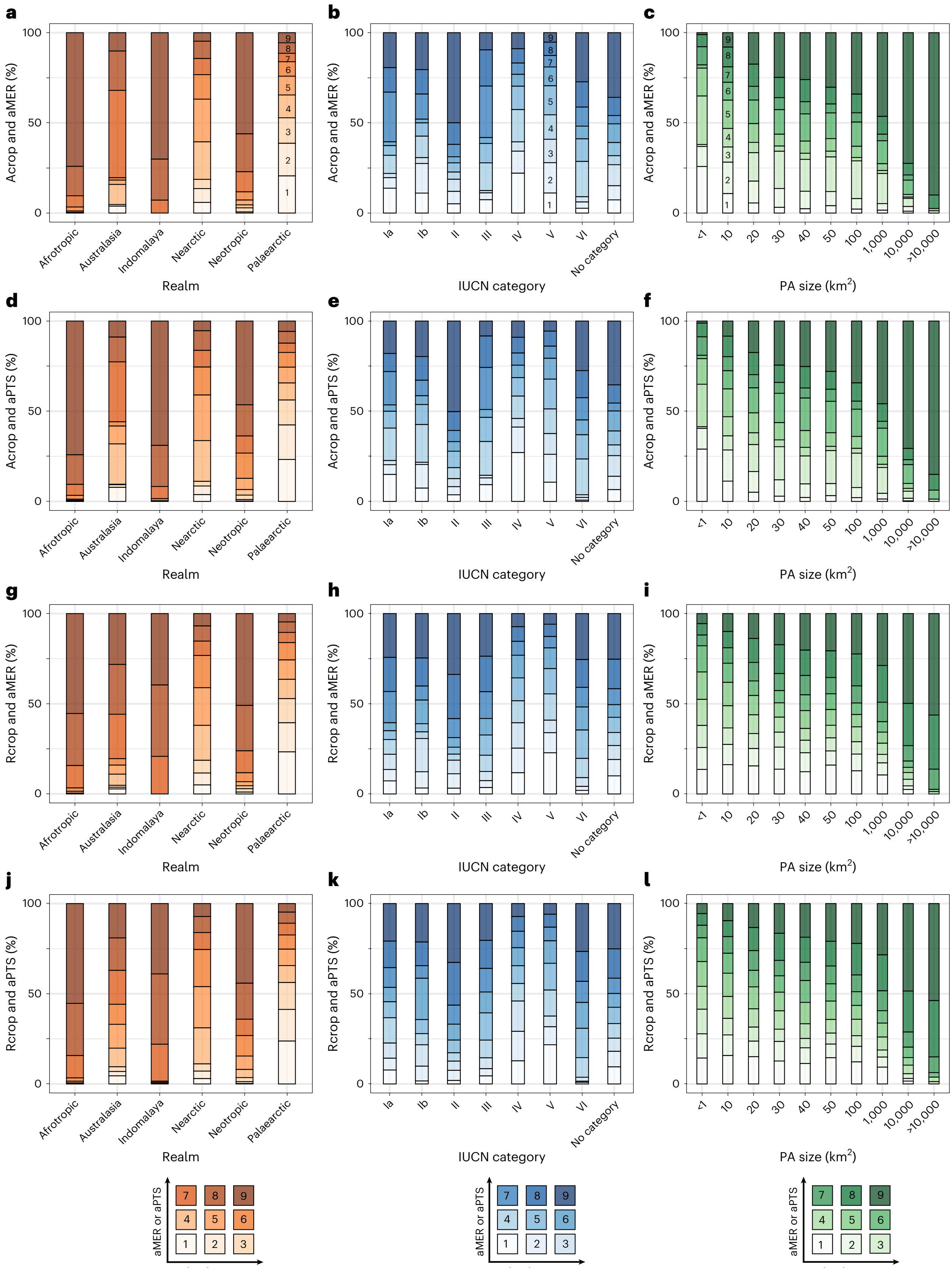

Fig. 4 | Impact of cropland expansion in PAs on biodiversity extinction risks. **a**–**c**, Impact of absolute cropland expansion areas in PAs (Acrop) on extinction risks for agriculturally driven threatened species (aMER) based on biogeographic realm (left column), IUCN category (middle column) and PA size (right column). **d**–**f**, As in **a**–**c**, but impact of Acrop on percentage of threatened species for agriculturally driven imperiled species (aPTS). **g**–**i**, As in **a**–**c**, but impact of relative proportion of cropland expansion in PAs (compared with the 2000 initial cropland areas in PAs; Rcrop) on aMER. **j**–**l**, As in **a**–**c**, but impact of Rcrop on aPTS.

