Trade-offs between nature and people across Ethiopia's protected area network demonstrate challenges in translating global conservation targets into national realities

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Abstract

Achieving global biodiversity targets, such as the commitment to conserve 30% of the planet by 2030, depends on the ability of individual countries to translate targets into reality. While there has long been recognition that protected areas can bring costs as well as benefits, the implications of this for delivery of the global target have not been fully explored. We focus on Ethiopia, a country supporting globally important biodiversity but facing substantial poverty challenges. We characterise the extent and representativeness of Ethiopia's protected area network, demonstrating that a three-fold expansion — particularly into ecoregions with higher opportunity cost — would be required to meet the Kunming-Montreal Global Biodiversity Framework Target 3. Using a quasi-experimental approach (accounting for known confounders and exploring sensitivity to potential unobserved confounders), we show that the existing protected area network has reduced forest loss and agricultural expansion, and helped to maintain grasslands. Yet, this has brought social wellbeing costs equivalent to 3.9 million fewer household-months of adequate food. Surveys show that national conservation stakeholders recognise these challenges and prioritise improving effectiveness of the existing network over expansion. Our findings highlight that trade-offs between environmental and social outcomes, are not simply challenges to be managed, but are central to whether global biodiversity commitments can be delivered.

Introduction

Ambitious global targets provide a shared vision for halting biodiversity loss but achieving them depends on the ability of individual countries to turn commitments into action[1]. In 2022, 196 parties committed to conserve 30% of the planet by 2030 under the Kunming-Montreal Global Biodiversity Framework Target 3 (30-by-30)[2], a substantial increase from the current terrestrial protected and conserved area coverage of 17.2%[3]. While attention has largely been focused on area coverage[4], both 30-by-30 and its predecessor, Aichi Target 11, also require protected areas to be *ecologically representative*, *well connected*, *effectively managed* and *equitably governed*[2] – dimensions that are far less often systematically assessed or reported[5]. Evidence from the Global South shows that simple 'win-win' narratives can be misleading with costs often borne locally, especially by marginalised groups[6]. As the target deadline approaches, understanding what progress is realistically achievable at the national level, and at what cost, is essential.

Protected areas have predominantly been established on land with lower economic value and fewer opportunity costs, rather than in the locations that would yield the greatest benefits for biodiversity conservation[7,8]. As a result, many ecologically important areas remain under-protected. In 2020 only 44.5% of terrestrial ecoregions had reached the 17% coverage target outlined in Aichi Target 11[9]. To meet the more ambitious 30-by-30 target, and ensure ecologically representative networks, countries will need to expand into under-represented ecoregions which risks increasing competition with alternative land use such as agriculture. Consequently, both trade-offs with local food supplies, local livelihoods, and the number of people impacted are likely to increase dramatically[10,11].

While area-based approaches dominate global conservation policy[12,13], debates continue over whether protected areas are performing effectively[14,15]. A growing requirement for evidence to inform conservation policy decisions has driven an increase in research using quasi-experimental methods[16,17]. While studies exploring the impacts of protected areas vary in robustness[18], researchers have applied quasi-experimental designs to evaluate the effectiveness of protected areas across different outcome measures including forest cover[19–23], agricultural expansion[24], anthropogenic threats more broadly[25], species populations[26,27] and measures of human wellbeing[28–30]. Studies also vary in scale; however, global syntheses pool highly diverse socio-ecological contexts, which can mask heterogeneity in outcomes and limit national policy relevance[25,29,31].

There is also an ongoing debate about the extent to which conservation successes from protected areas come at the detriment of the wellbeing of local communities[11,32–35]. In low-income countries where rural poverty remains a considerable challenge, protected areas are increasingly expected to contribute to socio-economic development alongside conservation goals, despite environmental and social goals often conflicting with one another[36–38]. In such contexts, there is little credible evidence of sustained positive social outcomes[11] and transparent evaluation is needed to identify who bears the costs[33,39]. A few studies have explicitly looked at trade-offs between environmental and social outcomes of protected areas, however, many rely on data aggregated across large administrative units[40–45], limited outcome indicators[31,40–43,46], or global proxies for development[31] that are insensitive to local variation, and household-level multidimensional analyses remain rare[47–49]. With 30-by-30 requiring a near-doubling of the global protected and conserved area estate, understanding current effectiveness and trade-offs between environmental and social wellbeing outcomes – through robust analyses that capture multiple components of wellbeing at fine spatial scales – is increasingly urgent[11]. Without a clearer understanding of trade-offs, countries may be reluctant to support protected area expansion that risks harming local communities, or may require additional funding and international support to offset potential negative effects[11].

Ethiopia is a good example of a country where there is potential for trade-offs between environmental and social wellbeing outcomes[50]. Ethiopia encompasses two global biodiversity hotspots[51], but also faces long-standing poverty[52] and food security challenges[53]. Ethiopia is committed to conserving its biodiversity[54], having ratified the Convention on Biodiversity in 1995 and signed up to meet the Global Biodiversity Framework targets in 2022. However, its natural resources are facing growing pressures driven by the need for development and improved living standards[55,56]. In 2020, around 18 million people lived within 10 km of a protected area in Ethiopia, and tensions over land use in these areas has been widely documented[57–60].

Here, we provide a comprehensive national-scale evaluation of Ethiopia's progress towards the multiple dimensions of the 30-by-30 target. We assess the extent of Ethiopia's protected area network and how well it represents national ecoregions and species. We then apply a robust quasi-experimental approach to assess both environmental (forest, agriculture and grassland cover change) and human wellbeing (change in months of adequate food, dietary diversity and material wellbeing) impacts of Ethiopia's protected areas. Considering protected areas individually, we then examine predictors of performance across environmental and wellbeing outcomes. Finally, we explore the views of key national stakeholders in conservation policy and practice and consider the alignment of national priorities and global goals. This research highlights the very real challenges faced by those tasked with turning a global commitment into reality.

Results

Protected area extent.

As of September 2024, protected areas cover 9.4% of Ethiopia (Fig. 1A). Strict protected areas (International Union for Conservation of Nature (IUCN) category II) make up 3.8% of Ethiopia, while less strict (IUCN categories IV and VI) make up 5.6% (Supplementary Table 10). Including National Forest Priority Areas (NFPAs), which are not protected areas but are included on the World Database on Protected Areas (WDPA) would bring this national coverage up to 12.4%. This still differs from the 17% coverage reported on the WDPA (Supplementary Table 1) because our updated dataset removes degazetted or duplicate areas and updates boundaries of downsized or merged areas. Ethiopia's protected area network has expanded steadily over time (Fig. 1B), amid changing political regimes and evolving conservation policy (Extended Data Fig. 1). Newer protected areas have generally been established in areas of higher human pressures (Supplementary Results 1), and we estimate around 18 million people lived within 10 km of a protected area in 2020.

Ecological and taxonomic representativeness.

To be ecologically representative, protected area networks must contain adequate samples of the full range of existing ecoregions, environments and species, especially those that are threatened or are of particular importance[2]. Ten of the 11 global terrestrial ecoregions present within Ethiopia[61] are currently represented within the protected area network, but coverage is uneven (0-43%; mean = 13.5%). Four ecoregions exceed the 17% Aichi targets, whereas only one has over 30% in line with 2030 Global Biodiversity Framework targets (Fig. 2a). Relative to national protected area extent (9.4%), six ecoregions are currently well represented (Fig. 2a). Protected areas also encompassed 33% of Ethiopia's multidimensional environmental space, defined as the range of climatic and environmental conditions summarised across 19 bioclimatic variables (Supplementary Figure 5). Gaps in the network disproportionately occur in more accessible areas with more agriculture and higher population densities (Supplementary Results 2).

At the species level, across 2067 Red Listed species, Ethiopia's protected area network covers a higher average proportion of threatened species ($n = 294$) ranges than non-threatened ($n = 1773$) (Fig. 2b). However, threatened plants ($n = 193$) are less well represented with a significantly lower proportion of threatened plant species' ranges covered by Ethiopia's protected area network when compared with threatened mammals ($n = 50$, $p < 0.001$), birds ($n = 36$, $p < 0.001$) and herptiles ($n = 15$, $p = 0.009$; Dunn test with Bonferroni correction). Of the 31 Critically Endangered plant species in this study (30 of which are endemic), 25 are absent from Ethiopia's protected area network and a further three have less than 5% of their range protected (Fig. 2b). The number of species with their extent of occurrence overlapping each protected area is shown in Supplementary Table 11.

Protected area effectiveness.

We used a quasi-experimental approach to assess the effectiveness of Ethiopia's protected area network across six measures – three environmental outcomes (forest, grassland and agricultural land cover change) and three social wellbeing outcomes (months of adequate food, dietary diversity and material wellbeing) – compared to an estimate of what would have happened if protection had not been put in place (the counterfactual). Using covariate-adjusted regression comparing statistically matched cells and households within and outside Ethiopia's protected area network, we accounted for key environmental and socio-economic confounders (Extended Data Fig. 2, Supplementary Table 5), including elevation, slope, temperature, precipitation, agricultural suitability, access to cities, population, ethno-linguistic groups, and agriculture. For environmental outcomes we additionally included ecoregion and other baseline land cover variables (forest, grassland, majority land cover type). Descriptive statistics on the changes occurring across Ethiopia for both environmental and wellbeing outcomes, prior to statistical matching, are provided in Supplementary Results 3 with land cover changes shown in Supplementary Figure 6.

Strict protected areas moderately reduced forest cover loss by 25% relative to controls (Average Treatment Effect on the Treated (ATT) = 0.07, 95% confidence interval (CI): 0.0003 to 0.14, Wald test statistic (z_{4675}) = 2.04, p = 0.04), equating to approximately 30 km² (CI: 1 to 59)) of avoided deforestation. Strict protected areas also significantly reduced agricultural expansion by 44% (ATT = –0.61, 95% CI: –0.90 to –0.33, z_{4675} = –4.20, p < 0.001), corresponding to 262 km² (CI: 140 to 384) of avoided agricultural expansion, and significantly increased grassland by 76% (ATT = 4.34, 95% CI: 2.76 to 5.91, z_{4675} = 5.39, p < 0.001), resulting in an additional 1,850 km² (CI: 1178 to 2522) of grassland. Less strict protected areas showed no significant effect on forest loss (ATT = 0.001, 95% CI: –0.10 to 0.10, p = 0.98), but did achieve a 73% reduction in agricultural expansion compared to controls (ATT = –1.24, 95% CI: –1.52 to –0.96, z_{8884} = –8.78, p < 0.001), equating to 795 km² (CI: 615 to 974) of avoided agricultural expansion, and a 121% reduction in grassland loss (ATT = 1.44, 95% CI: 0.63 to 2.24, z_{8884} = 3.5, p < 0.001), corresponding to approximately 919 km² (CI: 412 to 1426) less grassland lost (Fig. 3; Extended Data Fig. 3A).

Although Ethiopia's protected area network was effective at resisting land cover changes across measured environmental outcomes, this success was associated with substantial local costs for wellbeing. Treatment households close to protected areas experienced a significantly greater decline in perceived months of adequate food, with an average decline of a month compared to almost no change in matched control households (ATT = –1.23, 95% CI: –1.54 to –0.92, z_{791} = –7.66, p < 0.001). Assuming similar impacts across the 3.2 million households living within 10 km of a protected area in 2011 translates to approximately 3.9 (CI: 2.9 to 4.9) million fewer household-months of adequate food. Material wellbeing, measured as an asset index derived from principal component analysis, also declined significantly for households near protected areas (ATT = –1.21, 95% CI: –1.90 to –0.52, z_{791} = –3.44, p < 0.001), while it improved in matched control areas. In contrast, there was no significant difference in dietary diversity (ATT = 0.13, 95% CI: –0.22 to 0.48, z_{791} = 0.72, p = 0.47) (Fig. 3; Extended Data Fig. 3B).

Our results are robust to both unobserved confounders and arbitrary matching choices. Sensitivity analysis using *Sensemakr* showed that, in all cases, an unobserved confounding variable would need to explain more of the residual variance of both the treatment and outcome than is explained by nine times the strength of an observed benchmark covariate, population size for environmental outcomes and agricultural suitability for social outcomes (robustness values for each outcome in each match are reported in Supplementary Table 12). To demonstrate robustness of our results to arbitrary matching choices, we tested 248 different matching model specifications for environmental outcomes, and 56 for wellbeing outcomes. Across valid matching specifications, between 87% and 100% (average 97%) of ATTs were in the same direction as our results for environmental outcomes where we found a significant effect. For human wellbeing outcomes, 100% of ATTs were in the same direction for months of adequate food and 70% for material wellbeing (Supplementary Figure 7).

Trade-offs between environmental and social outcomes.

Of the 25 individual protected areas which we assessed for all six effectiveness measures (a subset limited to those with surveyed households with 10 km), 68% demonstrated trade-offs between environmental and wellbeing outcomes (12 of the 17 protected areas that experienced trade-offs had positive environmental performance at the cost of social wellbeing); 20% experienced win-win outcomes, and 12% experienced lose-lose outcomes (Fig. 4a). We report estimated ATTs for individual protected areas for each outcome variable after rebalancing covariates at the individual protected area level using linear model weights (Supplementary Tables 13 and 14 and Supplementary Figure 8). For wellbeing outcome ATTs, the treated group comprises Living Standards Measurement Study-sampled households located within 10km of that protected area and is not necessarily representative of protected-area level population estimates. Despite the high proportion of protected areas showing trade-offs, environmental performance was not significantly associated with wellbeing performance. Comparing between individual protected areas, full model-averaged estimates (Supplementary Table 15) indicate improved environmental performance was associated with higher area-adjusted budgets (regression coefficient (β) = 0.54, z = 3.78, p < 0.001), less precipitation (β = -1.33, z = 4.07, p < 0.001) and less agricultural suitability (β = -0.42, z = 2.27, p = 0.02). For social wellbeing performance, full model averaged estimates (Supplementary Table 15) showed no significant associations, the best-supported model included only agricultural suitability and here higher suitability was weakly associated with greater improvements in wellbeing ($\beta = 0.68$, $t = 2.06$, $p = 0.051$; $R^2 = 0.15$).

Stakeholder priorities.

While a large increase in protected area coverage would be required to meet the area coverage component of 30-by-30, this is not a priority for stakeholders in Ethiopia. We asked 37 Ethiopian conservation professionals working in policy, research or practice (Supplementary Table 8) to rank three overarching priorities for Ethiopia's protected area network: (i) expanding the network, (ii) making the existing network more effective, and (iii) carrying out additional research to guide improvements. Most respondents (77%) ranked effectiveness as their top priority, followed by research, with expansion ranked the lowest. Kendall's coefficient of concordance indicated significant agreement between participants' rankings of these priorities ($W = 0.74$, $\chi^2 = 51.6$, $p < 0.001$).

The Ethiopian conservation community recognised issues around protected area effectiveness. The trade-offs found in our analysis align somewhat with stakeholder perceptions of protected area effectiveness which showed variation across different measures of effectiveness. The number of respondents who selected that protected areas are effective at reducing forest loss and conserving grassland were no different to that expected by chance ($\chi^2_1 = 0.03$, adj.p = 0.87 and $\chi^2_1 = 1.06$, adj.p = 0.61 respectively); however significantly more respondents than expected reported that protected areas were not effective at preventing agricultural expansion ($\chi^2_1 = 9.76$, adj.p = 0.009), reducing poverty ($\chi^2_1 = 7.26$, adj.p = 0.02), or improving food security ($\chi^2_1 = 8.00$, adj.p = 0.02).

Weak law enforcement, inadequate community engagement and land use conflict were the three challenges selected most often by respondents as potentially threatening the effectiveness of Ethiopia's protected area network. These were selected 22, 19 and 15 times respectively. In concordance with this, the three actions for improving effectiveness selected most were strengthening policy and law enforcement, strengthening community engagement and enhancing partnerships and collaborations; selected 26, 26 and 20 times respectively.

Discussion

International biodiversity targets advocate for dramatic expansion of protected areas[2]. Yet, the sustainability, effectiveness and social acceptance of protected area expansion depends on how much expansion occurs, where it happens, and how environmental benefits trade-off with social wellbeing impacts. Our study provides one of the most comprehensive assessments of a highly biodiverse country's progress towards 30-by-30, identifying where expansion would be needed to meet the target, and the real-world, context-specific impacts of the existing protected area network.

Given the magnitude of socioeconomic and environmental challenges Ethiopia has faced, and the limited resources available in their conservation sector[62], the success we report of Ethiopia's protected area network in terms of ecoregion and species representativeness and avoided land-use change is impressive. However, our quasi-experimental analysis provides compelling evidence that Ethiopia's protected areas are resulting in substantial local trade-offs. While protected areas consistently reduce environmental degradation, they are associated with significantly worse food security and material wellbeing changes among nearby communities (Fig. 3). Only a small subset of Ethiopian protected areas delivered 'win-win' outcomes (Fig. 4), often in places where local livelihoods were compatible with conservation (Supplementary Text 1). These findings make an important contribution to ongoing debates about the extent to which protected areas can be expected to deliver 'win-wins' in terms of positive impacts on both environmental and social wellbeing outcomes[6,11,29,31,33,34,39] and provide grounded evidence needed to inform protected area management or expansion decisions.

Ethiopia faces the challenge of meeting ambitious conservation targets while substantial proportions of its population experiences undernourishment and multidimensional poverty[53,63]. In such settings, agricultural development is justifiably a top policy priority[64,65] which can conflict with conservation goals[66]. For example, while Ethiopia's protected areas successfully limit agricultural expansion within their boundaries (a conservation gain), without increases in agricultural productivity[67], this same restriction can exacerbate local food insecurity. With Ethiopia's population size projected to nearly double from 119 million in 2020 to 225 million people by 2050[68], and 30-by-30 requiring more than tripling of their current protected area estate – managing these tensions is central to the future of conservation in Ethiopia. Balancing conservation with the urgent needs of a growing and largely agrarian population[69], will require a shift towards sustainable intensification: producing more food on less land without undermining the resilience of production systems[70,71].This challenge is not unique to Ethiopia: protected areas conflict with agricultural and grazing land in many parts of the world[72,73].

Expanding protected areas to pursue ecological representativeness may exacerbate trade-offs between environmental and social wellbeing outcomes. Ethiopia's underrepresented ecoregions (Fig. 2) are located in areas facing higher human pressures (Supplementary Results 2). For example, the Ethiopian montane grasslands and woodlands represents one of the most agriculturally productive areas in Ethiopia[74], and the Somali Acacia–Commiphora bushlands and thickets is among one of the most food insecure areas[75]. Expanding protected areas in these regions would likely incur high local opportunity costs, compounding existing livelihood challenges and trade-offs[10,76]. Consistent with this, we find that environmental outcomes of protected areas are worse in wetter and more agriculturally suitable areas where agricultural expansion and timber extraction likely produce better returns[77], while wellbeing outcomes are marginally better where agricultural suitability is greater. While economic transformation and urbanisation may reduce dependence on land-based livelihoods and help ease conservation-livelihood tension over time, future progress towards a more representative network will require careful spatial planning, using multi-objective spatial conservation prioritization tools to identify locations that help to deliver conservation goals at least cost to people[78,79]. Protected areas have often been established in areas with low opportunity costs[8,80], meaning that many countries – particularly lower-income countries[81] – are likely to face similar challenges when considering ecologically representative protected area expansion.

Chronic underfunding and capacity shortfalls in protected areas around the world[82] makes it difficult to see how dramatic protected area expansion can be achieved in ways which deliver effective conservation without undermining local wellbeing. While we find that higher area-adjusted budgets are associated with improved environmental outcomes, they show no detectable relationship with wellbeing performance. This is consistent with evidence that protected area funding and management capacity (e.g., enforcement and habitat management) underpin ecological effectiveness[83], but that insufficient resources are being allocated to strategies that support livelihood improvements for surrounding communities[11,32,84]. Avoiding negative social impacts of protected areas will require additional, targeted social investments that go beyond core protected area budgets[39]. The Ethiopian protected area network is already severely underfunded[62]. In this context, prioritising improvements to the existing network over expansion (as suggested by Ethiopian stakeholders) is sensible[85]. Realising the full potential of Ethiopia's protected area network, will require greater capacity to work with local communities — both to reduce negative livelihood impacts and to unlock the broader opportunities and benefits that conservation can bring[32,34]. Without coordinated action across sectors and stakeholders[66,78,86], more funding, and improved local community involvement, delivering both biodiversity conservation and development goals risks being impossible[71,87,88].

There are important caveats to our estimates of the impacts of Ethiopia's protected areas. While Ethiopia's protected areas were established over a long period, we use the year 2000 as the baseline in our quasi-experimental study design. This is because the year 2000 marks a major turning point, or 'reset' in Ethiopia's political and conservation landscape (Extended Data Fig. 1). Using this baseline allows us to evaluate contemporary protected area performance by aligning the analysis with the governance, budgeting and reporting context under which conservation decisions are currently made, rather than conflating our analysis when conservation operated under a very different political context. This design also allows us to use higher quality time-variant covariates measured in 2000. Our estimates therefore rely on the assumption that, conditional on the matched covariates, treated and control units would have followed similar trajectories in the absence of protection. Violation of this assumption could bias estimates; however, sensitivity analyses indicate that an unobserved confounder would need to be substantially stronger than the most influential observed covariates to overturn our conclusions. Alternative quasi-experimental approaches[89] could potentially strengthen internal validity but would substantially restrict the scope for inference. For example, a difference-in-differences design would require protected areas established after 2000 accounting for only around one quarter of Ethiopia's protected areas. Restricting the analysis to this subset would not only reduce the sample size but would focus on newer, often smaller protected areas that are unlikely to be representative of the national system. Such an approach would therefore shift the estimand away from the performance of Ethiopia's protected area network as currently implemented, which is central to national planning under the Global Biodiversity Framework. Given Ethiopia's need to balance conservation targets with development priorities at the national scale, we therefore retain a system-wide assessment while transparently acknowledging and empirically testing the assumptions required by the matching design. Finally, our outcomes – land cover change, food security and material wellbeing – reflect where Ethiopia has reliable longitudinal data. As a result, species dynamics and ecosystem-service flows, which may provide broader scale benefits, are not measured directly. We also note timing mismatches between environmental (2000–2020/21) and wellbeing (2011–2016) outcomes. Although the shorter wellbeing timeframe may miss longer-run effects, it uses the longest household panel available which allows us to track the same households over time, reduces bias from migration, and keeps both outcome sets within the same post-2000 policy regime. These design choices reflect data realities, but provide a transparent, reproducible foundation upon which future work can extend.

Translating global conservation targets, such as the Global Biodiversity Framework's 30-by-30 target, into national realities, presents substantial challenges that must be navigated across a wide variety of contexts and capacities[90,91]. To bridge the global–local divide, conservation must reflect economic and institutional realities, with governments balancing land-use trade-offs through cross-sector collaboration and inclusive, livelihood-aligned spatial planning. Too often the benefits of protected areas are realised at much greater regional or global scales, while the costs are borne locally by vulnerable communities[11,33,35]. Ensuring that conservation contributes to local livelihoods and aligns with national development objectives is therefore essential for transforming global ambitions into actionable, equitable outcomes on the ground.

Materials and Methods

Protected area extent.

We collated all Ethiopian protected areas from the World Database of Protected Areas (WDPA)[92] and then revised these using the most recent information from Ethiopian Wildlife Conservation Authority (EWCA) and cross referenced with IUCN categories. Through this process we added 12 newly gazetted and one missing protected area, and removed 12 degazetted, one duplicated and two which had been amalgamated into other protected areas (the boundaries of which were updated; further details on gazettement years and area changes are provided in Supplementary Table 1). We also exclude from the WDPA database 57 National Forest Priority Areas (NFPAs), which identify areas with important forest resources but do not meet the IUCN definition of a protected area and often have little natural forest remaining[93,94]. Twenty-six of these NFPAs overlap at least partially with gazetted protected areas (Supplementary Figure 1); for these, we retain the overlapping portions to ensure that all legally recognised protected areas are included. Using the revised dataset and associated metadata, we determined the contemporary area under protection, as of September 2024, and document the historic expansion of the protected area network in relation to Ethiopian conservation history and international targets (Extended Data Fig. 1). We also assessed whether newer protected areas have been established in areas of higher human pressure using Spearman's rank correlation (Supplementary Methods 1). For year of establishment, we use the earliest record of the protected area either regionally or nationally, as this more closely reflects when on-the-ground protection began, whereas the designation year in the WDPA often refers to later legal updates or IUCN reclassifications.

Ecological representativeness of Ethiopia's protected area network

We assessed the percentage overlap of the protected area network across ecoregions using the RESOLVE terrestrial ecoregions dataset[61] and compare this to the 30% Global Biodiversity Framework target (for 2030), 17% Aichi target (should have been achieved in 2020), and to the current protected area extent. To highlight ecoregions which are of particular importance to be conserved within Ethiopia, we also identified ecoregions which Dinerstein *et al*. class as '*Nature Imperilled*' and calculate the proportion of their global extent that is found in Ethiopia. We then compare human and land-use pressures across ecoregions relative to their representation in protected areas (Supplementary Methods 2). Representativeness of Ethiopia's protected area network in environmental space, defined as the range of climatic and environmental conditions across the country summarised through a principal component analysis of 19 bioclimatic variables, was also assessed (Supplementary Methods 3).

To assess species representation, we used IUCN Red List range data to calculate the proportion of each species' range covered by protected areas. Birds, mammals and herptiles (amphibians and reptiles) have been widely assessed on the Red List, whereas vascular plants are comparatively under-evaluated[95] and many lack IUCN Red List range data. We therefore created range estimates for assessed plant species that did not have range data on the IUCN Red List, using occurrence records (Supplementary Methods 4). This resulted in range data for 2067 species (785 plants, 767 birds, 274 mammals and 241 herptiles). We determined the average proportion of range protected across taxonomic groups, separately for threatened (N = 294) and non-threatened (N = 1773) species and used Kruskal-Wallis and post-hoc Dunn tests with Bonferroni correction to investigate how protected area coverage varied across taxa and threat status categories. For all critically endangered species assessed (N = 45), we also calculated the proportion of their global extent within Ethiopia, to highlight global priorities for conservation in Ethiopia. The species' ranges were then used to estimate the number of species expected to occur within each of Ethiopia's protected areas.

Effectiveness of Ethiopia's protected area network during the period 2000-2020

Outcomes

Here, we are interested in evaluating the effectiveness of protected area management since 2000 under Ethiopia's current approach to conservation (Extended Data Fig. 1). We examined effectiveness of protected areas for both environmental and social wellbeing outcomes across a suite of six proxy indicators. Environmental outcomes included changes over time in forest (2000-2021), grassland (2000-2020) and agricultural (2000-2019) land cover (Supplementary Table 2; Supplementary Methods 5). These were all measured as the change in percentage land cover using publicly available global remote sensing panel datasets aggregated at 1 km resolution across Ethiopia (time series based on data availability). Sankey diagrams (Supplementary Methods 6) showing overall changes inside and outside protected areas were produced using the MODIS Land Cover dataset [96].

Wellbeing outcomes were changes from 2011-2016 for two indicators of food security: Months of Adequate Household Food Provisioning (months of adequate food) and Household Dietary Diversity Status (dietary diversity), and one indicator of material wellbeing (asset ownership) (Supplementary Tables 2, 3 and 4). Wellbeing outcomes were derived from the Living Standards Measurement Study Ethiopian Socio-economic Survey, a household level panel survey where households were first visited in 2011/2012 and revisited in 2015/2016 with attrition, resulting in 3699 households[97,98]. Measuring change using the panel data reduces bias from people immigrating and emigrating from an area, however it does not fully eliminate bias due to attrition (Supplementary Methods 7).

To ensure we are not measuring changes in outcomes prior to protected area establishment and that included protected areas existed throughout the outcome measurement period, we excluded from the analysis protected areas established after 2000 (63 of 79 protected areas remained in the analysis). National Forest Priority Areas (in the WDPA but not considered protected areas) were also analysed separately for forest cover outcomes (Supplementary Methods 8)

Quasi-experimental design

To estimate a causal effect of protection on the outcomes of interest we need a credible estimate of the counterfactual: what would have happened in areas had they not been designated as protected. Given protected areas are not randomly assigned in a landscape, we use a quasi-experimental matching design (further justification provided in Supplementary Methods 9) which controls for observed confounding variables likely to affect both exposure to the treatment (being protected during the period 2000-2020) and the outcome (the change in each indictor)[89,99]. Focusing the analysis on the post-2000 period, aligns it with the policy context in which decisions are currently made. By assuming that there are no important unobserved confounders we can estimate the treatment effect of protection. We test the sensitivity to the assumption of no hidden confounders [100,101], allowing us to put bounds on our estimate of the treatment effect of protection.

Directed acyclic graphs were used to visually represent and better understand the variables influencing exposure to the treatment and links to the outcomes of interest and therefore to identify confounding variables that should be controlled for to isolate the treatment effect of protected area status (Extended Data Fig. 2). We match on confounders presumed to be time invariant including elevation, slope, precipitation, temperature, agricultural suitability, ethno-linguistic group, and ecoregion (Supplementary Tables 5 and 6). These variables are included specifically to reduce bias due to confounding. We also match on some additional time variant covariates measured in 2000 (after protected area establishment but prior to our outcome measures): access, population, percentage forest cover, percentage grassland cover, percentage agricultural land cover, and majority land over type (Supplementary Tables 5 and 6). These variables were included to improve our estimates by accounting for additional variation in the outcomes. We use the year 2000 as this represents the period following high instability under the Derg regime and the subsequent targeted exploitation of protected areas after its fall, during which there was limited funding for conservation[102] (Extended Data Fig. 1). This period effectively acted as a reset for protected area management in Ethiopia, before the relatively more stable post-2000 period where management has been more aligned with the goals of the Convention on Biodiversity. While the reset should limit the impact of controlling on covariates measured in 2000 on our results, we assume that any impact would be in the direction of underestimating rather than overestimating the true impact of protected areas by blocking potential mechanisms through which protected areas may impact land cover change or human wellbeing[18], further details on these assumptions are provided in Extended

Data Fig. 2. We also test whether our results are driven by this assumption by iteratively excluding these covariates in alternative matching approaches (see '*Sensitivity checks*').

Units of assessment

For environmental outcomes, data for covariates and outcomes were aggregated across each 1 km sampling unit[103]. Treatment units comprised gridcells completely within protected area boundaries and were categorised into two classes: strict (IUCN category *II*) and less strict (Biosphere reserves and IUCN categories *IV* and *VI*). Protected areas in IUCN categories *Ia*, *Ib III* and *V*, and Other Effective area-based Conservation Measures are not present in Ethiopia. We excluded gridcells which intersected a 10 km buffer zone around each protected area to avoid underestimating effects due to local leakage[20,104]. The remaining gridcells outside of both protected areas and buffer zones were classified as potential control units. Using a gridded sampling technique, we checked a range of sampling densities (Supplementary Table 7) to identify the closest distance between gridcells that did not show spatial autocorrelation (2 km between each cell). We then sampled gridcells using a gridded sampling technique which ensured each gridcell was 2 km from another gridcell, and checked for spatial autocorrelation in treatment units using semi-variograms[104].

For wellbeing outcomes, due to household coordinates being randomly offset by 0-2 km to maintain participant confidentiality (Supplementary Methods 10), covariate data were aggregated across a 2 km buffer around each household unit. The sampling unit was individual households, and we compared households living near or within protected areas to those unaffected by protected areas. Households were classified as treatment units if their 2 km buffer overlapped a 10 km buffer zone around a protected area. Households further than 20 km from a protected area were classified as control units, ensuring controls were at least 10 km further from protected areas than treatment units. A map showing the locations of survey enumeration areas is provided in Supplementary Figure 2.

Statistical matching

Assessing the effectiveness of protected areas by comparing them to unprotected areas is likely to produce biased results[19]. Effectiveness assessments that use statistical matching can help to overcome this spatial bias[105] by selecting control units (e.g., unprotected areas) which have similar baseline characteristics to the units experiencing treatment (e.g., protected areas)[89,106]. Following Schleicher et al. (2020) we iteratively tested several matching methods and compared the resulting match quality before the deciding upon the main matching specification using the R package *MatchIt*[107]. The modelling choices included variations of propensity score nearest neighbour matching and Mahalanobis distance matching with and without calipers and replacement. All models tested used exact matching for categorical covariates (ecoregion and majority land cover type). The quality of matches were compared to determine the best matching approach based on the proportion of treated units that were matched and the covariate balance achieved (using a threshold standardised mean difference of 0.25[104,108]). Love plots showing the balance achieved across covariates (as the standardised mean difference between treatment and control samples) for each matching model choice tested are shown in Supplementary Figure 3. The best match for environmental outcomes for strict treatment samples was nearest neighbour propensity score matching with 0.5 standard deviation calipers and replacement which retained 93% of treatment units and a maximum standardised mean difference of 0.16. For less strict, the best match was Mahalanobis distance matching without replacement which retained 98% of treated units and a maximum standardised mean difference of 0.13. For household outcomes the best match was nearest neighbour propensity score matching with 1 standard deviation calipers without replacement, this retained 75% of treatment units and a maximum standardised mean difference of 0.11. Comparisons of pre- and post-match boxplots demonstrate the reduced variance of covariates between treatment and control units achieved through matching (Supplementary Figure 4).

Treatment effect

Using the three matched datasets (strict protected areas, less strict protected areas, and households across all protected areas), we estimate the Average Treatment Effect on the Treated (ATT) for each outcome using a covariate-adjusted regression model. This represents the average difference in the change in each outcome between matched treated and control units, after adjusting for covariates. By combining both matching and regression adjustment, we obtain more accurate and robust estimates than either matching or regression alone[109]. We applied weights from the matching procedure and clustered by subclass according to the matched data structure to calculate robust standard errors[110]. Statistical significance was determined using two-sided Wald z-tests of the treatment coefficient. For all outcome variables (except change in agricultural land) a positive ATT would indicate that protected areas are performing better than matched controls. We converted ATTs into relative percentage changes by dividing each ATT by the mean change in the control group, to report the proportional effect of protection relative to expected land cover change in the absence of protection. Finally, for environmental outcomes, we estimated the total area of avoided loss attributable to protection by multiplying the ATT by the total treated area. Likewise, to estimate the aggregate social effect of protected areas on local communities we multiplied the ATT for social outcomes by the estimated total number of households living within 10 km of a protected area in 2011 (calculated using gridded population estimates and the average household size of surveyed households, see Supplementary Methods 11).

Sensitivity checks

The sensitivity of the results to hidden bias due to the presence of unobserved confounding variables was assessed[101] with the R package *Sensemakr*[111]. This approach identifies the proportion of residual variance of both the treatment and the outcome that would need to be explained by an unobserved confounder to nullify the treatment effect, and compares this to the strength of a benchmark observed covariate[100].

To provide further validation, we compared our estimate of the ATT to results from 248 alternative model specifications for strict and less strict matching, and 56 for household matching[112,113] to confirm whether they are robust to arbitrary modelling choices. Comparison models differed in the combination of covariates used keeping all time invariant confounders and cycling though different combinations of the covariates measured in 2000, the distance measure (Propensity Score Matching or Mahalanobis), caliper sizes (0.25, 0.5 or 1 standard deviation), and whether replacement was allowed or not.

Identifying trade-offs between environmental and human wellbeing outcomes.

Treatment units for individual protected areas were extracted from the matched datasets and covariates were rebalanced against the control units using linear model weights using the R package *lmw*[114]. This weights the data to achieve approximate balance between covariates across treatment and control units, using a uniform risk increase weighting method. Weighted outcome models were estimated using the lmw_est() function and ATTs were calculated for individual protected areas as the difference in the weighted means for each outcome variable between treatment and control groups.

To evaluate the trade-offs between environmental and wellbeing outcomes, we set non-significant ATTs to zero and scaled significant ATTs for each outcome variable, with negative values indicating that protected areas performed worse than their matched controls and positive values indicating that protected areas performed better (the ATTs for agricultural land change were inverted to aid interpretation). The scaled values for the three environmental variables and three wellbeing variables were then summed to produce single environmental performance and wellbeing performance value, and we identify which protected areas perform worse than the counterfactual for both environmental and wellbeing outcomes (lose-lose), experience trade-offs (win-lose), or perform better for both (win-win).

We assessed correlates of variation in protected area performance using data on main ecoregions, management strictness, non-governmental organisation involvement (Supplementary Table 8) as well as average temperature, precipitation, elevation, agricultural suitability, agricultural land cover, accessibility (data sources in Supplementary Table 5) and area-adjusted budgets. Protected area budget data (Figure 4B) was obtained from the Ethiopian Wildlife Conservation Authority as average annual budgets (in USD adjusted to 2014 inflation levels). To account for non-linear scaling of costs across protected area sizes[115,116], we modelled budget as a function of area and used the residuals as an area-adjusted measure of financial input. Continuous predictors were standardised, and variables with high multicollinearity (variance inflation factor > 5) were excluded. We then modelled both environmental and wellbeing performance outcomes separately to maintain as much data as possible (as fewer protected areas were assessed for wellbeing outcomes, due to not all protected areas having households surveyed in the Living Standards Measurement Survey). For each outcome, we fitted linear mixed-effects models with ecoregion as a random intercept and compared them to fixed-effects models using Akaike Information Criterion (AIC) and likelihood ratio tests. Using the better fitted base model, we then performed model selection and averaging with the package *MuMIn*[117], ranking models by AIC and averaging across all models with AIC < 2. Residuals were examined for normality and homoscedasticity. Analyses examining correlates of variation in protected area performance are intended as exploratory, as ATT estimates are themselves subject to uncertainty that is not fully propagated into second-stage models.

Understanding priorities of Ethiopian conservation practitioners.

We surveyed Ethiopian conservation researchers, practitioners and policy makers on the priorities and challenges in making progress towards 30-by-30, as well as their perceptions of protected area effectiveness (Supplementary Methods 12; Approved by the University of Kent Conservation Ethics Committee: Ethics ID 20251741251220900). We specifically targeted those working directly or indirectly in protected area policy, management or research using a purposive, opportunistic, snowball sampling approach[118]. Participation was voluntary and informed consent was obtained from all respondents prior to data collection. We obtained 37 responses from stakeholders representing non-governmental organisations, private companies and research institutes/universities, with the majority in governmental bodies. The largest proportion of respondents were aged 31-40 (41%), male (86%) and educated to Masters level (57%) (Supplementary Table 9). These characteristics reflect the demographic and professional composition of the sampled conservation practitioner community rather than the general population. We used Kendall's coefficient of concordance, using the R package *irr*[119], to assess levels of rank-order agreement for prioritising overarching goals for Ethiopia's protected area network; and chi-squared tests (with Holm-Bonferroni correction) to determine overall perceptions of success for each measure of effectiveness .All analyses were conducted in R version 4.2.1.

Data availability

Updated protected area shapefiles are available https://github.com/SCJago/protected_area_performance/tree/main/data. Protected area budget data is available in categorical format in Supplementary Table 9, continuous numerical budget data requests should be directed to the Ethiopian Wildlife Conservation Authority. Species' range data is available for download from the IUCN Red List, either via a manual search (https://www.iucnredlist.org/search) or through the spatial database (https://www.iucnredlist.org/resources/spatial-data-download). Point data for plant species without IUCN Red List ranges can also be obtained from the same sources. Occurrence data for Ethiopia's endemic plant species is stored in the "Endemic Plants of Ethiopia" database on RBG Kew BRAHMS Online. BRAHMS data requests should be directed to the relevant contact listed on this webpage: https://brahmsonline.kew.org/kewbol/Websites. All open source datasets used are referenced in the article or supporting information.

Code availability

Code used in this manuscript available at: https://github.com/SCJago/protected_area_performance/tree/main/scripts

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Author contributions statement

S.J., G.G., W.A., and J.S.B designed the research; S.J led formal analysis, data visualisation and wrote the original draft; G.G. and T.G. contributed to data curation; G.G., W.A., K.W. and F.R. contributed to project administration; S.J., J.D.M.W., E.L., A.N.R., J.P.G.J., R.J.S contributed to conceptualisation and methodology and provided advice on results; B.G., and J.L. contributed to formal analysis; G.G. and S.D. contributed to stakeholder engagement; B.G. provided translations; G.G., B.G., J.L., E.L., J.D.M.W., A.N.R., K.W., F.R., S.D., F.W., W.A., J.P.G.J., R.J.S. and J.S.B provided feedback on the draft and assisted in interpreting the results; J.S.B and R.J.S provided supervision.

Competing interests statement

The authors declare no competing interests.

Figures

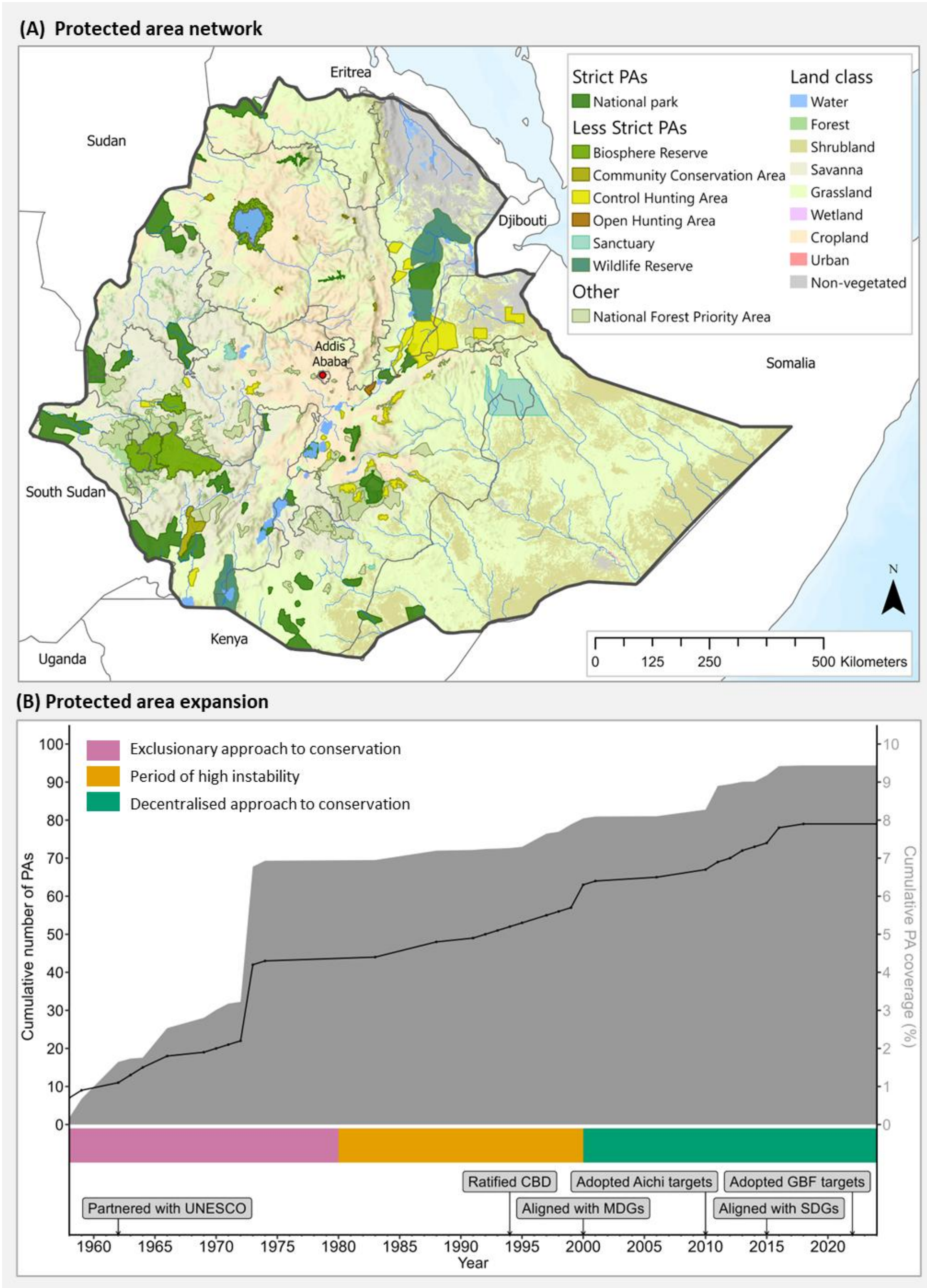
(A) Protected area network
Eritrea
Sudan
Djibouti
Somalia
South Sudan
Kenya
Uganda
Addis Ababa
Strict PAs
National park
Less Strict PAs
Biosphere Reserve
Community Conservation Area
Control Hunting Area
Open Hunting Area
Sanctuary
Wildlife Reserve
Other
National Forest Priority Area
Land class
Water
Forest
Shrubland
Savanna
Grassland
Wetland
Cropland
Urban
Non-vegetated
N
0 125 250 500 Kilometers
(B) Protected area expansion
Exclusionary approach to conservation
Period of high instability
Decentralised approach to conservation
Cumulative number of PAs
Cumulative PA coverage (%)
Year
Partnered with UNESCO
Ratified CBD
Aligned with MDGs
Adopted Aichi targets
Aligned with SDGs
Adopted GBF targets

Fig. 1 Ethiopia's protected area network. (A) Map of Ethiopia's protected areas indicating the distribution of strict (IUCN category II) and less strict (IUCN categories IV and VI) protected areas (as of September 2024), coloured by their national designations, overlayed onto a reclassified MODIS V6 landcover map showing hill shade. (B) The expansion in the number of protected areas and the percentage land coverage of protected areas over time under different overarching approaches to conservation, while highlighting major conservation events that have occurred over the timeline. These include Ethiopia's engagement with international institutions and frameworks, such as UNESCO (the United Nations agency responsible for promoting education, science and cultural heritage conservation) and the Convention on Biological Diversity (CBD), which Ethiopia ratified and subsequently adopted the global biodiversity targets under it including the Aichi Biodiversity Targets and the Global Biodiversity Framework (GBF), as well as alignment with broader global development agendas such as the Millenium Development Goals (MDGs) and Sustainable Development Goals (SDGs). Further information on these time periods is available in Extended Data Fig. 1.