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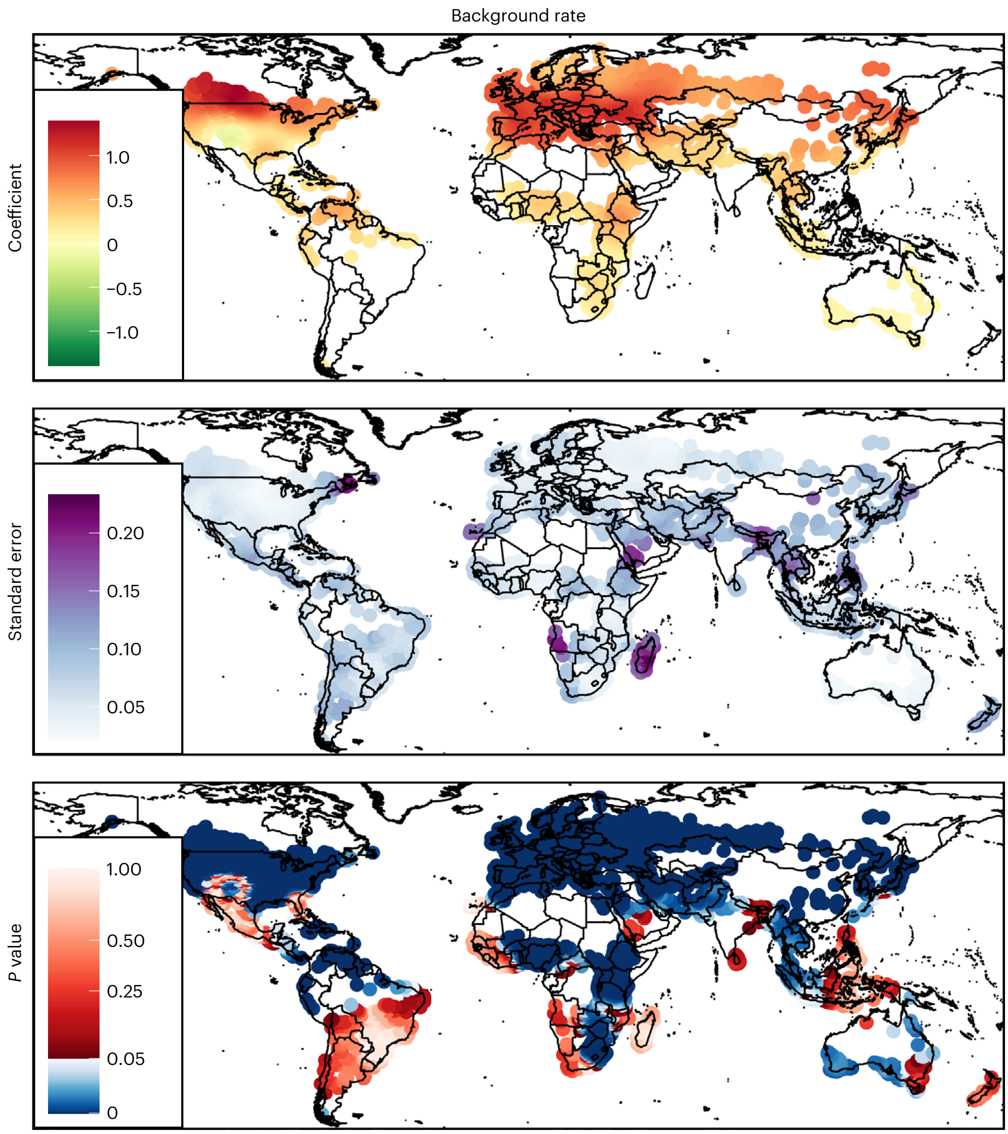

Fig. 5 | Effects of background cropland expansion rate on cropland change rates in PAs. Only coefficients with an associated *P* value of less than 0.05 are mapped. The SNVC method assumed a two-sided *t*-test to evaluate the *P* value, which is available for statistical testing, and adjustments were not made for multiple comparisons.

of the social impacts of PAs is thus needed to ensure that the global community does not push for more forceful implementation of PAs at the expense of already vulnerable communities.

The overall trends in cropland expansion may be due to the difficulty in managing larger PAs[6] or due to differences in the benefits that farmers get from small PAs. However, there are structural differences in PA pressure across countries with different socioeconomic backgrounds. Many countries in the global north, like the United States, have more resources available for PA management, economic incentives to prevent cropland expansion into PAs (such as paying farmers not to clear their land) and lower pressure to expand into PAs[31] as much of the new food demand is outsourced to countries in the tropics[32].

In the United States, farmers receive payment for retiring their land, so reductions in cropland expansion there already indicate that the opportunity costs of re-clearing the land (that is, overall pressure to clear) are less than the payment level. However, the total retired crop acreage enrolled in the Conservation Reserve Program peaked in 2007, and has since declined. Some grasslands have returned to cropland in recently established conservation priority zones[33,34], which has increased the expansion of croplands in small PAs in the following decade. In addition, some small PAs that showed large cropland expansion, especially in European countries (Supplementary Fig. 9) where there was a long history of intensive agricultural management, should be of particular concern because of its potential impact on species decline[14,35].

Further considerations and uncertainties

Our estimates of cropland area in global PAs may be conservative for two main reasons. The first is that we omitted processes where agriculture-driven deforestation does not follow immediate cropland use[36]. That process could be caused by speculative land clearing[36] and lead forest-related species to extinction, because the impact of deforestation exceeds any other contemporary land cover changes[37]. However, the spatially explicit data on indirect pressures for agriculture-driven deforestation were unavailable. Second, the cropland dataset used from Potapov et al. excluded shifting cultivation, which is widespread in Africa and Southeast Asia[38]. Thus, large areas in the tropics that experience agricultural change due to this particular land management practice were not included in our analyses.

Policies and interventions focused on enforcement and management of PAs are important[39,40], but analyses on how different levels of enforcement and management strategies affect cropland expansion in PAs are yet to be realized because there are no standardized, broad geographical coverage datasets with such information. In this regard, inter-operable datasets that can capture, store and share data related to the enforcement and management of PAs are urgently needed to enable a more comprehensive and in-depth understanding of which policy instruments and management options are successful in preventing cropland expansion. Our work emphasizes that further guidance on establishing new PAs to reach the 2030 target of the post-2020 biodiversity conservation framework should not overlook the pressures (socioeconomic and political) and consequent negative impacts of rapid cropland expansion in PAs, existing or newly established.

Conservation implications

Tackling accelerated cropland expansion in PAs requires innovative strategies that account for multiple goals linked to conservation, food security and equity for local stakeholders. In countries with strong food security and governance systems that promote social justice, adequate funding should be given to restoring native ecosystems, especially for remaining wildlands, as these are the cornerstone for maintaining endangered species. Ensuring the PAs in wilderness areas are managed effectively is a global priority[6]. In countries with substantial food insecurity and high inequality, efforts should focus on policies that simultaneously address hunger and malnutrition and biodiversity conservation in established PAs[14]. As for the hotspots of high cropland expansion in the PAs of the Afrotropics, conservation policies that benefit both local actors and stakeholders may be needed[6].

The role of the entire international community in supporting PA conservation in global biodiversity hotspots cannot be overstated. The global food supply is projected to double by 2050 to meet global food demand, which will put additional pressure on landscapes for food production and increase the risk of cropland expansion in PAs[41–43]. A global shift towards plant-based diets could help alleviate this pressure, as cattle ranching and the production of feed for pork and poultry are key drivers of deforestation[44]. International finance is urgently needed to provide adequate, long-term, systematic funding support in Africa's PAs to prevent further wildlife declines[45] and lessen the risk of future zoonotic disease pandemics[28]. Yet, in order to ensure that conservation is not promoted at the expense of vulnerable people's prosperity, it is important to take a more holistic approach to how ecological and social objectives can be promoted simultaneously, rather than simply focusing on how to make conservation itself more effective[46].

Typically, governments of most countries may change the management strategy for PAs and adopt the right area-based conservation strategies to mitigate threats to biodiversity[47]. For example, China has implemented the national Ecological Redline Policy to establish the most stringent ecological protection system, which can provide innovative solutions for global biodiversity conservation[48]. Notably, although agriculture activities are allowed in IUCN category V and uncategorized PAs, sustainable agriculture should be developed to avoid the negative effect of exacerbated cropland expansion on biodiversity loss[49].