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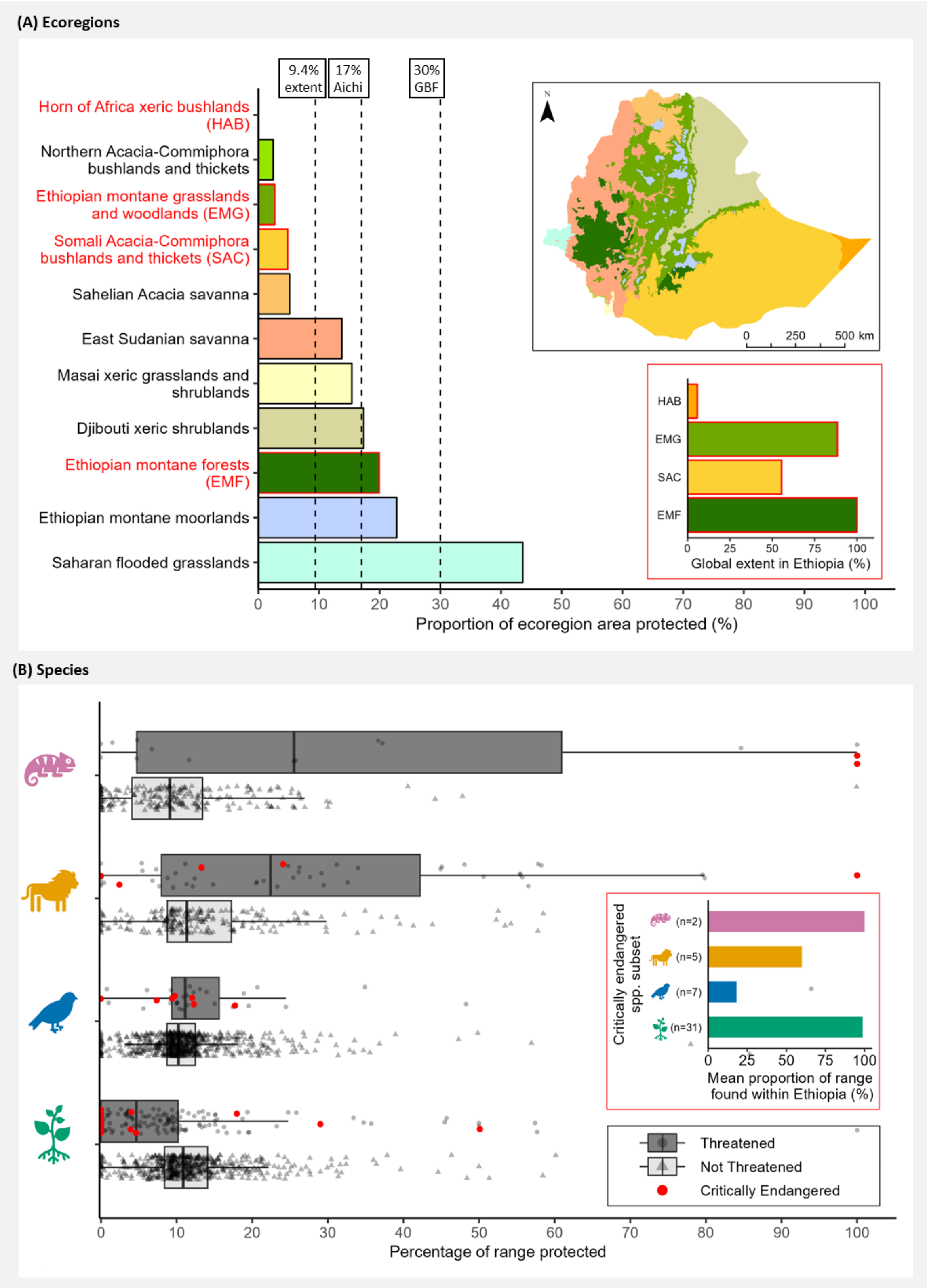


(A) Ecoregions
9.4% extent
17% Aichi
30% GBF
Horn of Africa xeric bushlands (HAB)
Northern Acacia-Commiphora bushlands and thickets
Ethiopian montane grasslands and woodlands (EMG)
Somali Acacia-Commiphora bushlands and thickets (SAC)
Sahelian Acacia savanna
East Sudanian savanna
Masai xeric grasslands and shrublands
Djibouti xeric shrublands
Ethiopian montane forests (EMF)
Ethiopian montane moorlands
Saharan flooded grasslands
0 10 20 30 40 50 60 70 80 90 100
Proportion of ecoregion area protected (%)
N
0 250 500 km
HAB
EMG
SAC
EMF
0 25 50 75 100
Global extent in Ethiopia (%)
(B) Species
Critically endangered spp. subset
(n=2)
(n=5)
(n=7)
(n=31)
0 25 50 75 100
Mean proportion of range found within Ethiopia (%)
Threatened
Not Threatened
Critically Endangered
0 10 20 30 40 50 60 70 80 90 100
Percentage of range protected

Fig 2. Representativeness of Ethiopia's protected area network. (A) Percentage of each ecoregion that is protected with dashed lines indicating the current total proportion of Ethiopia's land area protected (9.4%), the 17% Aichi 2020 target and the 30% GBF 2030 target. Terrestrial ecoregions in red are classed as "*Nature Imperilled"* by Dinerstein et al.[61] and the inset graph indicates the proportion of these ecoregions that are found in Ethiopia. (B) Percentage of range protected for each species, with the spread of this grouped for herptiles (n = 241), mammals (n = 274), birds (n = 767) and plants (n = 785) and separated for threatened (circles; n = 294) and non-threatened species (triangles; n = 1773). Boxplots show the median (centre line), the interquartile range (box bounds: 25th–75th percentiles), and whiskers extending to 1.5 × interquartile range. Critically endangered species are shown in red and the inset graph indicates the average proportion of their ranges that are found in Ethiopia

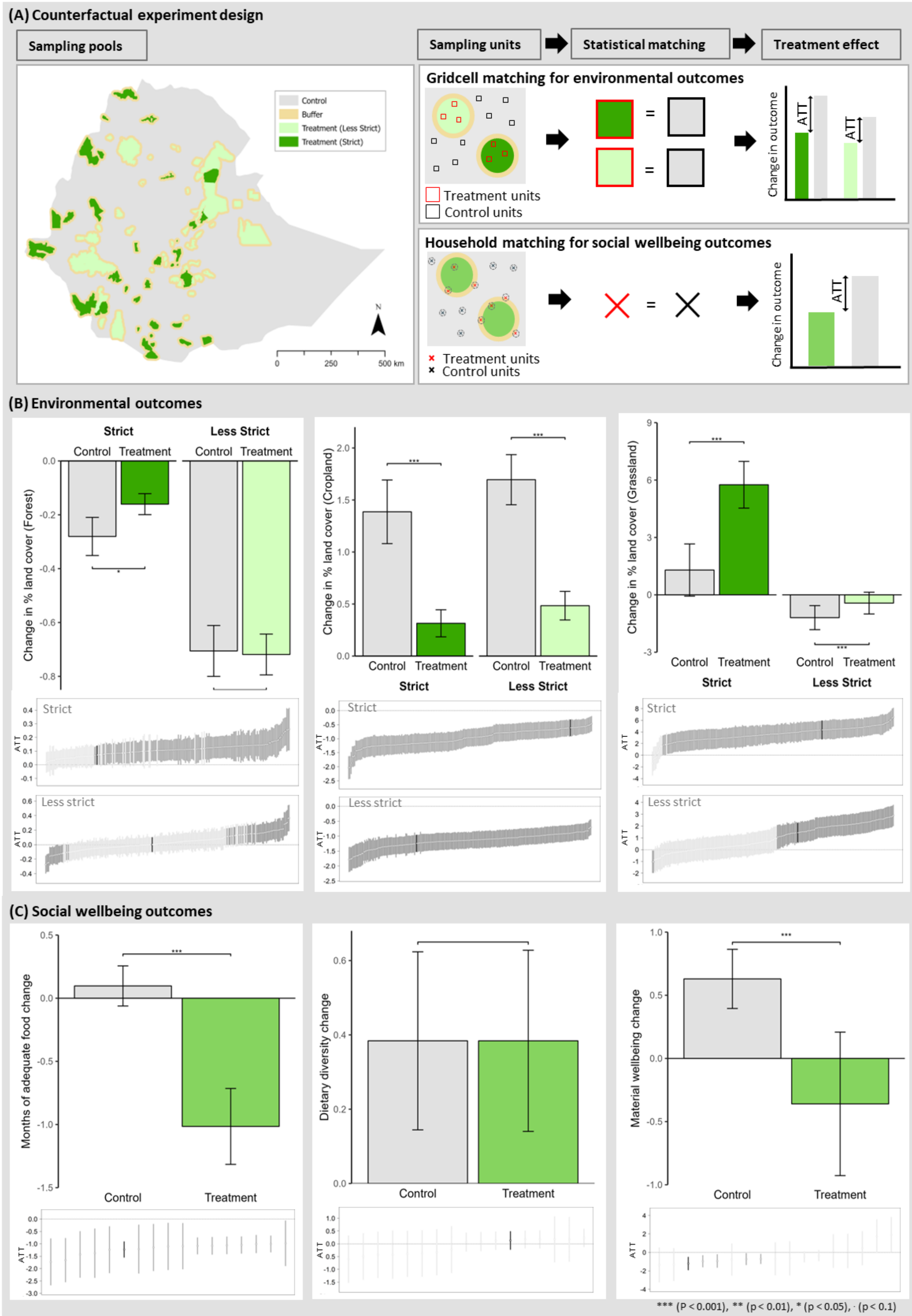

(A) Counterfactual experiment design
Sampling pools
Sampling units
Statistical matching
Treatment effect
Control
Buffer
Treatment (Less Strict)
Treatment (Strict)
N
0
250
500 km
Gridcell matching for environmental outcomes
Treatment units
Control units
ATT
Change in outcome
Household matching for social wellbeing outcomes
Treatment units
Control units
(B) Environmental outcomes
Strict
Less Strict
Control
Treatment
Change in % land cover (Forest)
Change in % land cover (Cropland)
Change in % land cover (Grassland)
Strict
Less strict
ATT
(C) Social wellbeing outcomes
Months of adequate food change
Dietary diversity change
Material wellbeing change
Control
Treatment
ATT
*** (P < 0.001), ** (p < 0.01), * (p < 0.05), · (p < 0.1)

Fig. 3 Effectiveness of Ethiopia's protected area network. (A) Summarises the counterfactual experiment design. Average changes for each effectiveness measure for treatments and controls are shown in barcharts in (B) for environmental outcomes separately across statistically matched gridcell samples for strict (n = 4702; 2639 treated and 2063 control units) and less strict (n = 8908; 4454 treated and 4454 control units) protected area matches and (C) for social wellbeing outcomes across statistically matched households (n = 802; 401 treated and 401 control units). Bars represent mean change in each outcome and error bars indicate a 95% confidence interval calculated across all matched units. Average Treatment Effect on the Treated (ATT) were estimated using covariate-adjusted linear regression on the matched samples, incorporating matching weights and subclass-clustered robust standard errors. Statistical significance of treatment–control differences was assessed using two-sided Wald z-tests of the treatment coefficient. For strict protected areas forest cover change, ATT = 0.071 (95% CI: 0.003–0.138), z = 2.04, p = 0.041; other significant effects had p < 0.001. ATTs for each effectiveness measure were then compared to results from 248 different matching specifications for environmental outcomes and 56 for social outcomes, with the main matching approach highlighted in black, other significant results in dark grey and non-significant results in light grey, and error bars showing standard error for the ATE, only models which produced a valid match where the maximum standardised mean difference for covariates was below the 0.25 threshold, and at least 75% of treatment cells were kept. Larger versions of these showing model choices made are available in Supplementary Figure 7.

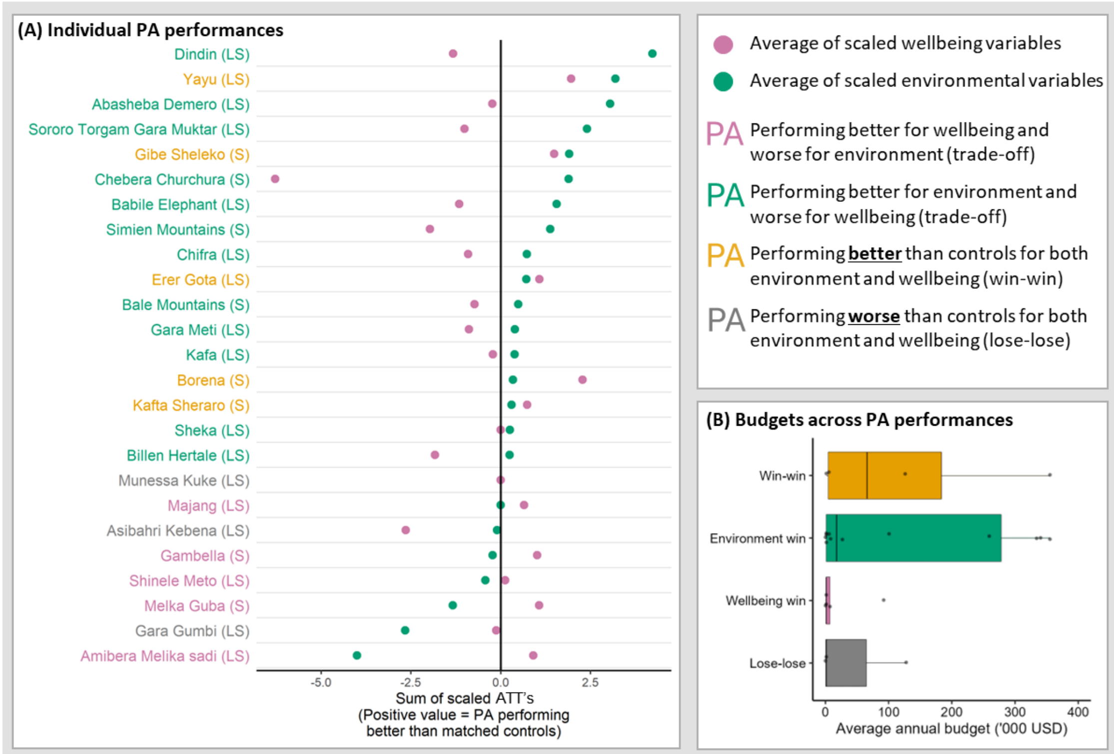
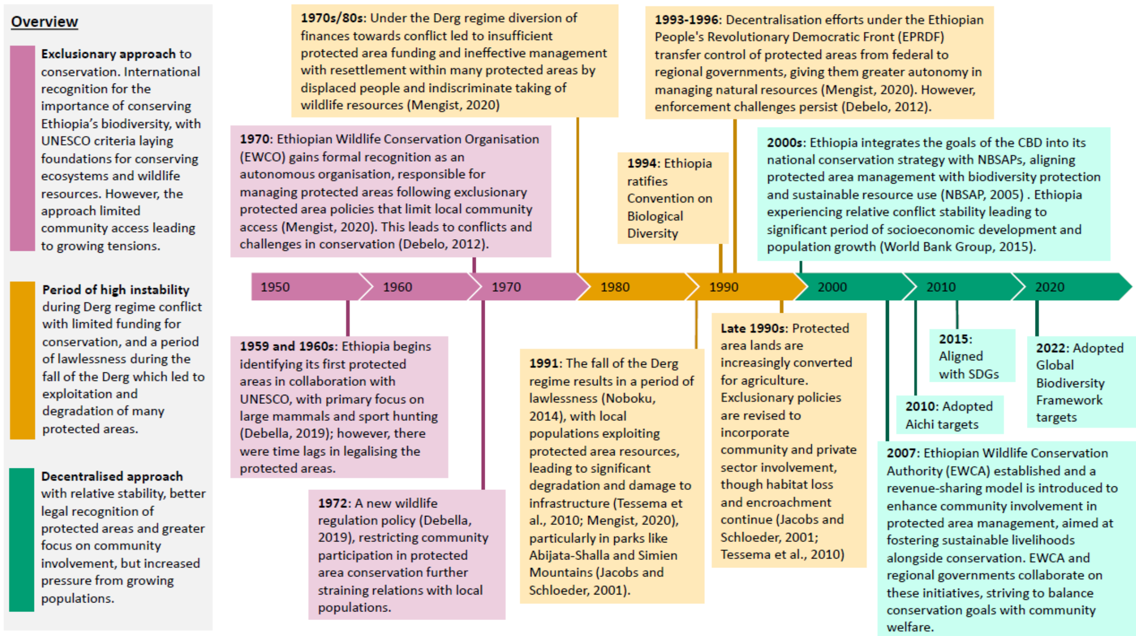
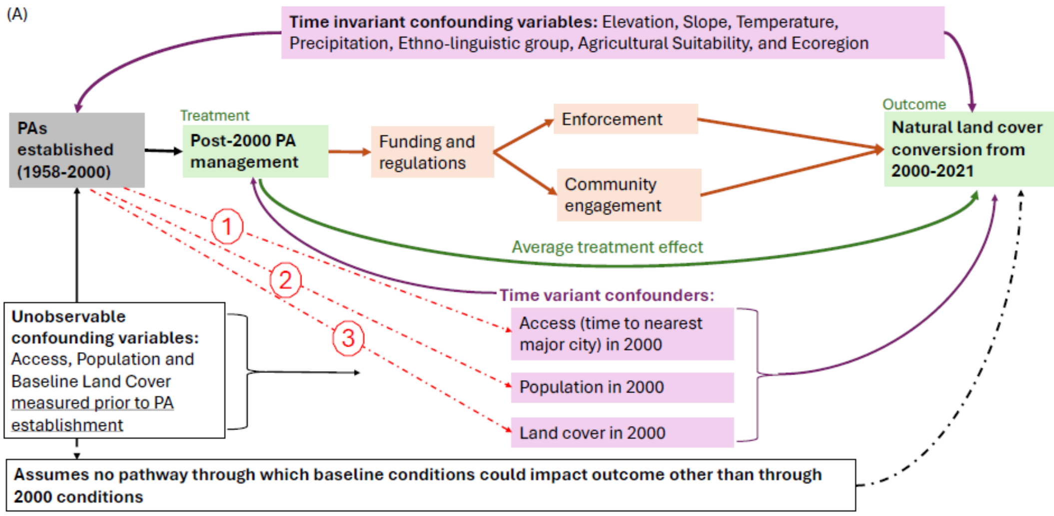


Fig. 4 Trade-offs between biodiversity and poverty across Ethiopia's protected areas. (A) displays the sum of the Average Treatment Effect on the Treated (ATT) for each protected area across all wellbeing related variables (pink) and environmental variables (green). Prior to summing each, any non-significant ATTs were set to 0, the ATTs were then divided by the number of years over which they were measured, scaled and transformed such that a positive value indicates better performance than the counterfactual. Protected area names are coloured according to whether they are performing better for biodiversity (green; n = 12) or poverty (pink; n = 5), those performing better than the counterfactual for both poverty and biodiversity, i.e. win-win outcomes (orange, n = 5) and those performing worse than the counterfactual for both, i.e. lose-lose (grey; n = 3) and brackets after each protected area name indicate if the protected area is strict (S) or less strict (LS). (B) shows spread of average annual budgets, in USD scaled to 2014 inflation rates, allocated to protected areas performing at different levels. Only protected areas assessed for both environment and wellbeing outcomes are included here. Boxplots show the median (centre line), the interquartile range (box bounds: 25th–75th percentiles), and whiskers extending to 1.5 × interquartile range.



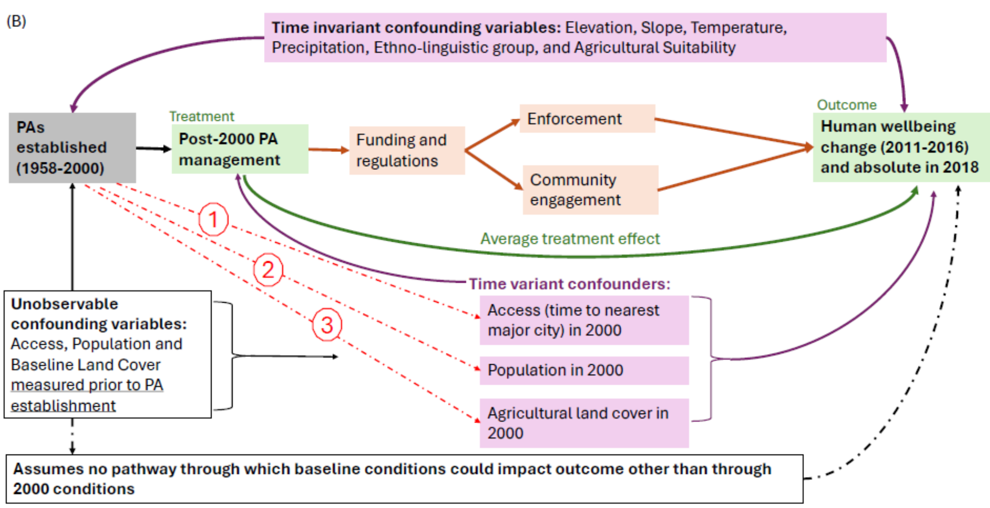
Extended Data Fig. 1 A review of history of conservation in Ethiopia. Ethiopia has been formally establishing protected areas since 1958. Since then, there has been three overarching time periods with different conservation management approaches due to changing national priorities [102,120–122]. From the 1950s to the late 1970s Ethiopia had an exclusionary approach to conservation, limiting community access. From the 1980s to the early 2000s there was a period of high instability with limited funding for conservation during the Derg regime, where protected areas are thought to have been largely ineffective. Since 2000, Ethiopia developed a decentralised approach with better legal recognition of protected areas and greater focus on community involvement, aligning protected area management with sustainable resource use.



1. Earlier PAs expected to limit improvements to access and therefore limit potential for land cover conversion, so when matching with controls that have similar access in 2000, we are comparing to areas less likely to undergo improvements to access so underestimate the impact of PAs by eliminating any effect PAs have on land cover conversion through access as a mediator prior to the year 2000.

2. Earlier PAs expected to limit population growth and therefore limit potential for land cover conversion, so when matching with controls that have similar population size in 2000, we are comparing to areas less likely to undergo increases in population size so underestimate the impact of PAs by eliminating any effect PAs have on land cover conversion through population as a mediator prior to the year 2000.

3. Earlier PAs expected to reduce land cover conversion, so when matching with controls that have similar land cover in 2000, we are comparing to areas less likely to undergo changes in land cover so underestimate the impact of PAs.

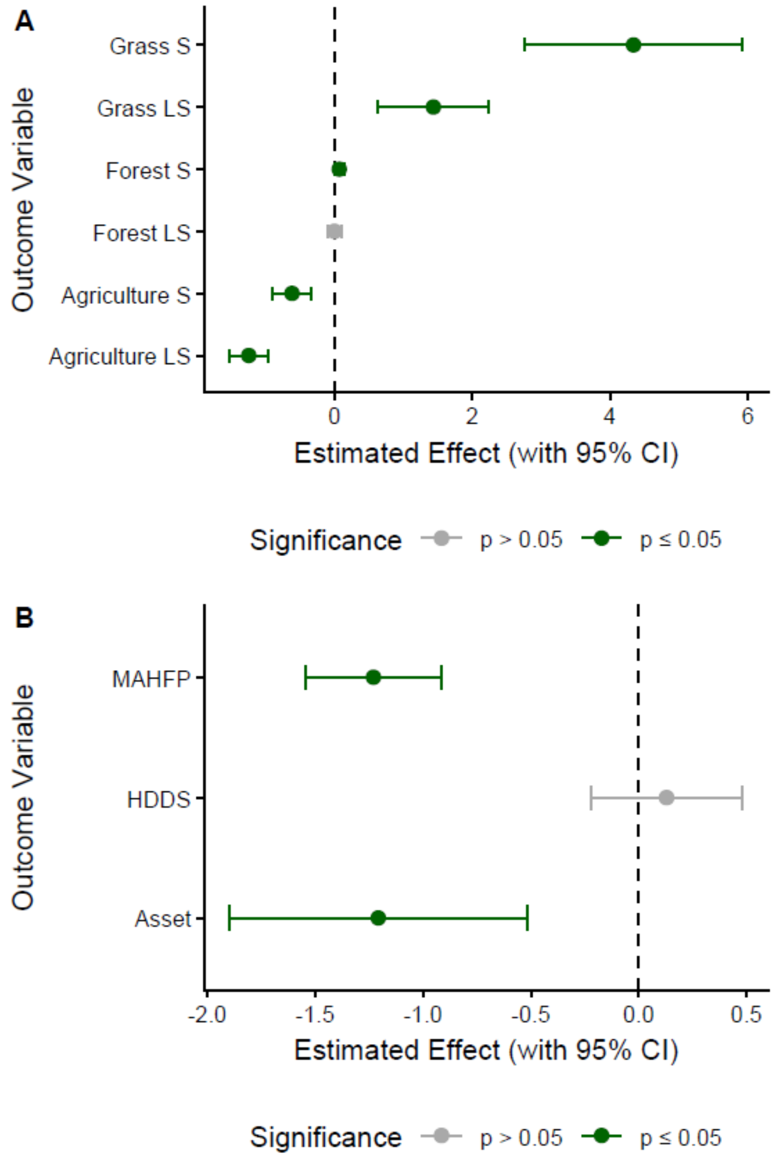


1. Earlier PAs expected to limit improvements to access and therefore limit potential for wellbeing improvements, so when matching with controls that have similar access in 2000, we are comparing to areas less likely to undergo improvements to access so underestimate the potential negative impact of PAs by eliminating any effect PAs have wellbeing through access as a mediator prior to the year 2000.

2. Earlier PAs expected to limit population growth and therefore limit potential for wellbeing improvements, so when matching with controls that have similar population size in 2000, we are comparing to areas less likely to undergo increases in population size so underestimate the potential negative impact of PAs by eliminating any effect PAs have on wellbeing through population as a mediator prior to the year 2000.

3. Earlier PAs expected to reduce agricultural land cover expansion, so when matching with controls that have similar agricultural land cover in 2000, we are comparing to areas less likely to undergo increases in agriculture in land cover so underestimate the potential negative impact of PAs.

Extended Data Fig. 2 Directed acyclic graphs for the quasi-experimental design. Directed acyclic graphs show the confounding variables controlled for and assumptions made in determining the average treatment effect on the treated for (A) environmental and (B) wellbeing outcomes of protected areas. We use both confounding variables considered to be time invariant and some time variant confounders measured in the year 2000. We use the year 2000 as this represents the time immediately after the period of instability, which we assume acted as a reset for protected areas due to these areas being targeted for exploitation of resources during the Derg regime conflict (Extended Data Fig. 1). While the reset should limit the impact of controlling on covariates in 2000 on our results, we assume that any impact would be in the direction of underestimating rather than overestimating the true impact of protected areas by blocking potential mechanisms through which protected areas may impact land cover change or human wellbeing. This design assumes no hidden confounding variables, we test the assumption of no hidden confounders, allowing us to put bounds on our estimate of the treatment effect of protection.



Extended data Fig. 3 Average Treatment Effects on the Treated (ATT) across Ethiopia's protected area network calculated using a covariate adjusted regression model on the matched samples, incorporating matching weights and subclass-clustered robust standard errors for (A) environmental outcomes separated into strict (S) and less strict (LS) protected areas, and (B) social wellbeing outcomes. For all outcomes except agricultural land cover change, as positive effect indicates the protected areas are performing better than matched controls. Statistical significance of treatment–control differences was assessed using two-sided Wald z-tests of the treatment coefficient. For strict protected areas forest cover change, ATT = 0.071 (95% CI: 0.003–0.138), z = 2.04, p = 0.041; other significant effects had $p < 0.001$.

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Supplementary methods

Supplementary Methods 1 Assessing whether newer protected areas were established in areas of higher human pressure

The protected area network was divided into 1km gridcells and sampled such that we maintained 10% of the gridcells in each protected area and these were a minimum of 2km apart. We then extracted variables assumed to indicate human pressure including population[1], agricultural land cover[2], accessibility[3], and elevation[4]. We used the year 2000 for time variant variables to avoid confounding the results by population growth or development over time. Relationships between protected area year of establishment and each human pressure variable were assed using Spearman's rank correlation. Correlation coefficients and associated p-values were reported to indicate the strength and significance of relationships.

Supplementary Methods 2 Assessing whether expanding protection into underrepresented ecoregions would result in greater human and land-use pressures

We classified each ecoregion as either under-represented or over-represented based whether the proportion of its extent within protected areas was below or above 9.4%, respectively (9.4% represents current protected area land coverage in Ethiopia. We then sampled 250 points within each group and the number of points allocated to each ecoregion was proportional to ecoregion area multiplied by its deviation from the 9.4% benchmark. At each sampled point, we extracted variables indicative of potential pressures including population[1], agricultural land cover[2], agricultural suitability, accessibility[3], and elevation[4]. To compare the groups while respecting the spatial structure, we used blocked permutation test using the R package *coin*, which repeatedly shuffles group labels while preserving local spatial structure to generate a null distribution. We used 999 permutations and report two-sided p-values with Benjamini–Hochberg FDR correction.

Supplementary Methods 3 Representativeness of Ethiopia's protected area network in multidimensional environmental space

A principal component analysis (PCA) was performed on 19 environmental variables from CHELSA Bioclim [5] to plot 100,000 random points sampled from across Ethiopia into the environmental space defined by these variables. Additionally, we sampled 9400 random points from within Ethiopia's protected area boundaries. Sample sizes were proportional to the extent of Ethiopia's protected area network. The protected area points were projected into multidimensional space using the *predict* function and overlaid onto the PCA plot to visualise the distribution of protection across Ethiopia's environmental space. Using the R package *alphahull*, we then delineated flexible boundaries around the plotted points. Multiple values of alpha were visually inspected to find the best compromise between overfitting and underfitting. We set the alpha of both the background and protected area network's environmental space to 0.3 and calculated the area of each's hull. The percentage of Ethiopia's environmental space represented within the protected area network was then calculated. Variable loadings of the first and second principal components are reported in Supplementary Figures S5C and S5D, respectively. The coordinates of the points where then plotted in geographical space to identify the locations containing underrepresented environmental conditions.

Supplementary Methods 4 Generating plant species ranges

Using occurrence records from the IUCN Red List and the Royal Botanic Gardens Kew's Botanical Research And Herbarium Management System [6] database, we created range estimates for plant species that did not have range data on the IUCN Red List. For species with three or more occurrence records, we used the subLocRapoport function from the rCAT package to generate ranges and used the default buffer width (mean branch length of the Euclidean Minimum spanning tree). For species with 1 or 2 occurrence records, we manually assigned a 5 km buffer to each point.

Supplementary Methods 5 Understanding grassland changes

Using the statistically matched units (1km gridcells), we produced sankey diagrams highlighting what land cover grassland had changed from or to. Units where grassland remained grassland or where changes did not involve grassland were excluded from the diagrams. Sankey diagrams are displayed separately for strict and less strict PAs and their respective matched controls. Where grassland changed to savanna or shrubland, it was important to identify whether this was due to bush encroachment (a negative impact) or savanna recovery (a positive impact). Many of Ethiopia's ecoregions are classified as containing more than one land cover type (e.g. Ethiopian montane grasslands and woodlands or Ethiopian xeric grasslands and shrublands) making it challenging to determine which natural baseline one would target without archaeobotanical evidence. Bush encroachment may be a consequence of several potentially interacting drivers, with the primary putative drivers including changes to herbivore management and fire regimes or increasing atmospheric carbon dioxide [7]. Fire is mostly limited to the western lowland ecoregions (East Sudanian savanna and Saharan flooded grasslands) and only up to 8% of the land area is burned annually [8], CO_2 enrichment is homogenous, while Ethiopia has the highest densities of domestic herbivores in Africa [9]. We therefore focused on the potential role of domestic herbivory in vegetation changes via overgrazing and densities of grazers versus browsers. Grazing can impact the cover and distribution of grasses, altering fire regimes and competitive interactions resulting in an increased cover in woody plants (Archer et al. 2017). This is often seen with high cattle densities, but not with high goat and sheep densities which, as browsers, consume more woody vegetation. Therefore, those cells that converted from grassland to savanna/shrubland, despite having high sheep and goat densities would most likely not be due to bush encroachment, whereas cells with high cattle densities could be a putative driver of shifts to woodier plant communities.. To decipher whether the main driver was bush encroachment (i.e. high cattle densities) or savanna recovery (high goat and/or sheep densities), we used a linear regression to identify the relationship between cells which changed from grassland to savanna or shrubland and the density of cattle, sheep and goats. If conversion of grassland to savanna or shrubland is due to bush encroachment, we would expect to see a positive relationship with cattle density and a no relationship or a negative relationship with sheep and goat density. Livestock densities (number of animals per 10km pixel) in 2015 were obtained from the Gridded Livestock of the World database v4 and resampled to our matching units [10].

Supplementary Methods 6 Sankey landcover changes

Land cover was derived from the MODIS Land Cover Type (MCD12Q1) Version 6 [11] dataset, resampled to 1km for the years 2001 and 2020. Sankey diagrams illustrate land cover changes from 2001 to 2020 for protected and unprotected gridcells, plotted via *networkD3* [12]. The percentage of forest, grass and agricultural land cover remaining the same was then compared inside and outside PAs.

Supplementary Methods 7 Socio-economic survey household attrition

Attrition rates between survey years were low and similar (14% and 12% respectively) between households close to protected areas (within 10km) and further away (more than 20km). While attrition can bias estimates, the low rates and small difference suggest only limited potential for this. Additionally, there is no significant difference in months of adequate food in 2011 between households that were lost over survey rounds and those that remained ($t_{595.6}$ = 1.61, p = 0.11).

Supplementary Methods 8 National Forest Priority Area counterfactual analysis

The statistical matching approach was repeated for National Forest Priority Areas (NFPAs). 1km gridcells within NFPA boundaries were classified as treatment units and gridcells outside of a 10km buffer zone around NFPAs and outside other protected areas were classified as control units. Treatment and control units were matched using the same covariates as the statistical matching for strict and less strict PAs (excluding baseline grassland and baseline agriculture, as the only outcome being assessed was forest change). Post-matching analysis confirmed covariate balance (standardised mean differences of less than 0.25) and robust sample sizes (100% of treatment units) had been achieved with nearest Mahalanobis matching with replacement. Average change in forest cover from 2000-2021 was the compared between matched treatment and control cells (Supplementary Figure S9).

Supplementary Methods 9 Justification for the use of matching methods

Protected areas are not randomly located and are often biased towards areas with lower opportunity costs, which have particular biophysical and socioeconomic characteristics which may also influence the outcomes of interest[13]. Simple comparisons between protected and unprotected areas are therefore inherently biased. Evaluating the causal impacts of protected areas, requires constructing a credible counterfactual (what would have happened if protection had not been put in place) which can be achieved through the use of quasi-experimental methods. Common approaches included statistical matching, difference-in-differences, synthetic control, instrumental variables and regression discontinuity and each of which relies on specific assumptions[14,15].

The suitability of different quasi-experimental approaches depends on the nature of the intervention being assessed, the available data and the spatial scale of inference [14,15]. In Ethiopia, protected areas have been established gradually over decades through context-specific decisions rather than a consistent eligibility threshold. There is no variable that plausibly influences protected areas designation but does not affect the outcomes of interest (land cover and human wellbeing changes) other than through protection. This rules out a valid instrumental variables[16] or regression discontinuity methods[17]. Synthetic control methods are best suited to discrete treatment event such as a policy or a single protected area with a specific start date [14]. Difference-in-differences approaches require temporally consistent pre-and post-intervention data at comparable spatial resolution for both treated and untreated units [18], which were unavailable for our outcomes.

Among quasi-experimental methods, statistical matching combined with post-matching covariate-adjusted regression was the most appropriate design for our data and research questions. This approach is widely used in conservation impact evaluation [15,19], and provides a transparent and replicable way to reduce selection bias by constructing a comparable sample of treatment and control units that are statistically similar based on observable covariates. To ensure robust causal inference from matching, we followed established best practice guidelines[14,15]: all covariates likely to influence both protected area placement and the outcomes were included; balance was assessed post-matching and post-matching; covariate-adjusted regression was applied to reduce residual bias; and multiple matching algorithms were applied to test sensitivity to specification choice. While matching cannot account for potential unobserved confounders and is sensitive to the matching specification used, we explicitly assess these limitations. We conducted sensitivity analyses using *sensemakr* [20] to quantify the amount of variance in the treatment and outcome an unobserved confounder would need to explain compared to a benchmark observed covariate before it nullified the result.

Supplementary Methods 10 Socio-economic survey household offset information

The GPS locations of households surveyed in the Ethiopian Socioeconomic Survey are offset by 0-2km with 1% being offset by 10km. This ensures the known range for all points is 10km but limits the noise added by offsets. Additionally, offsets are constrained within Ethiopia's administrative zones.

Supplementary Methods 11 Estimating impacted populations

Using the average treatment effects for social wellbeing outcomes across the matched treatment (protected) and control households, we estimate the likely number of people impacted using the UN-adjusted gridded population count [1] at 1km resolution in 2011 (the start of the survey period used) summed across all locations within 10km of a protected area. To ensure a conservative estimate we first determined the highest population density at any of the surveyed household locations, and then removed any gridcells with a higher population than this before summing population counts. We also merged any overlapping buffers into a single polygon to avoid double counting. To convert this to the household level, we used the average number of people per household from the household survey which was 4.6.

Supplementary Methods 12 Stakeholder questionnaire

This questionnaire was sent to target respondents via email or taken as physical copies (in cases where internet access was problematic). Prior to being asked for consent, potential respondents were made aware of the purpose of the questionnaire, how their responses would be used, and assured it would be treated anonymously and confidentially. This process was approved through an ethics board (Ethics ID of 20251741251220900).

Questionnaire: Challenges, Opportunities, Methods, and Specific Information on Ethiopia's Protected Area Network
በኢትዮጵያ ጥብቅ ስፍራዎች ላይ የሚያጋጥሙ ፈተናዎች/ ተግዳሮቶች፣ እድሎች፣ ዘዴዎች እና ልዩ መረጃዎች

Thank you for participating in this questionnaire. Your valuable insights will contribute to understanding the challenges, opportunities, and methods to enhance the effectiveness of Ethiopia's protected area network. Please provide your feedback by answering the following questions. በዚህ ጥያቄ ላይ ስለተሳተፋችሁ እናመሰግናለን። ጠቃሚ አስተያየቶቻችሁን የኢትዮጵያ ጥብቅ ስፍራዎች ውጤታማነትን ለማጎልበት የሚያስችሉ ትንተናዎችን፣ እድሎችን እና ዘዴዎችን ለመረዳት አስተዋፅኦ ያበረክታሉ። እባኮ የሚከተሉትን ጥያቄዎች በመመለስ አስተያየታችሁን ይስጡ።

Section 1: Demographic Information **የዴሞግራፊ መረጃ**

1. How old are you? እድሜዎ ስንት ነው?

<21	
21-30	
31-40	
41-50	
51-60	
61-70	
>70	

2. What is your gender? ፆታዎ ምንድን ነው?

Male ወንድ	
Female ሴት	

3. What is your highest level of education? የእርስዎ ከፍተኛ የትምህርት ደረጃ ምንድን ነው?

Primary school የመጀመሪያ ደረጃ ትምህርት	
Secondary school ሁለተኛ ደረጃ ትምህርት	
Bachelor’s degree የባችለር ዲግሪ	
Masters degree ማስተርስ ዲግሪ	
PhD ዶክትሬት	
Other (please specify) ሌላ (እባክዎን ያመልከቱ): ______________________________	

4. What type of organisation do you work for? በምን አይነት መስሪያ ቤት ውስጥ ነው የሚሰሩት?

University ዩኒቨርሲቲ	
Research institute የምርምር ተቋም	
NGO መንግስታዊ ያልሆነ ድርጅት	
Private/consultant የግል/አማካሪ	
National government ብሔራዊ መንግሥት	
Regional government ክልላዊ መንግስት	
Other (please specify) ሌላ (እባክዎን ያመልከቱ):______________________________	

Section 2: Future of Ethiopia’s protected areas **የኢትዮጵያ ጠባቂ አካባቢዎች ወደፊት**

1. What should be the goals of Ethiopia’s protected areas over the next 20 years? በሚቀጥሉት 20 ዓመታት የኢትዮጵያ ጥብቅ ስፍራዎች ግባቸው ምን መሆን አለበት?