Methods

PAs

Terrestrial PA data were obtained from the July 2021 edition of the World Database on Protected Areas[3,50]. We only used the polygon boundary data layer, and point data layers were excluded from our analysis. All the PAs established after 2000 and the ones smaller than 0.09 ha were removed to improve compatibility with the spatial resolution of cropland data (30 m), resulting in a total of 115,495 PAs. The IUCN classifies PAs as Ia (strict nature reserve), Ib (wilderness area), II (national park), III (natural monument or feature), IV (habitat or species management area), V (protected landscape or seascape) or VI (PA with sustainable use of natural resources)[3], and PAs without an IUCN category, which we called uncategorized (no category). The IUCN categories I and II are often considered strict categories that include PAs with strict biodiversity conservation objectives, and IUCN categories III, IV, V and VI are often considered less-strict categories that permit multiple human activities[5].

Cropland change analyses

We used Potapov et al.'s[8] cropland data, which are global time series cropland maps from 2000 to 2019 at a spatial resolution of 30 m. The definition of cropland used was mainly consistent with that of the Food and Agriculture Organization of the United Nations (FAO). This dataset was performed in four-year intervals (2000–2003, 2004–2007, 2008–2011, 2012–2015 and 2016–2019) to minimize the effect of fallow lands on classification, and there was one cropland layer per four-year period (referred to as 2003, 2007, 2011, 2015 and 2019). We selected this cropland dataset for primary analysis as it had a rigorous validation process and had the highest accuracy (overall accuracy >97%) among all existing 30-m datasets. Also, it agreed well with FAO cropland data ($R^2 > 0.94$, sample-based comparison) and strictly verified cropland changes. More reasons for our choice to use this dataset and more details are provided in Supplementary Notes 1 and 2.

We also used AGLC[16] (2000–2015) and GlobeLand30[17] (2000, 2010 and 2020) datasets, which were at 30-m resolution, for sensitivity analyses to make our work more comprehensive. We extracted cropland from multiple land cover types in AGLC and GlobeLand30 and performed spatial analyses through ArcGIS Pro 2.8, QGIS 3.26.0 and Google Earth Engine. More details about the differences between the three cropland datasets are provided in Supplementary Note 1.

The absolute change and relative change methods were used to explore cropland dynamics in PAs. Absolute change reflected the difference of cropland area in PAs over the first and last two periods during the study period. Here we used two indices to represent relative change: (1) the fraction of cropland changes relative to the 2000 initial cropland areas in PAs; and (2) the fraction of cropland changes relative to PA size. We also used the linear regression method to calculate trend of cropland change in PAs with statistical significance less than 0.1 for the counterfactual matching analysis, as described in the following section. We believe that these different methods more comprehensively aided our investigation into the dynamics of cropland expansion in global PAs.

Counterfactual matching method

The site-level matching method can help reduce the non-random effects due to the location bias of PAs[51]. Here, we identified the correspondent control pixel for each treatment pixel within PAs using one of the most widely used non-experimental matching methods, that is, propensity score matching[6] using the MatchIt R package[52]. Matching was based on six covariates that were potentially associated with cropland expansion: (1) elevation[53]; (2) slope[53]; (3) agricultural suitability (including climatic, soil and topographic conditions)[54]; (4) initial human footprint (including built environments, pasture lands, population density, electric power infrastructure and roads)[55]; (5) initial cropland area[8]; and (6) country. The propensity score matching was done without replacement using the nearest method for elevation, slope, agricultural suitability and initial human footprint based on the caliper = 0.25 standard deviations of the propensity score[56]. We used exact matching for initial cropland area and country, which means that protected pixels were only compared with unprotected pixels in the same country and same initial cropland status. All of these covariate values were resampled to 1 km resolution and then extracted at the location of each pixel.