   Please rank 1-3 with 1 being the highest priority and 3 being the lowest እባክዎ ደረጃ 1-3 ይስጡ 1 ከፍተኛ ቅድሚያ እና 3 ዝቅተኛ መሆን

Expanding the protected area network ጥብቅ ስፍራዎችን ማስፋት	
Making the existing protected area network more effective አሁን ያሉትን ጥብቅ ስፍራዎች ውጤታማ ማድረግ	
Carrying out additional research to understand how to improve the protected area network ጥብቅ ስፍራዎችን እንዴት ማሻሻል እንደሚቻል ለመረዳት ተጨማሪ ምርምር ማካሄድ	

Section 3: **Effectiveness of Ethiopia's protected area network የኢትዮጵያ ጥብቅ ስፍራውች ይዘት ውጤታማነት**

2. Do you feel that Ethiopia's protected areas are effective at የኢትዮጵያ ጥበቃ ቦታዎች የተደረገላቸው አካባቢዎች ከስር በተዘረዘሩት መስኮች ውጤታማ እንደሆኑ ይሰማችኋል:

	Yes (አዎ)	No (አይ)	I don't know (አላውቅም)
Reducing forest loss የደን መጥፋት መቀነስ			
Preventing agricultural expansion with protected area boundaries በጥብቅ ስፍራ ድንበሮች አካባቢ የእርሻ መስፋፋትን መከላከል			
Conserving grassland የሳር መሬት ጥበቃ			
Reducing poverty among neighbouring communities በአጎራባች ማህበረሰቦች መካከል ያለውን ድህነት መቀነስ			
Increasing food security among neighbouring communities በአጎራባች ማህበረሰቦች መካከል የምግብ ዋስትና እየጨመረ መጥቷል			

Section 4: **Challenges ተፈታታኝ ሁኔታዎች/ ተግዳሮቶች**

3. What are the three biggest challenges which threaten the effectiveness of Ethiopia's protected area network? የኢትዮጵያ ጥብቅ ስፍራዎችን ውጤታማነት ስጋት ላይ የሚጥሉት ሶስት ትልልቅ ፈተናዎች ምንድን ናቸው?

Select only three most important በጣም አስፈላጊ የሆኑትን ሶስት ብቻ ይምረጡ እና

Inadequate community engagement በቂ ያልሆነ የማህበረሰብ ተሳትፎ	
Limited public awareness የህዝብ ግንዛቤ ውስንነት	
Land use conflict የመሬት አጠቃቀም ግጭት	
Lack of collaboration between stakeholders በባለድርሻ አካላት መካከል ያለው ትብብር አለመኖር	
Weak law enforcement የህግ ማስክብር ድክመትደካማ ሕግ አስከባሪ	
Inadequate financial resources በቂ የገንዘብ ሀብት አለማግኘት	
Climate change የአየር ንብረት ለውጥ	
Inadequate representation of threatened species አደጋ ላይ የወደቁ ዝርያዎች በበቂ ሁኔታ አለመወከል	
Alien and Invasive species መጤ እና ወራሪ ዝርያዎች	

Expansion of agriculture የእርሻ መስፋፋት	
Settlement and Urbanisation የሰፈራና ከተማ መስፋፋት	
Political conflict የፖለቲካ ግጭት	
Lack of food security among local communities በአካባቢው ማህበረሰብ ዘንድ የምግብ ዋስትና እጥረት	
Free Grazing within protected area boundaries በጥብቅ ቦታዎች ውስጥ ልቅ ግጦሽ	
Poverty in neighbouring areas በአጎራባች አካባቢዎች ድህነት	
Other ሌላ	

4. If other please specify ሌላ ካለ እባክዎን ይግለጹ:

____

Section 5: **Priorities ቅድሚያ የሚሰጣቸው**

5. What are the three most important actions which should be prioritised to improve the effectiveness of Ethiopia's protected area network? የኢትዮጵያን ጥብቅ አካባቢዎች ውጤታማነት ለማሻሻል ቅድሚያ ሊሰጣቸው የሚገቡ ሶስት አስፈላጊ እርምጃዎች ምንድን ናቸው?

   Select only three most important. በጣም አስፈላጊ የሆኑትን ሶስት ብቻ ይምረጡ እና

Strengthening community engagement የህብረተሰቡን ተሳትፎ ማጠናከር	
Improving public awareness የህዝብን ግንዛቤ ማሻሻል	
Enhancing partnerships/collaborations with local communities, NGOs, and academic institutions የአካባቢው ማህበረሰብ ከመንግስታዊ ካልሆኑ ድርጅቶችና ከትምህርት ተቋማት ጋር አጋርነትን/ትብብርን ማጎልበት	
Developing sustainable nature-based tourism ተፈጥሮ-ላይ የተመሠረተ ዘላቂ ቱሪዝም ማዳበር	
Strengthening policy and enforcing the law around protected area management ጥበቃ በተደረገለት አካባቢ አስተዳደር ዙሪያ ፖሊሲንና የህግ ትግበራን ማጠናከር	
Expanding and establishing new protected areas አዳዲስ ጥብቅ ቦታዎችን ማስፋትእና ማቋቋም	
Incorporating traditional ecological knowledge and practices into protected area management ባህላዊ እና ሥነ-ምህዳራዊ ዕውቀቶችንን እና ተግባራትን ወደ አካባቢ ጥበቃ አስተዳደር ማምጣት	
Increasing funding resources የገንዘብ ድጋፍ እየጨመረ መሄድ	
Promoting research to inform evidence-based conservation strategies በማስረጃ ላይ የተመሰረቱ የጥበቃ ስልቶችን ለማሳወቅ ምርምርን ማስፋፋት	
Improving food security የምግብ ዋስትና ማሻሻል	
Reducing poverty ድህነትን መቀነስ	
Reducing conflict	

ግጭትን መቀነስ	
Strengthening capacity building and training for park rangers and staff የአቅም ግንባታ እና ስልጠና ለአካባቢ ጥበቃ ሰራተኞች መስጠትን ማጠናከር	
Implementing robust monitoring and evaluation systems ጠንካራ ክትትል እና ግምገማ ስርዓት መተግበር	
Other ሌላ	

6. If other please specify ሌላ ካለ እባክዎን ይግለጹ:

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Supplementary results

Supplementary Results 1 Newer protected areas are being established in areas of higher human pressure

Spearman's rank correlations indicate that more recently established protected areas tend to be located in areas with higher population density ($r_s = 0.24$, $p < 0.001$), and more agricultural land ($r_s = 0.24$, $p < 0.001$). They are also weakly associated with shorter travel times to cities ($r_s = –0.045$, $p < 0.001$) and higher elevations ($r_s = 0.096$, $p < 0.001$) indicating they newer protected areas are generally being established in areas of higher human pressure.

Supplementary Results 2 Human and land-use pressures across under- and over- represented ecoregions

Blocked permutation tests show that underrepresented ecoregions had higher agricultural land cover (Underrepresented = 19.68, Overrepresented = 9.76; p = 0.002, FDR-adjusted p = 0.005), shorter travel time to cities (Underrepresented = 538.14, Overrepresented = 638.92; p = 0.002, FDR-adjusted p = 0.005), and higher population density (Underrepresented = 64.37, Overrepresented = 47.14; p = 0.030, FDR-adjusted p = 0.050). We found no evidence of differences for agricultural suitability (FDR-adjusted p = 0.47) or elevation (FDR-adjusted p = 0.47).

Supplementary Results 3 Overall land cover changes

Analysis of land cover changes across the whole landscape from 2001-2020 (Supplementary figure S6) showed that natural land cover classes were more likely to remain stable inside protected areas. For example, a larger proportion of forest remained as forest inside protected areas (88%) compared to outside (76%). Grassland also remained more stable inside protected areas (92% compared to 84% outside). By comparison, a larger proportion of cropland reverted to natural vegetation inside protected areas (64%) compared to outside (20%). Across all surveyed households, months of adequate food declined by half a month in households within 10km of a protected area while remaining stable in households more than 20km from a protected area; and material wellbeing remained stable for households close to protected areas while improving further away. Conversely dietary diversity increased 15% more among households close to protected areas.

Supplementary Results 4 Interpreting grassland changes

The most dominant landcover changes either to or from grassland were with cropland, savanna and shrubland (Supplementary Figure S10). In the context of biodiversity conservation, changes from cropland to grassland is interpreted as positive impact, while changes from grassland to cropland is negative. Changes from grassland to savanna or shrubland could either be a) savanna recovery from grassland (where loss of grassland would be a positive impact in PAs) or bush encroachment as a result of grassland degradation (where loss of grassland would be a negative impact in PAs). We found significant positive correlations between matching units which changed from grassland to either savanna or shrubland and the density of cattle, and negative relationships with density of sheep and goat (Supplementary Table 16). This suggests that loss of grassland due to bush encroachment is more likely than savanna recovery as sheep and goat are expected to reduce woody plant cover, while cattle are expected to reduce grass cover, while increasing woody plant cover. Bush encroachment transitions are negative from a conservation perspective and therefore loss of grassland in this case is viewed as a negative. In strict PAs, we saw greater increase in grassland in PAs compared to matched control (main text Fig 3) and sankey diagrams demonstrate that the majority of increases in grassland were from cropland (Supplementary Figure S10A) which suggests abandonment of farms may be the main driver and this is a positive impact. In less strict PAs we saw less decline in grassland compared to matched controls (main text Fig. 3), and the majority of this was to savanna or shrubland (Supplementary Figure S10C), through bush encroachment. This may be due to livestock foraging occurring more frequently in less strict compared to strict protected areas (although at lower intensities than outside), suggesting that although woody cover is still increasing in less strict protected areas, management is having a positive impact at reducing the extent and/or rate of change.

Supplementary text

Supplementary Text 1 Context for win-win sites

We identify five protected areas experiencing win-win outcomes: Yayu Biosphere Reserve, Gibe Sheleko National Park, Erer-Gota Controlled Hunting Area, Borena National Park, and Kafta Sheraro National Park. Below we summarise plausible descriptive reasons consistent with these results.

Yayu Biosphere Reserve

Households in Yayu obtain substantial income for forest coffee and other non-timber forest products [21]. This aligns both livelihood and conservation incentives for maintaining forest. Additionally it has a high budget (Supplementary Table 10) and associations with the international climate initiative with a project focused on restoring degraded coffee landscapes in Ethiopia [22]

Gibe Sheleko National Park

Gibe Sheleko is located in an area of high agricultural suitability[23] which may help communities to maintain food security with less expansion of agricultural land. Local livelihoods include honey bee rearing and eucalyptus plantations, and non-timber forest products and are recognised by local communities as a benefit from the park, improving their perceptions of it [24].

Erer-Gota Controlled Hunting Area

Ethiopia's controlled hunting area framework allows community revenue shares, and contributes to the rural economies neighbouring the parks[25] It is located in a hot arid region of Ethiopia that more suited to pastoralist lifestyles reducing pressure of agricultural conversion[26].

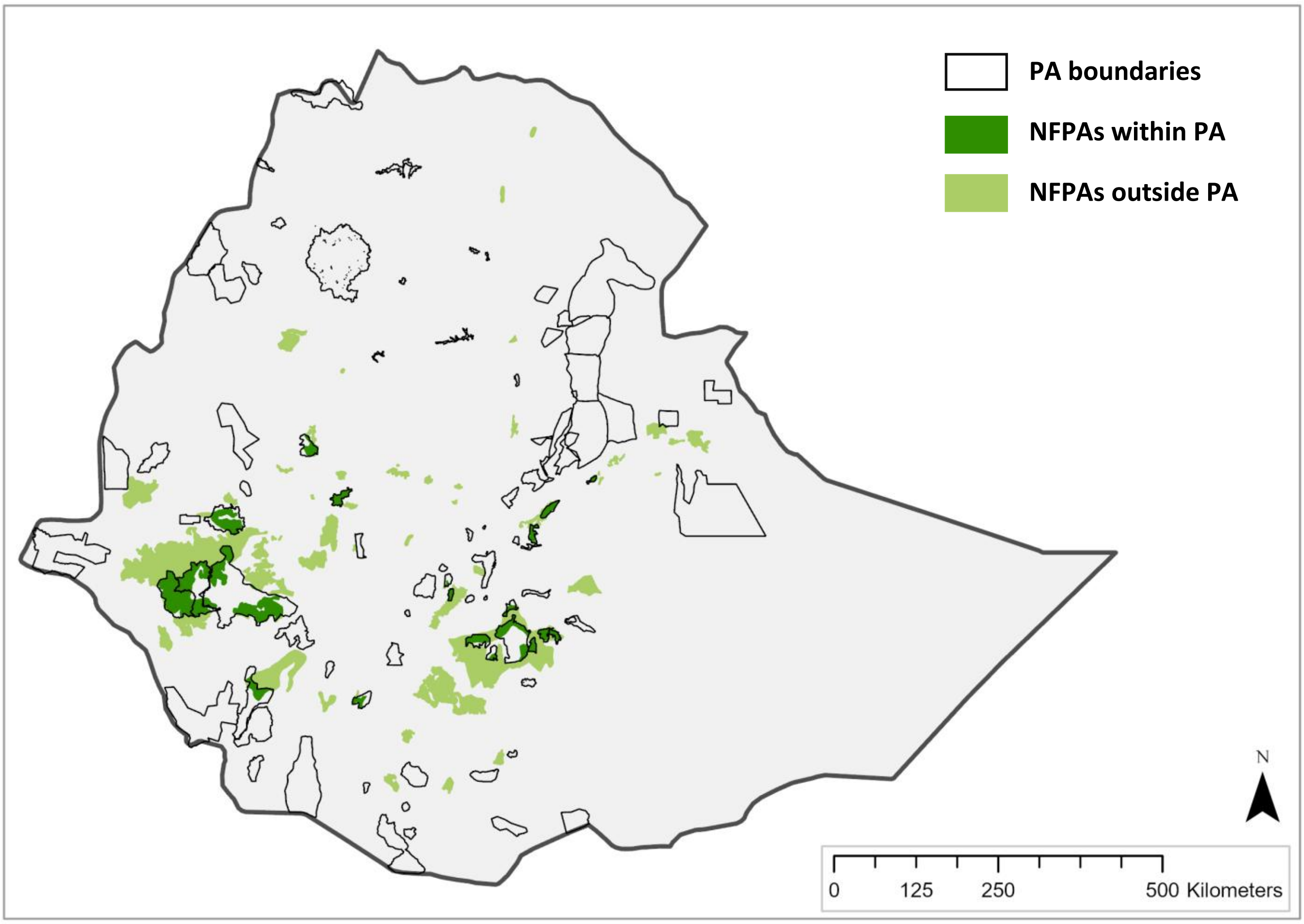
Borena National Park

Borena is also located in an arid region dominated by pastoralist livelihoods[26]. In Borana zone, Gadaa based institutions historically organised pasture use and participatory rangeland management is prioritised[27]. It also has a comparatively high budget (Supplementary Table 10).

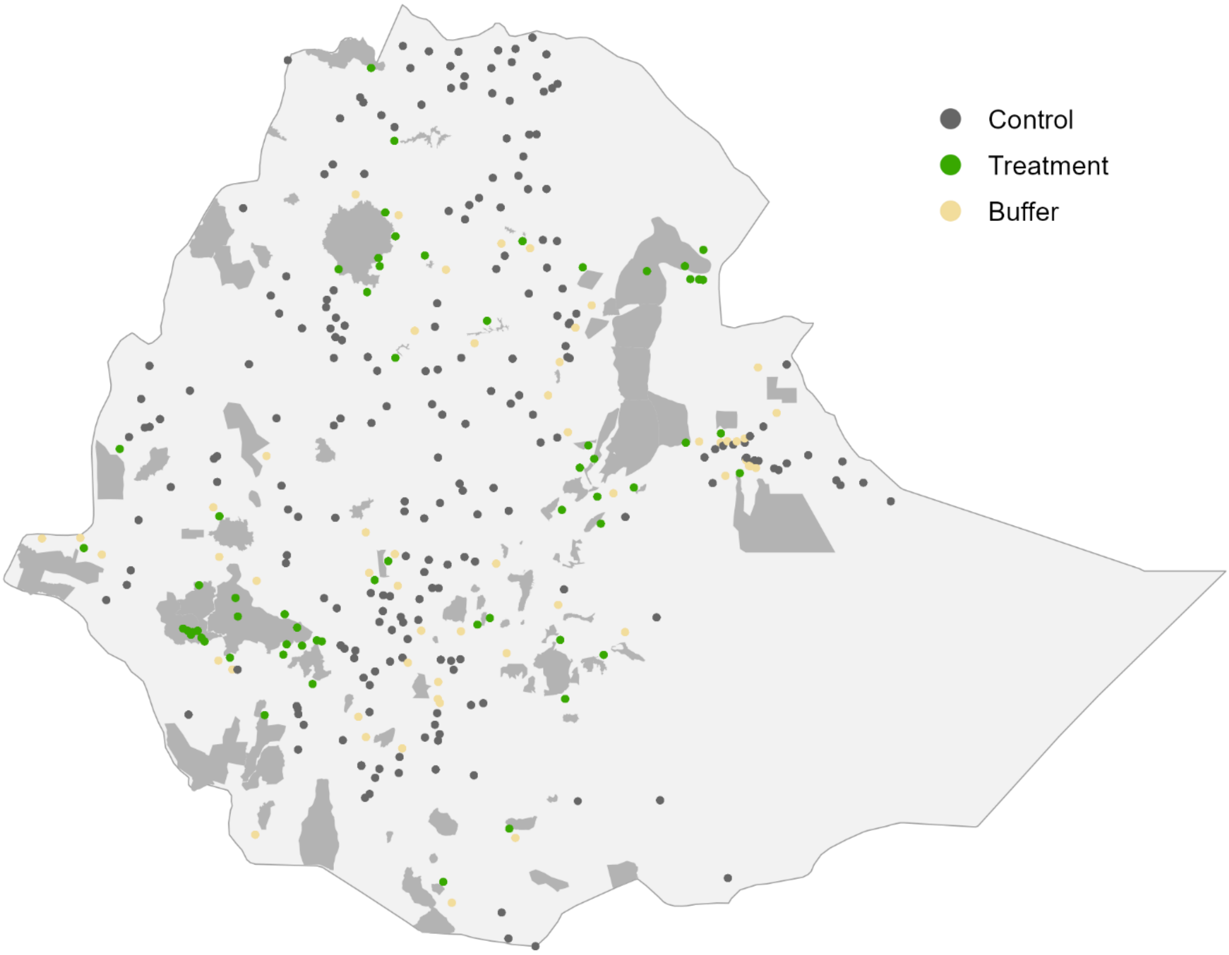
Kafta Sheraro National Park

Kafta Sheraro also has a high budget (Supplementary Table 10) which likely supports better environmental outcomes and it is has a flagship transboundary elephant population making it a national priority and attracting external support[28].

Supplementary figures

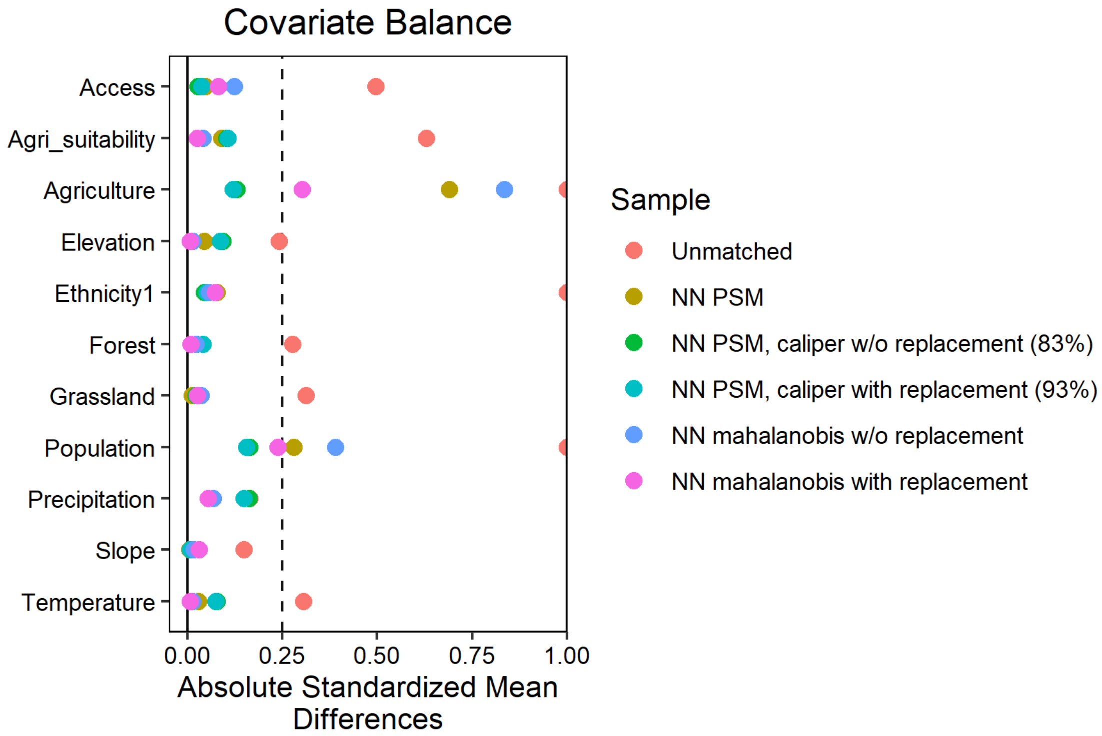


Supplementary Figure 1 The overlap of National Forest Priority Areas (NFPAs) with gazetted protected areas



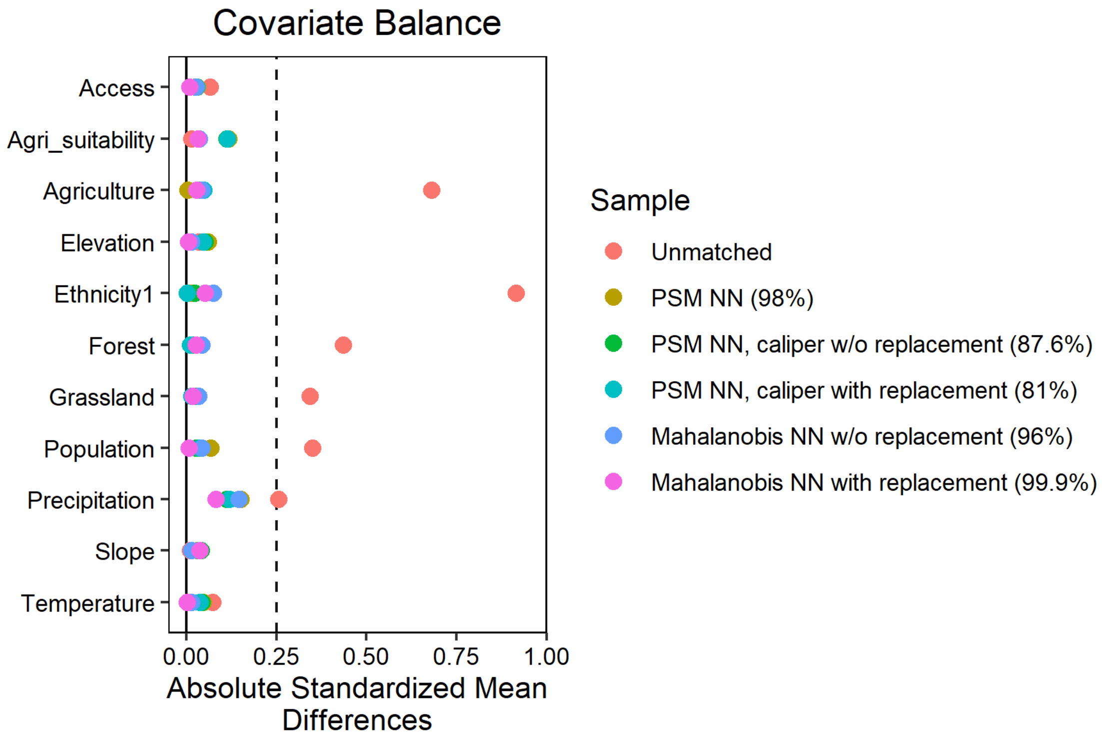
Supplementary Figure 2 Map of enumeration area locations from households surveyed in both the 2011 and 2016 Living Standards Measurement Survey[29,30] (333 enumeration areas comprising 3917 households). The control pool (2560 households) are more than 20km from a protected area, treatment pools (721 households) are less than 10km from a protected area and buffer pools (636 households) are in between.

A



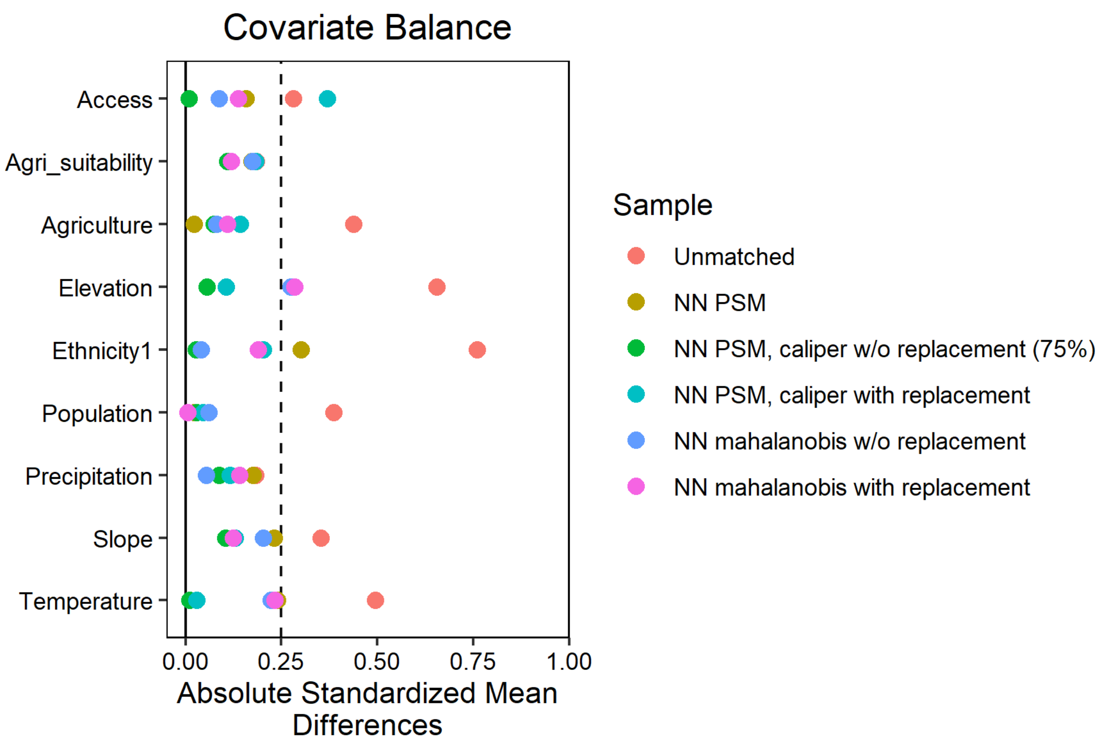
Covariate Balance
Access
Agri_suitability
Agriculture
Elevation
Ethnicity1
Forest
Grassland
Population
Precipitation
Slope
Temperature
0.00
0.25
0.50
0.75
1.00
Absolute Standardized Mean Differences
Sample
Unmatched
NN PSM
NN PSM, caliper w/o replacement (83%)
NN PSM, caliper with replacement (93%)
NN mahalanobis w/o replacement
NN mahalanobis with replacement

B

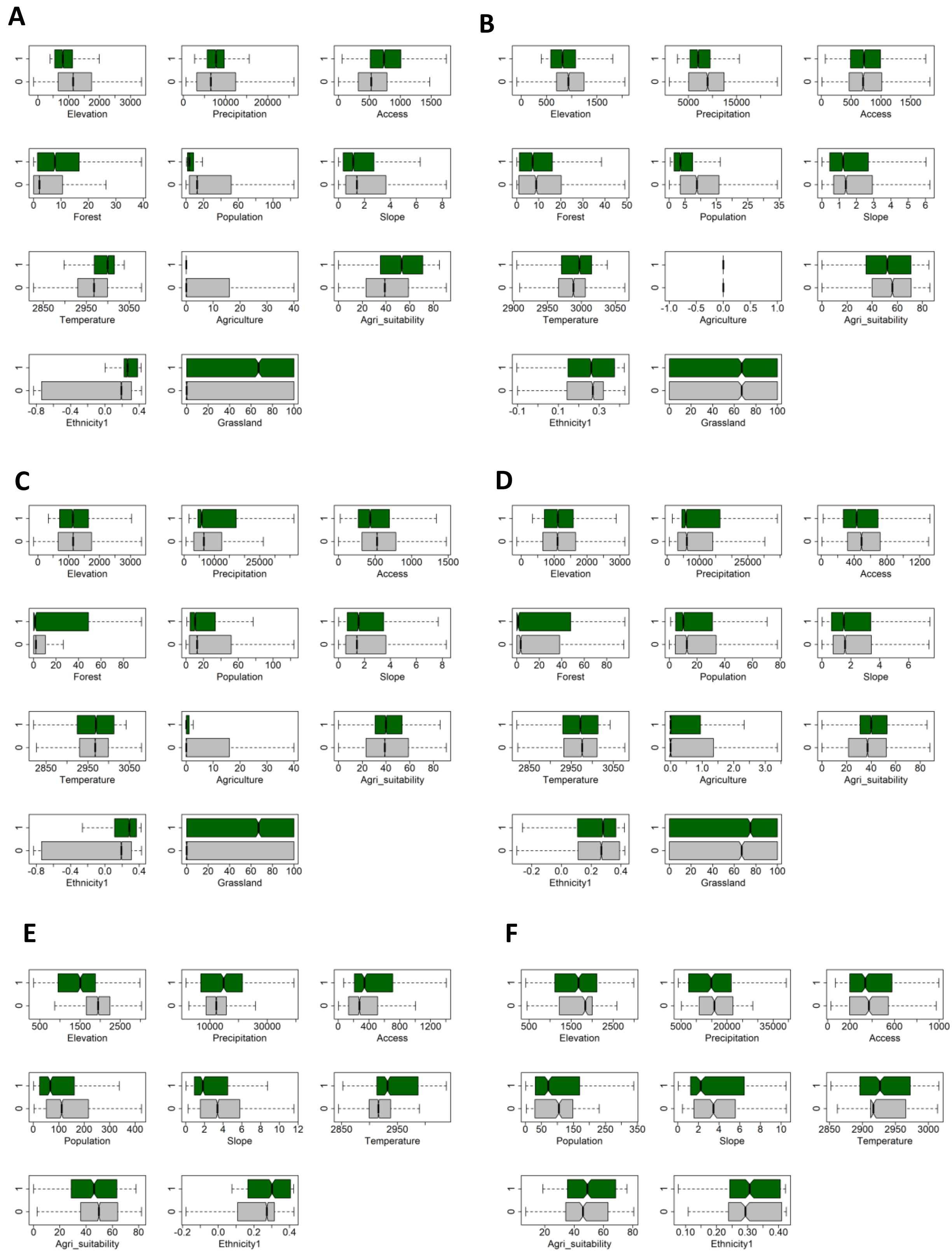


Covariate Balance
Access
Agri_suitability
Agriculture
Elevation
Ethnicity1
Forest
Grassland
Population
Precipitation
Slope
Temperature
0.00
0.25
0.50
0.75
1.00
Absolute Standardized Mean Differences
Sample
Unmatched
PSM NN (98%)
PSM NN, caliper w/o replacement (87.6%)
PSM NN, caliper with replacement (81%)
Mahalanobis NN w/o replacement (96%)
Mahalanobis NN with replacement (99.9%)

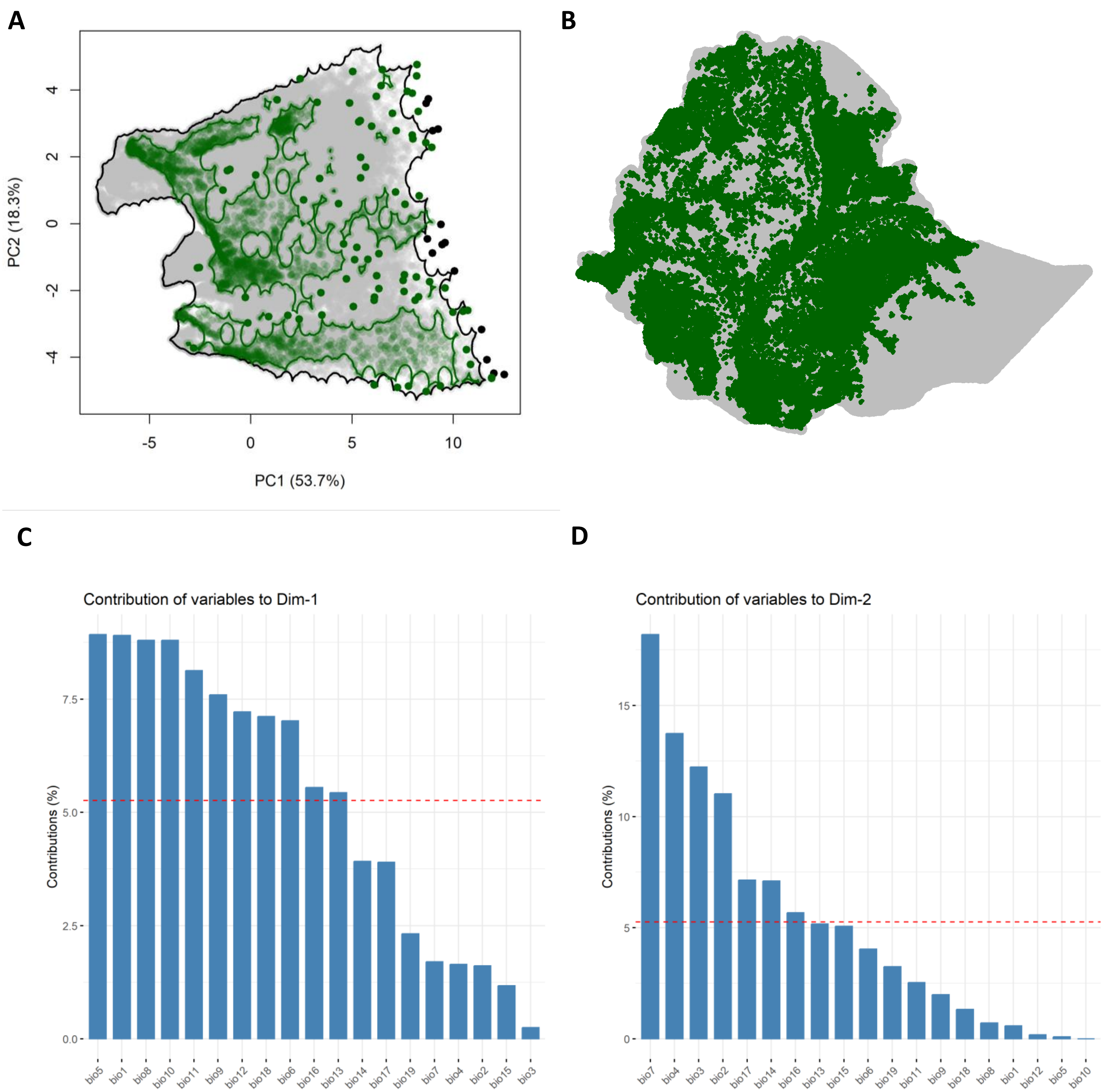
C



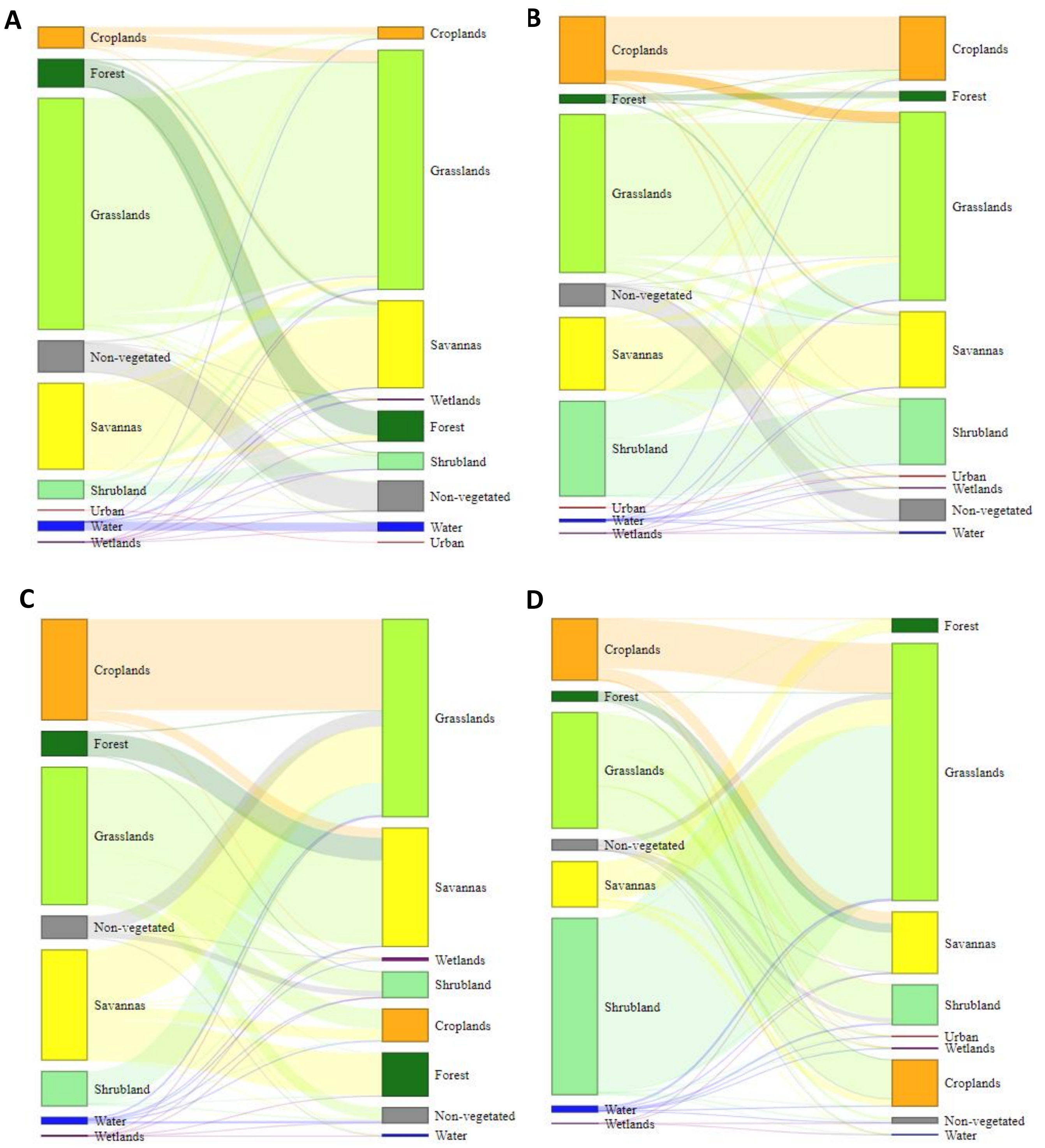
Supplementary Figure 3 Comparison of statistical matching specifications. Comparing the covariate balance achieved and sample unit retention (shown in in the legend) across six statistical matching specifications for (A) statistical matching for strict protected areas, (B) statistical matching for less strict, and (C) household matching. Different coloured points represent different matching specification. The matching specifications selected for further analysis were the specifications with the highest sample unit retention which achieved covariate balance below the threshold of 0.25 (dashed line). PSM = propensity score matching, NN = nearest neighbour.



Supplementary Figure 4 Comparison of treatment (green boxes) and control (grey boxes) covariate values for (A) strict pre-match data, (B) strict post-match data, (C) less strict pre-match data, (D) less strict post-match data, (E) household pre-match data and (F) household post-match data.

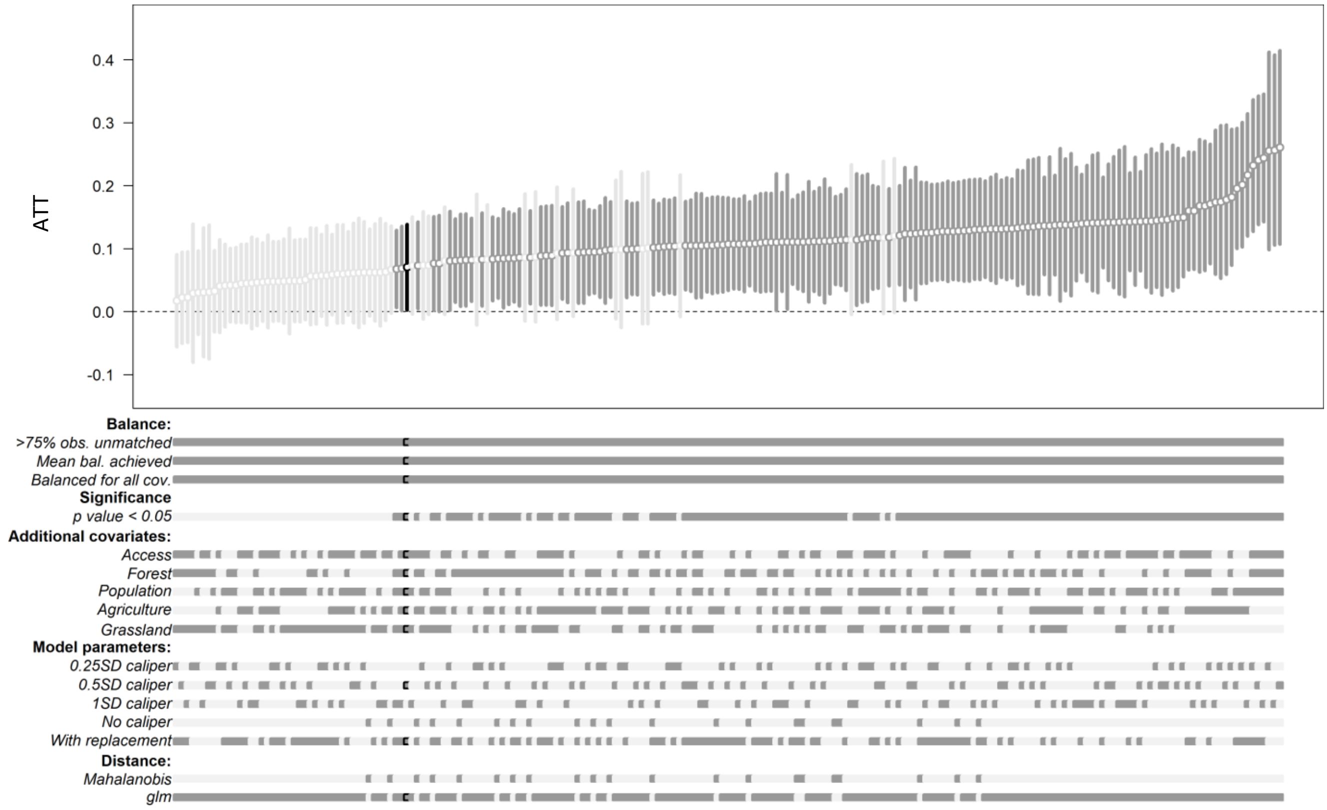


Supplementary Figure 5 Representativeness of Ethiopia's environmental space within the protected area network. (A) shows a principal component analysis plotting Ethiopia's background environmental space (grey) and the environmental conditions found within the protected area network (green), with alpha hulls where alpha is set to 0.3. 33% of the Ethiopia's environmental space matched the environment found within protected areas. (B) shows the PCA converted into geographical space, where green highlights areas which match the environmental conditions already found within the protected area network. Variable loadings for the first and second principal component axes are shown in (C) and (D) respectively, where dashed lines represent the value expected if all contributions were uniform.