Specifically, we did not select control areas adjacent to PAs to avoid spillover effects from the establishment of PAs (that is, human impacts inside PAs may displace to a nearby unrestricted area)[57]. However, the real extent to which PAs have spillover effects on surroundings is unclear and varied with PA size[58]. Considering that a certain distance such as 10 km, 20 km or some other specific size[18,58,59] may only fit PAs of a specific size[60], here we created buffer areas of the same size as the PAs to highlight the uniqueness of each PA using the 'Buffer by Percentage' plugin in QGIS 3.26.0. For each PA, we considered three zones: the PA; the equal-area buffer zone (outside the PA of one-fold size of the PA; we also tested five-fold and ten-fold sizes, where we expect spillover effects to occur); and the control area (outside the PA and buffer zones). We then assessed the effectiveness of each PA by calculating the mean cropland change rates for all pixels within each PA relative to the mean cropland change rates for all identified matching control pixels. Therefore, in our analysis, a PA was considered to have a positive impact on conservation if it had experienced less cropland expansion across the years compared with its matched control. More details are provided in Supplementary Note 4.

Species extinction risks and threatened species proportions

We used bird, mammal, amphibian and reptile species distribution maps to determine two metrics of the extinction risks: the mean extinction risk value for agriculturally driven imperiled species in a PA; and the percentage of agriculturally driven imperiled species that are threatened with extinction[21,61,62]. For each species, we used only areas where species were classified as Extant or Probably Extant. We used each species' global Red List category and did not distinguish subspecies. To evaluate which species are specifically imperiled by cropland expansion, we used the IUCN classification of threat types, which was 'Agriculture', to identify these species and did not distinguish sub-agriculture threats.

To calculate mean extinction risks (aMER) of agriculturally driven birds, mammals, amphibians and reptiles for each PA, we assigned a value to each IUCN Red List category following ref. [21], with equally weighted values of 0 (Least Concern, LC), 1 (Near Threatened, NT), 2 (Vulnerable, VU), 3 (Endangered, EN), 4 (Critically Endangered, CR) and 5 (Extinct, EX and Extinct in the Wild, EW). We then averaged all species of birds, mammals, amphibians and reptiles within each PA, excluding Data Deficient (DD) and Not Evaluated species, and assumed that these species were threatened at the same rate as the evaluated species to minimize the uncertainties:

$$\mathrm{aMER} = \frac{N_{\mathrm{LC}} \times 0 + N_{\mathrm{NT}} \times 1 + N_{\mathrm{VU}} \times 2 + N_{\mathrm{EN}} \times 3 + N_{\mathrm{CR}} \times 4 + (N_{\mathrm{EX}} + N_{\mathrm{EW}}) \times 5}{N_{\mathrm{LC}} + N_{\mathrm{NT}} + N_{\mathrm{VU}} + N_{\mathrm{EN}} + N_{\mathrm{CR}} + N_{\mathrm{EX}} + N_{\mathrm{EW}}} \tag{1}$$

where aMER represents the mean extinction risks for agriculturally driven imperiled species, and N_{LC}, N_{NT}, N_{VU}, N_{EN}, N_{CR}, N_{EX} and N_{EW} represent the number of LC, NT, VU, EN, CR, EX and EW species, respectively.

To calculate the percentage of threatened species (aPTS) for agriculturally driven imperiled species in a PA, we classified VU, EN and CR species as 'threatened'. The estimate is the number of threatened species divided by the total number of species (non-DD), that is:

$$\mathrm{aPTS} = \frac{N_{\mathrm{VU}} + N_{\mathrm{EN}} + N_{\mathrm{CR}}}{N_{\mathrm{LC}} + N_{\mathrm{NT}} + N_{\mathrm{VU}} + N_{\mathrm{EN}} + N_{\mathrm{CR}} + N_{\mathrm{EX}} + N_{\mathrm{EW}}} \tag{2}$$

where aPTS represents the percentage of threatened species for agriculturally driven imperiled species, and N_{LC}, N_{NT}, N_{VU}, N_{EN}, N_{CR}, N_{EX} and N_{EW} represent the number of LC, NT, VU, EN, CR, EX and EW species, respectively.

We first divided the PAs into three equal parts according to the absolute (or relative) cropland expansion areas and species extinction risks (aMER or aPTS) in PAs in ascending order (the 33rd and 66th percentiles are shown in Supplementary Table 3). Second, we created a bivariate map between the cropland expansion in PAs and the species extinction risks in PAs based on distribution quantiles, which resulted in nine different classes (Fig. 4). Third, we calculated the proportion of the number of PAs in different classes to the total number of PAs based on different realms, different IUCN management categories and different PA sizes. For instance, class 9 in the Afrotropics indicates that high rates of cropland expansion coincide well with high rates of species extinction in PAs.