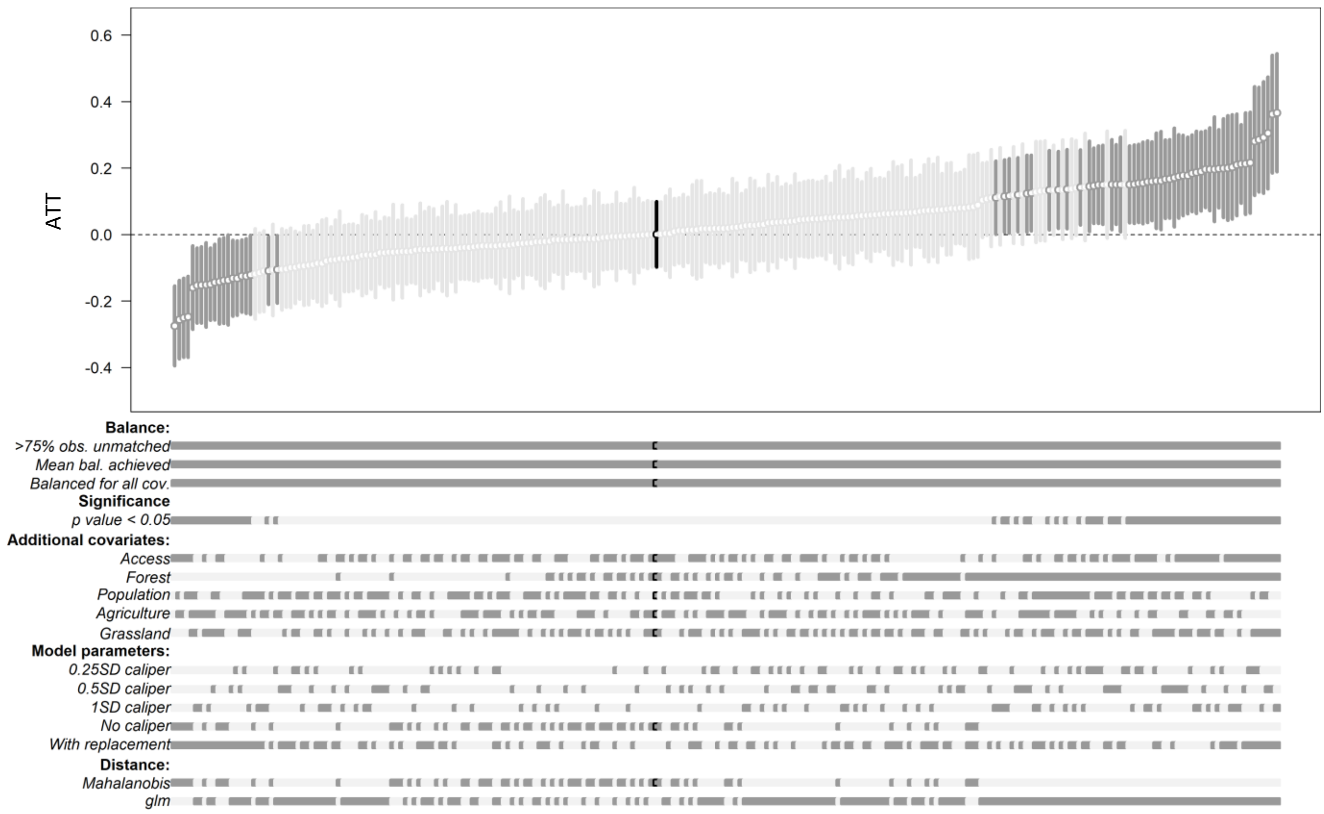


Supplementary Figure 6 Landcover changes in each 1x1km gridcell that occurred between 2000 and 2021 (A) inside PAs, (B) outside PAs, (C) inside PAs excluding gridcells where the landcover remained constant and (D) outside PAs excluding gridcells where the landcover remained constant.

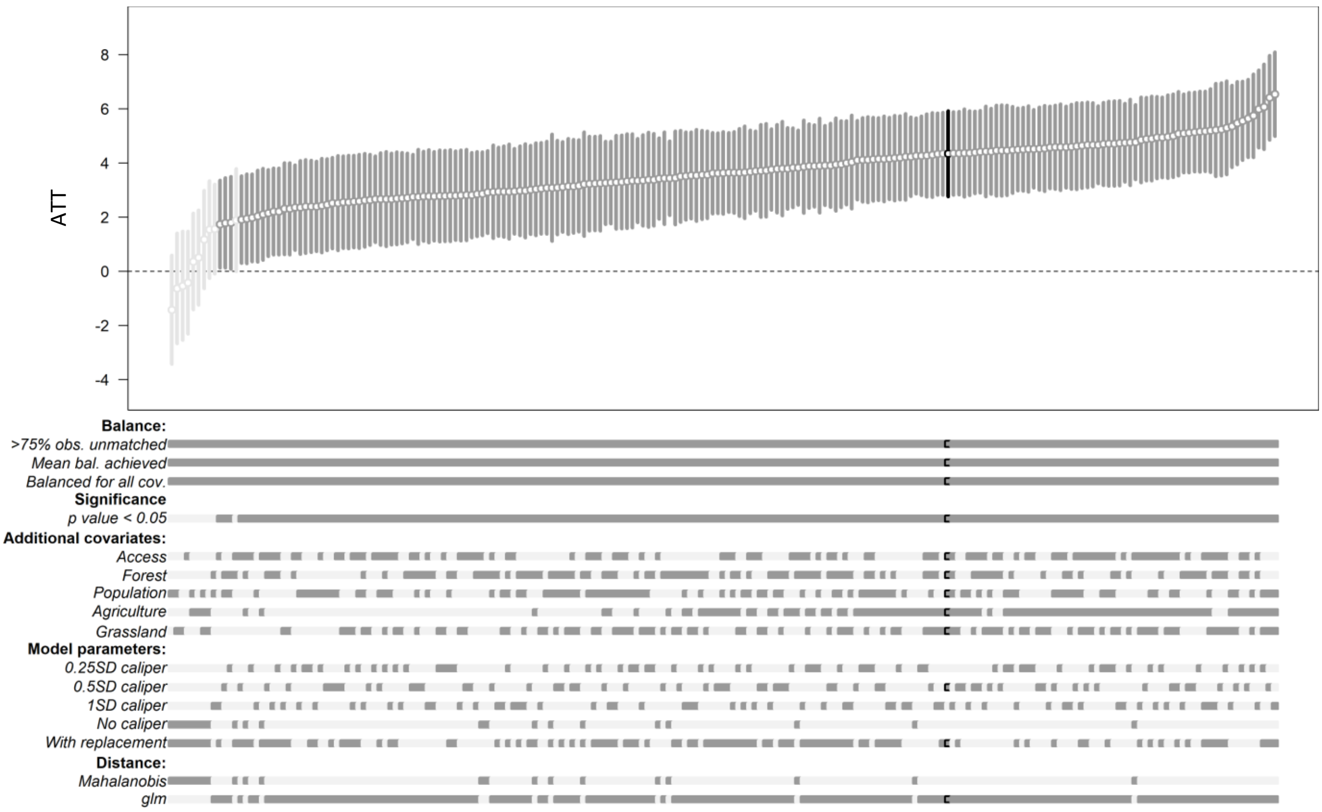
(**A**) Matching treatment: **Strict PAs**; outcome variable: **Forest** (207 models with sufficient balance and sample size)



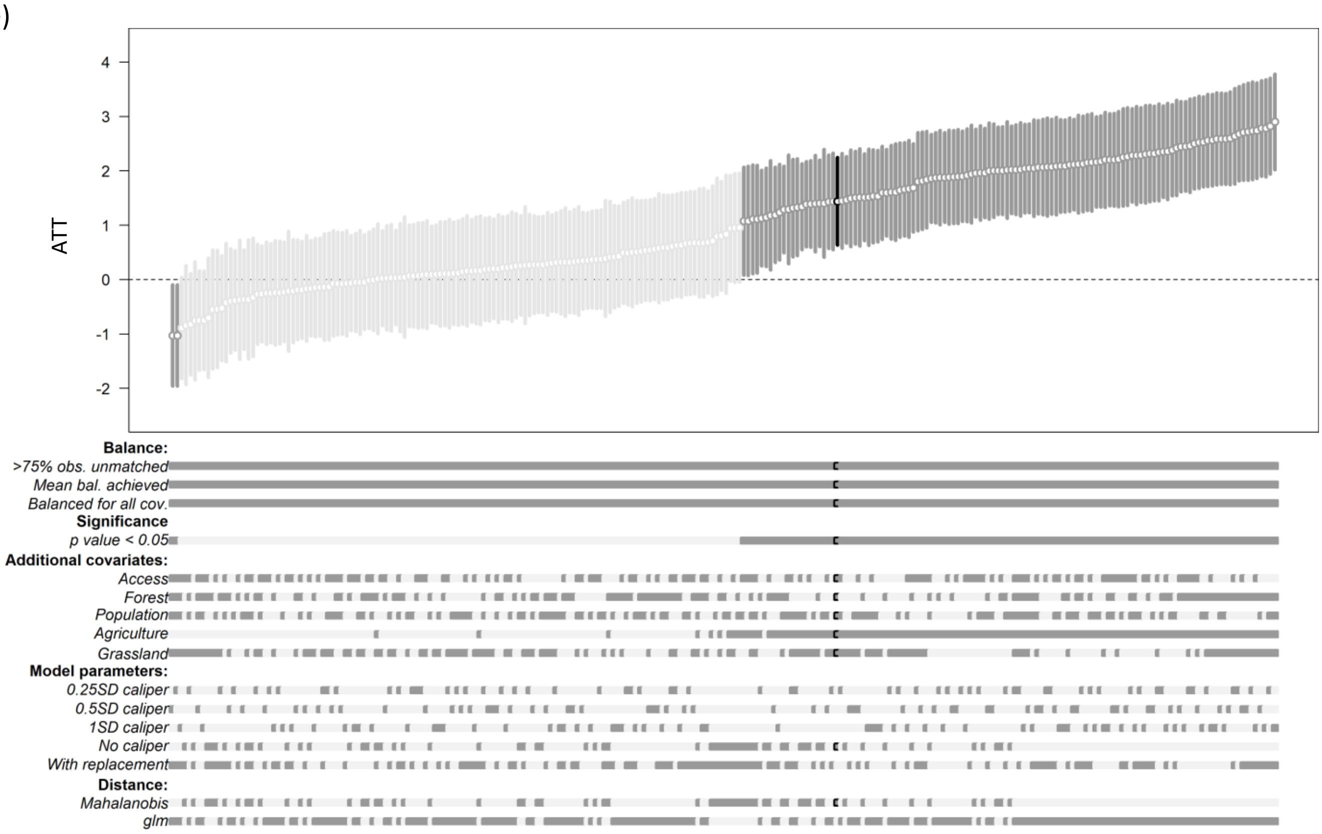
(**B**) Matching treatment: **Less strict PAs**; outcome variable: **Forest**; (248 models with sufficient balance and sample size)



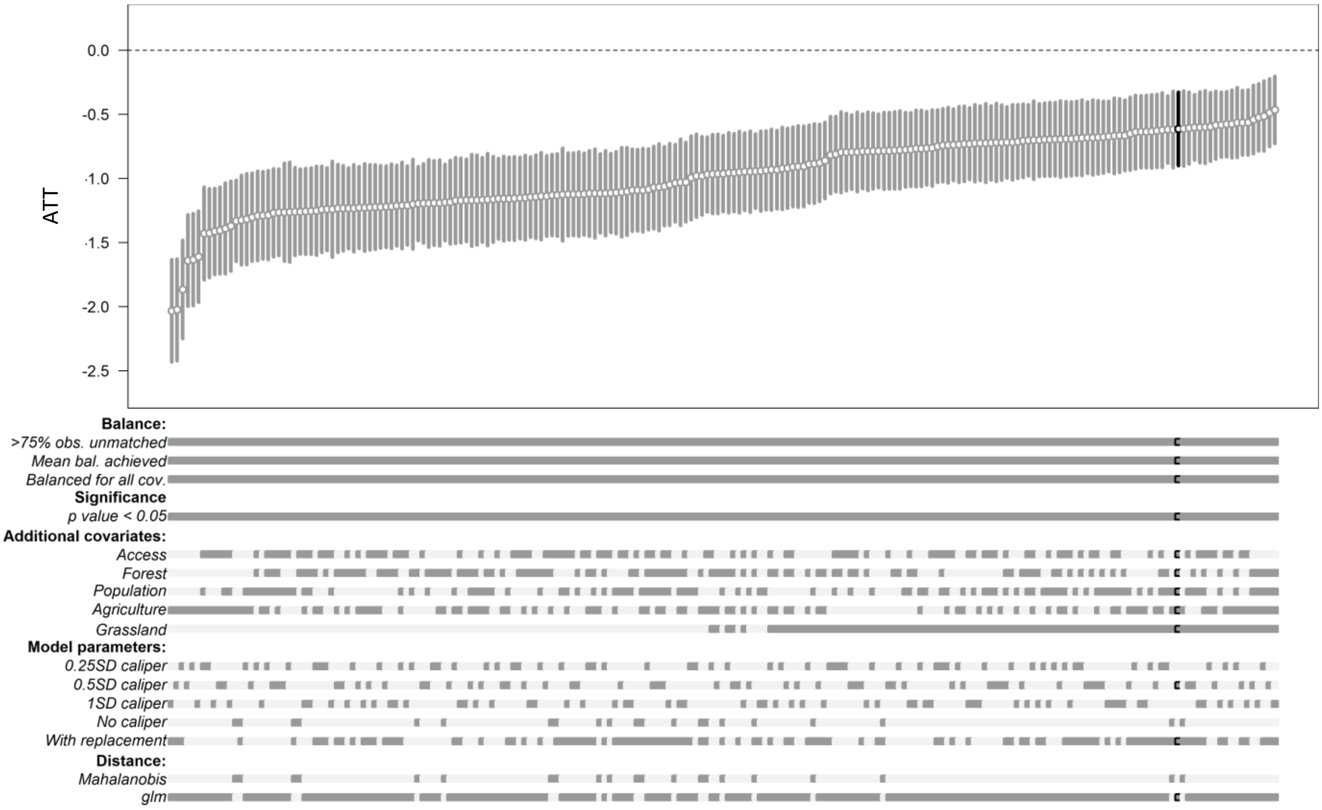
(**C**) Matching treatment: **Strict PAs**; outcome variable: **Grassland** (207 models with sufficient balance and sample size)



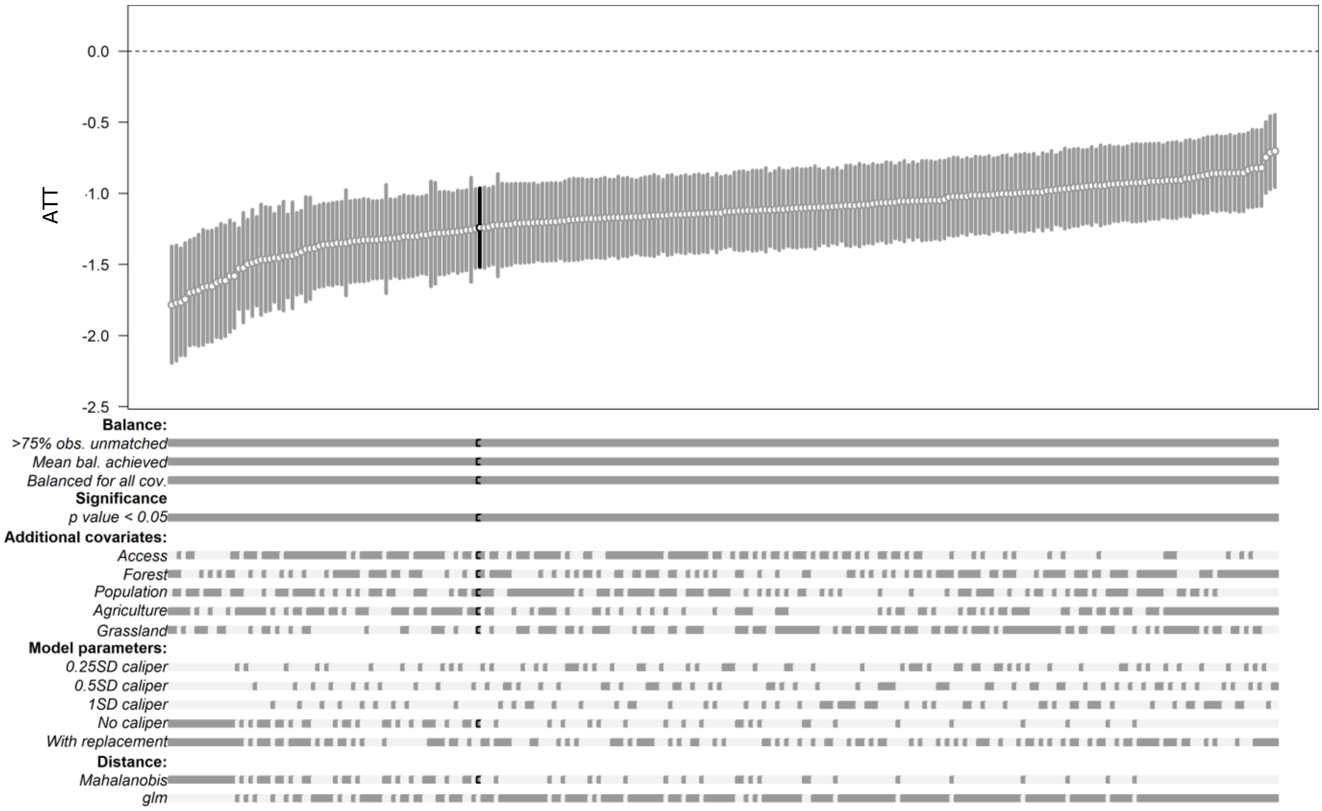
(**D**) Matching treatment: **Less strict PAs**; outcome variable: **Grassland** (248 models with sufficient balance and sample size)



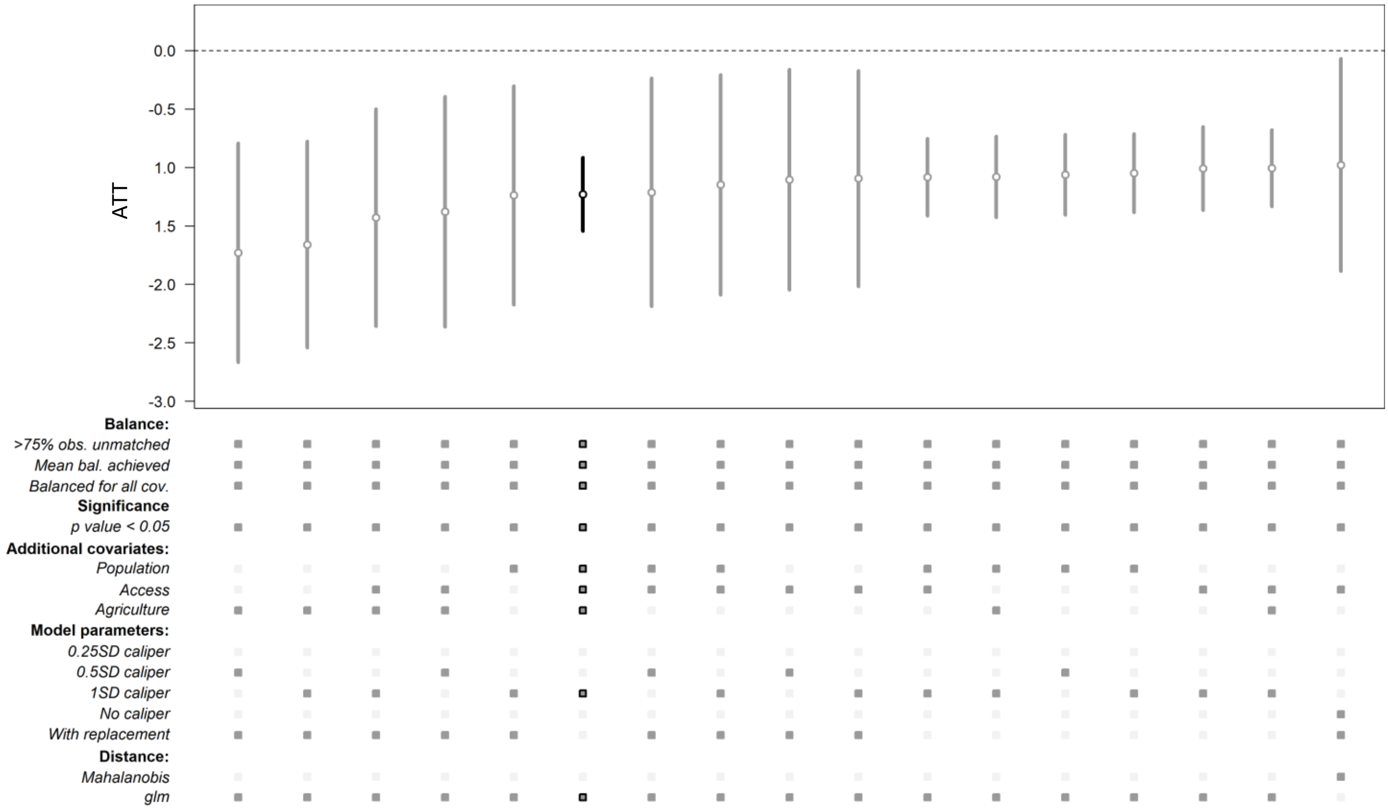
(**E**) Matching treatment: **Strict PAs**; outcome variable: **Agriculture** (207 models with sufficient balance and sample size)



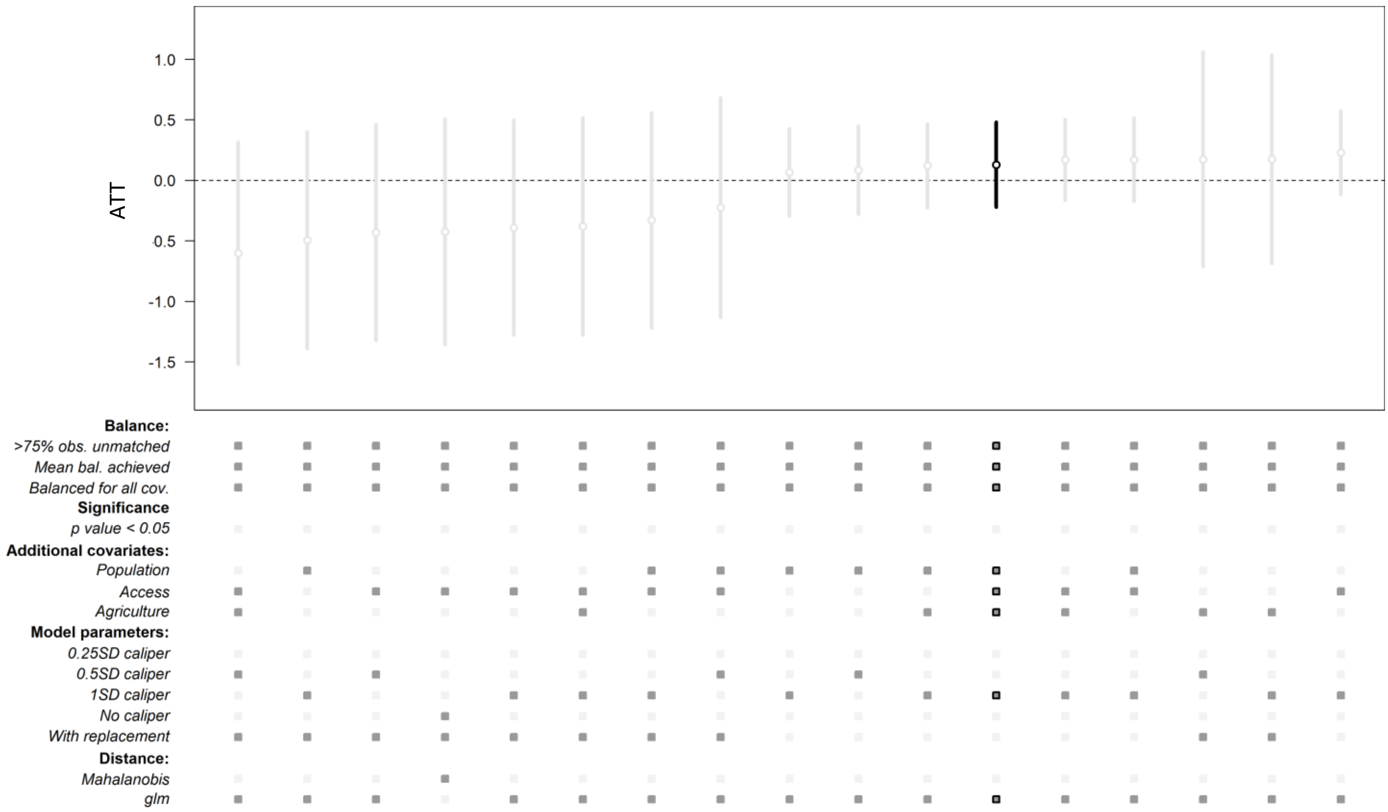
(**F**) Matching treatment: **Less strict PAs**; outcome variable: **Agriculture** (248 models with sufficient balance and sample size)



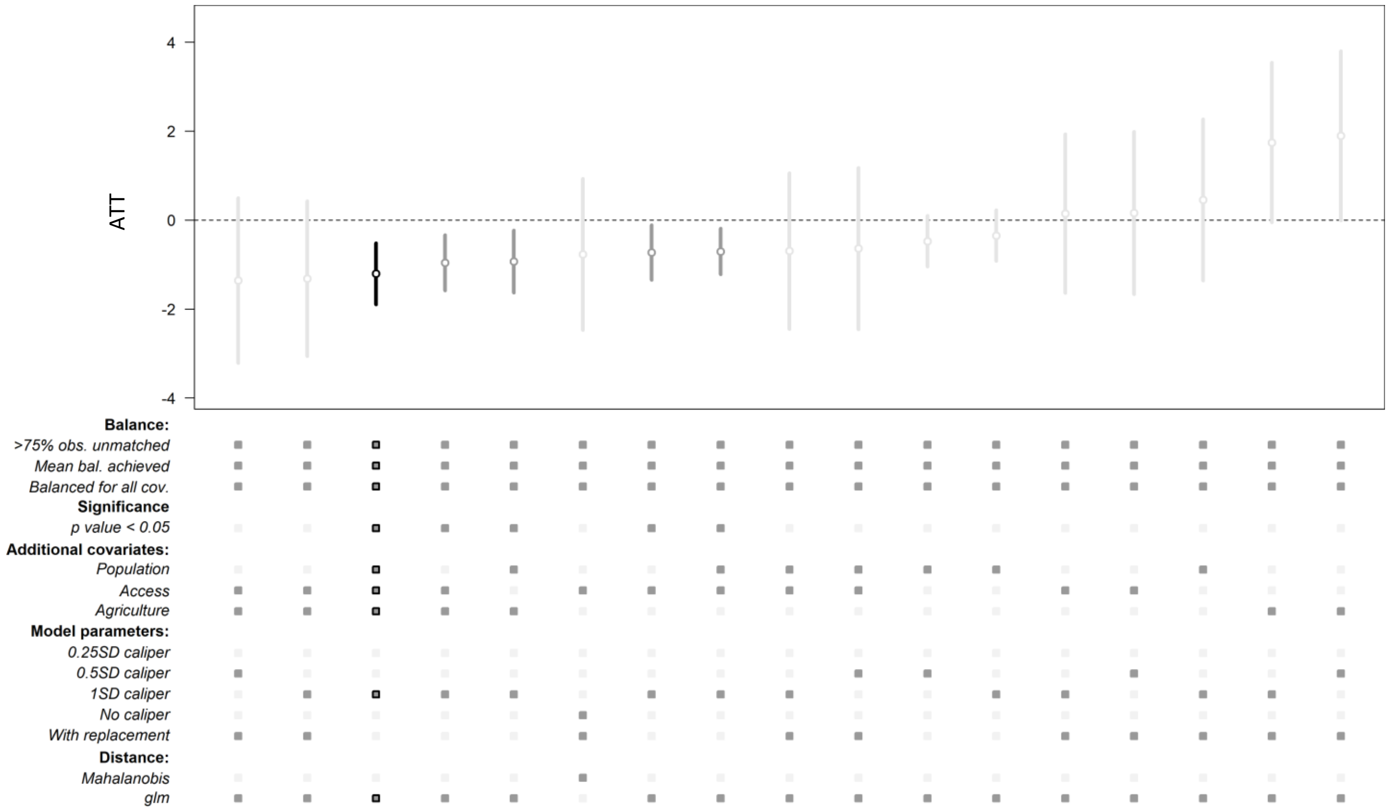
(**G**) Matching treatment: **Households near PAs**; outcome variable: **Months of adequate food** (17 models with sufficient balance and sample size)



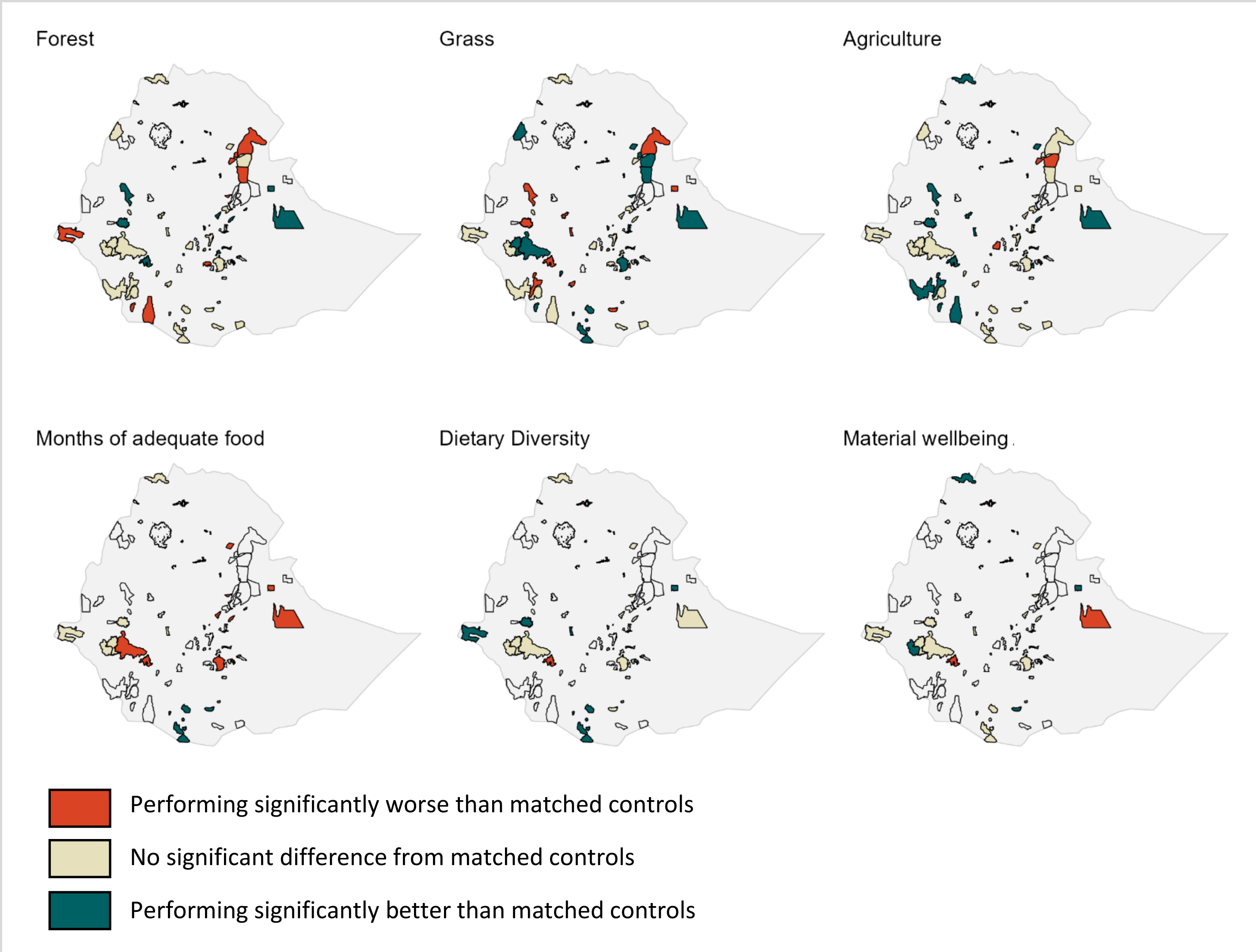
(**H**) Matching treatment: **Households near PAs**; outcome variable: **Dietary diversity** (17 models with sufficient balance and sample size)



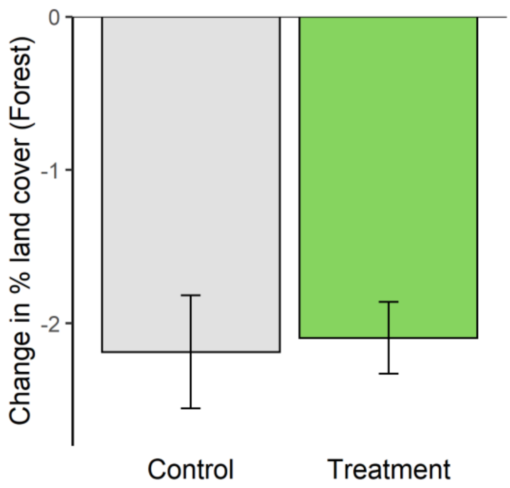
(**I**) Matching treatment: **Households near PAs**; outcome variable: **Material wellbeing** (17 models with sufficient balance and sample size)



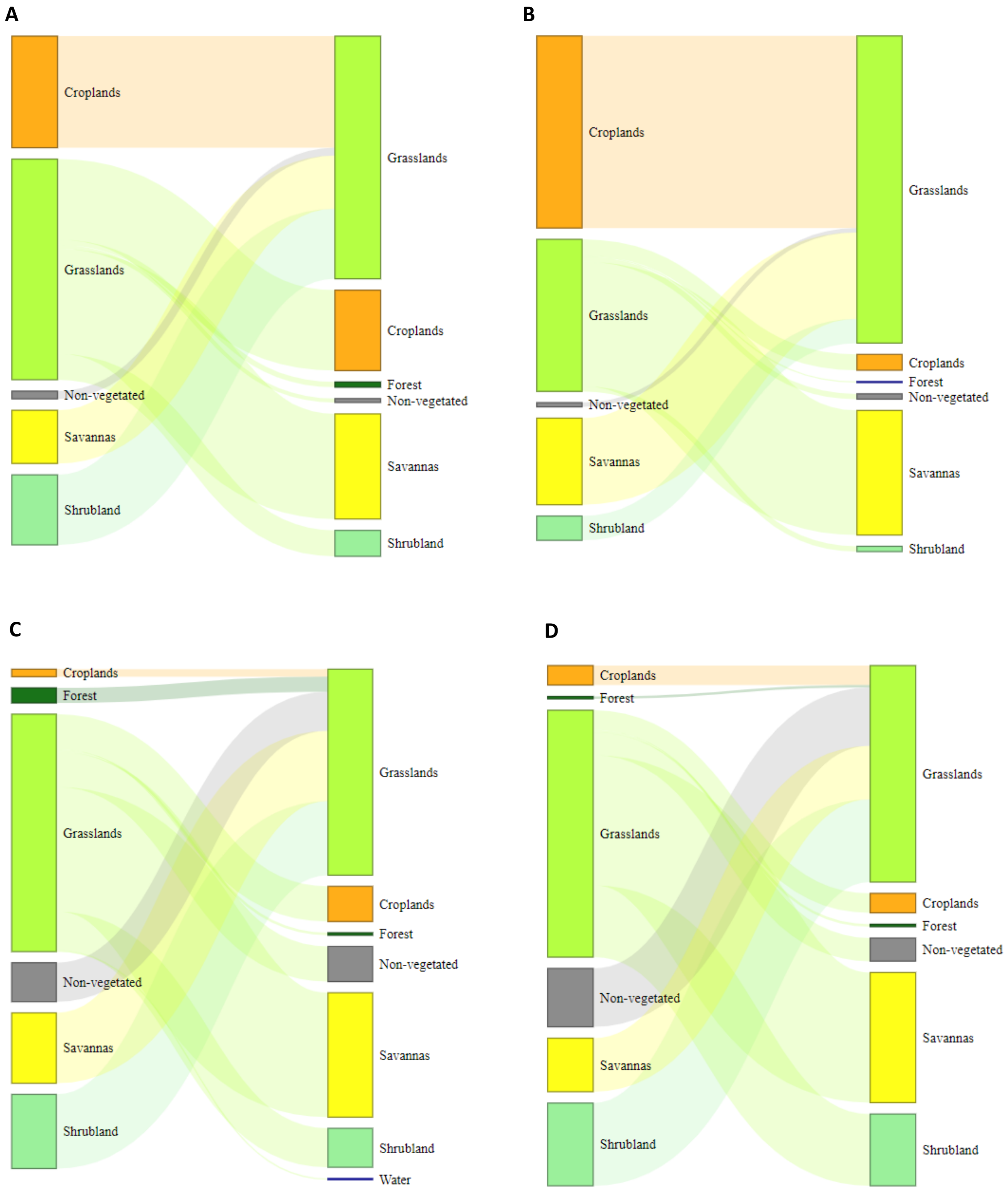
Supplementary Figure 7 Comparing results from the primary matching approach to 248 different matching model specifications for each matching treatment and corresponding outcome variables (A-I). The result from the primary matching approach is shown in black. For all comparison models, those where there was a significant difference between treatments and controls are shown in dark grey and those with no significant difference are shown in light grey. Average Treatment Effect on the Treated (ATT) were estimated using covariate-adjusted linear regression on the matched samples, incorporating matching weights and subclass-clustered robust standard errors. Statistical significance of treatment–control differences was assessed using two-sided Wald z-tests of the treatment coefficient. Results from models which did not achieve sufficient balance (standardised mean difference for all covariates <0.25) or sample size (at least 75% of treatment units matched) during matching were removed from the figures to reduce noise.



Supplementary Figure 8 Maps showing the performance of each protected area compared to matched controls. A protected area is found to be performing better than matched controls if its average treatment effect (ATT) is significantly positive (agriculture ATTs were inverted to conform with this), and worse if the ATT is significantly negative.



Supplementary Figure 9 National Forest Priority Area (NFPA) counterfactual analysis comparing forest loss from 2000-2021 within NFPAs and in matched control areas outside of both NFPAs and protected areas



Supplementary Figure 10 Sankey diagrams showing landcover changes from and to grassland (2001-2020) in statistically matched units (A) treatment units for strict PAs, (B) control units for strict PAs, (C) treatment units for less strict PAs, and (D) control units for less strict PAs. Gridcells which remained grassland and gridcells which changed between land cover types that were not grassland were excluded for easier interpretation.

Supplementary tables

Supplementary Table 1 List of protected areas removed and added cleaning the World Database of Protected Areas dataset for Ethiopia with updated information from the Ethiopian Wildlife Conservation Authority, along with their metadata and the reason for the change.

Name	Designation	IUCN	Additional information
Removed PAs – degazetted			
Akobo	Controlled hunting area	VI	5870 km^2
Awash West	Controlled hunting area	VI	11821 km^2
Awash West	Wildlife Reserve	IV	1494 km^2
Boyo swamp	Controlled hunting area	VI	324 km^2
Dabus valley	Controlled hunting area	VI	1909 km^2
Donkoro Chaka	National Park	II	78 km^2
Eastern Hararghe	Controlled hunting area	VI	33009 km^2
Mizan-Teferi	Controlled hunting area	VI	3146 km^2
Segen Valley	Controlled hunting area	VI	396 km^2
Tedo	Controlled hunting area	VI	2379 km^2
Removed PAs – encompassed into another PA			
Omo West	Controlled hunting area	VI	Encompassed into Omo (Omo expanded from 3885 – 5144 km^2)
Yabello	Sanctuary	II	Encompassed into Borena (Borena downsized from 45821 – 3726 km^2)
Removed PAs – duplicate			
Simien National Park	World heritage site	VI	Duplicate of Simien Mountains National Park
Added PAs - gazetted			
Abune Yosef Zigit Abohoy Gara	Community Conservation Area	VI	80 km^2, gazetted in 2014
Anole Amude	Controlled Hunting Area	VI	102 km^2, gazetted in 2018
Bakusa	National Park	II	518 km^2, gazetted in 2012
Choke Mountain	Community Conservation Area	VI	60 km^2, gazetted in 2011
Godebie	National Park	II	186 km^2, gazetted in 2017
Guna Mountain	Community Conservation Area	VI	46 km^2, gazetted in 2016
Tana	UNESCO Biosphere Reserve		6972 km^2, gazetted in 2015
Majang	UNESCO Biosphere Reserve		2258 km^2, gazetted in 2017
Mahbere Silasie	Community Conservation Area	VI	191 km^2, gazetted in 2017
Menze Guassa	Community Conservation Area	VI	77 km^2, gazetted in 2011
Sheka	UNESCO Biosphere Reserve		2334 km^2, gazetted in 2012
Yayu	UNESCO Biosphere Reserve		1670 km^2, gazetted in 2010
Added PAs – missing in WDPA			
Shedeme Berbere	Controlled Hunting Area	VI	183 km^2, gazetted in 1988
Borena Sayint Worehimano	National Park	II	152 km^2, gazetted in 2007

Supplementary Table 2 Measures of effectiveness. Table showing the three environmental (forest, grassland and agricultural land cover change) and three social wellbeing (months of adequate food, dietary diversity, material wellbeing) outcome variables used to understand protected area effectiveness. All outcome variables were calculated as a change over their corresponding time period. Expectation refers to the expected direction of change for PAs compared to matched counterfactuals in the case the PAs are effective.

Outcome variable	Dataset	Time	Details	Expectation
Forest cover change	Global Forest Change v 1.9 datasets: *treecover2000* and *lossyear* [31,32]	2000-2021	Using the *treecover2000* dataset, we defined each 30 x 30 m pixel as forested if they had >40% tree coverage, where trees were defined as vegetation taller than 5 m. Then using the *lossyear*, we identified pixels which remained forested in 2021. Binary values for pixels were then aggregated across 1 x 1 km gridcells to calculate percentage forest cover in 2000 and in 2021.	Less decrease
Grassland cover change	MODIS V6 [11]	2000-2020	Grassland is defined as land cover dominated by herbaceous annuals (<2 m) and was based on University of Maryland land cover classifications at 500 m resolution. Datasets for 2000 and 2020 were aggregated across 1 x 1 km gridcells to calculate percentage grassland cover in both years.	Greater increase or less decrease (see Supplementary Methods S2 and Supplementary Results S2)
Agricultural land cover change	Global Land Analysis and Discovery [2]	2000-2019	Agricultural land cover is defined as land dominated by annual or perennial herbaceous crops at 30 x 30 m resolution. Using datasets for 2000-2003 and 2016-2019, binary values for pixels were then aggregated across 1 x 1 km gridcells to calculate percentage agricultural land cover in both years.	Less increase
Months of Adequate Household Food Provisions (months of adequate food) change	World Bank Living Standards Measurement Study (LSMS), Ethiopian Socioeconomic Surveys [29,30]. (Further information is available in Supplementary methods)	2011-2016	MAHFP calculated from panel data in 2011 and 2016 as the number of months in the year the household had enough food to eat [33].	Greater increase or less decrease
Household Dietary Diversity Score (dietary diversity) change			HDDS calculated from panel data in 2011 and 2016 as the number of different food items (from a list of 16 items shown in Supplementary Table 3) consumed by the household in the week prior to the survey [33].	Greater increase or less decrease
Material wellbeing status (proxied through a weighted asset ownership score) change			Material wellbeing was proxied through weighted asset ownership scores were calculated from panel data in 2011 and 2016 for each household. This was based on the number of different assets they owned (from a list 24 asset items shown in Supplementary Table 4), weighted using a principal component analysis [34]	Greater increase or less decrease

Supplementary Table 3 Food items considered in determining household dietary diversity status

Food item
Enjera (teff)
Other cereal (e.g., rice/sorghum/millet/wheat)
Potatoes
Pasta
Sugar/sugar products (e.g., honey/jam)
Beans/lentils/nuts
Vegetables
Fruits
Beef/sheep/goat