Predictors of cropland changes in PAs

We used Moran's eigenvector-based SNVC model (equation (3)) to assess potential predictors of cropland dynamics in PAs following ref. [18], applying the 'besf_vc' function in the 'spmoran' R package[19,63]. This function assumes spatially dependent map patterns underlie regression coefficients. This exponential covariance model can perfectly identify true and spurious correlations among coefficients. The multicollinearity problem among coefficients can be addressed through the indicator of variance inflation factor, which should not exceed 10. This model can test the spatial (or non-spatial) variations of each predictor by minimizing the Akaike information criterion or minimizing the Bayesian information criterion (used in our study). Coefficient estimates, standard errors and P values can be obtained for the spatially varying coefficients (SVCs) in any location. However, if the coefficient is non-spatially varied, a single coefficient estimate, standard error and P value can be obtained[19].

$$\mathbf{y} = \sum_{k=1}^{k} \mathbf{x}_k \circ \boldsymbol{\beta}_k + \boldsymbol{\epsilon},\ \boldsymbol{\beta}_k = b_k 1 + \boldsymbol{\beta}_k^{(\mathrm{s})} + \boldsymbol{\beta}_k^{(\mathrm{n})},\ \boldsymbol{\epsilon} \sim N(\mathbf{0}, \sigma^2 I) \tag{3}$$

where $\mathbf{y}$ is a vector of the response variable, N is the sample sites, $\mathbf{x}_k$ is a vector of the kth covariate, $\boldsymbol{\epsilon}$ is a vector of disturbances with variance σ^2, $\mathbf{0}$ is a vector of zeros, I is an identity matrix, ° is the operator that multiplies each element of the left vector with each element of the right matrix, $\boldsymbol{\beta}_k$ is the coefficient vector, which is defined by [constant: $b_k\mathbf{1}$] + [SVC: $\beta_k^{(\mathrm{s})}$] + [non-SVC (NVC): $\beta_k^{(\mathrm{n})}$], b_k is a parameter and $\mathbf{1}$ is a vector of ones.

The coefficient $\boldsymbol{\beta}_k$ includes the following four specifications:

- Constant:

$$\boldsymbol{\beta}_k = b_k\mathbf{1} \tag{4}$$

- SVC:

$$\boldsymbol{\beta}_k = b_k\mathbf{1} + \boldsymbol{\beta}_k^{(\mathrm{s})} \tag{5}$$

- NVC:

$$\boldsymbol{\beta}_k = b_k\mathbf{1} + \boldsymbol{\beta}_k^{(\mathrm{n})} \tag{6}$$

- SNVC:

$$\boldsymbol{\beta}_k = b_k\mathbf{1} + \boldsymbol{\beta}_k^{(\mathrm{s})} + \boldsymbol{\beta}_k^{(\mathrm{n})} \tag{7}$$

We used the 'PA cropland expansion rate' instead of the 'cropland expansion area in PAs' as the response variable because it could remove the effect of PA sizes. Based on previous research[6,14] and available data, we identified the following associated predictors: PA size, IUCN category, realms, background (control area in the counterfactual method) cropland expansion rate, population density at PA level, government effectiveness, control of corruption of government, human development level and share of GDP from agriculture at country level. The units of all the variables used in the SNVC model were at PA level and some country-level variables' values were still assigned to each PA. These factors are considered relevant to cropland dynamics in PAs. Detailed sources and meanings for these variables are provided in Supplementary Table 1. We generated coefficient estimates, standard errors and adjusted P values for all the above variables at the PA centroid locations.

Reporting summary

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

Data availability

All underlying raw model data are publicly available online. Potapov et al.'s cropland data are available at https://glad.umd.edu/dataset/croplands. GlobeLand30 cropland data are available at http://www.globallandcover.com/. AGLC cropland data are available at https://code.earthengine.google.com/?asset=users/xxc/GLC_2000_2015. PA data are freely available online at https://www.protectedplanet.net/en. Expert-derived polygons of amphibians, mammals and reptiles are available online at the IUCN Red List Portal https://www.iucnredlist.org/resources/spatial-data-download. Polygons of bird distributions can be requested from BirdLife International http://datazone.birdlife.org/species/requestdis. Human population density data can be obtained at https://data.worldbank.org/. Human Development Index data are available at https://hdr.undp.org/. Government effectiveness and corruption datasets are available at https://info.worldbank.org/governance/wgi/. Share of GDP on agriculture data are available at https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators. Source data are provided with this paper.

Code availability

The code that supports our findings is available at https://github.com/ziqi123456/Cropland-expansion-in-globalPAs.

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Author contributions
J.D. and Z.M. conceptualized the study. Z.M. performed research, analysed data and made the visualizations in consultation with J.D., X.-P.S. and X.X. The writing and editing of the manuscript was done by Z.M., J.D., E.C.E., G.M., Y.Q., X.-P.S., S.L., R.D.G., X.J. and X.X.

Competing interests
The authors declare no competing interests.

Additional information
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Software and code

Policy information about availability of computer code

Data collection	No software was used to collect data.
Data analysis	The data analyses were performed using R 4.2.1 (MatchIt and spmoran packages), QGIS 3.26.0 (Buffer by Percentage plugin), ArcGIS Pro 2.8 softwares and Google Earth Engine. Details were reported in the section of the Methods. Data and code are available at https://github.com/ziqi123456/Cropland-expansion-in-globalPAs.

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All underlying raw model data are publicly available online. Potapov et al.’s cropland data is available at https://glad.umd.edu/dataset/croplands. GlobeLand30 cropland data is available at http://www.globallandcover.com/. Annual Global Land Cover (AGLC) cropland data is available at https://

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All studies must disclose on these points even when the disclosure is negative.

Study description	We used 30 m spatial resolution cropland data layers to characterize cropland dynamics over time in global protected areas (PAs) by different PA sizes, biogeographic realms, and the International Union for Conservation of Nature (IUCN) management categories. We then assessed the potential effects of cropland expansion on biodiversity by overlapping cropland dynamics and species extinction risks in PAs. Finally, we attributed the observed cropland changes within PAs to a set of associated factors, including background cropland expansion rates, IUCN category, realms, government effectiveness and corruption, development level, share of GDP on agriculture, and population density.
Research sample	Our sample consists of 115,495 terrestrial protected areas globally, with cropland datasets from 2000 to 2020. We selected bird, mammal, amphibian, and reptile species to determine the species extinction risks. All the datasets were obtained from open access available sources. Details can be seen in the Methods and Data Availability sections.
Sampling strategy	For protected areas (PAs) data, we only used the polygon boundary data layer, and point data layers were excluded from our analysis. All PAs established after 2000, and the areas with less than 0.09 ha were removed to improve compatibility with the spatial resolution of cropland data (30 m), resulting in a final list of 115,495 PAs. For cropland datasets, we used "Extract by mask" function in ArcGIS Pro 2.8 software to extract cropland within the protected areas. For species, we used only areas where species were classified as Extant or Probably Extant. We used each species' global Red List Category and did not distinguish subspecies. To evaluate which species are specifically imperiled by cropland expansion, we used the International Union for Conservation of Nature (IUCN) classification of threat types, that is "classification 2. Agriculture", to identify these species and did not distinguish sub-agriculture threats.
Data collection	All the datasets were obtained from open access sources available online as described in the Methods and Data Availability sections.
Timing and spatial scale	Our study used 30 m cropland datasets to investigate cropland dynamics in protected areas during 2000–2020. Potapov et al.,'s cropland datasets were performed in four-year intervals (2000–2003, 2004–2007, 2008–2011, 2012–2015, and 2016–2019). There is one cropland layer per epoch (five layers total), with the file name referring to the last year of the interval (2003, 2007, 2011, 2015, and 2019). Annual Global Land Cover (AGLC) dataset were from 2000 to 2015 at 30 m spatial resolution. GlobeLand30 datasets were for 2000, 2010, and 2020 at 30 m spatial resolution.
Data exclusions	For investigating the cropland expansion in protected areas (PAs) by different biogeographic realms or the International Union for Conservation of Nature (IUCN) management categories, we excluded PAs that did not fall into any biogeographic realm or had incomplete attribute table information. For investigating the potential drivers of cropland changes in PAs, we excluded PAs that did not have any socio-economic information.
Reproducibility	We have provided data source information to ensure reproducibility.

Randomization	We did not conduct experiments, so not relevant for our study.
Blinding	We did not conduct experiments, so not relevant for our study.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☒	☐	Clinical data
☒	☐	Dual use research of concern

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging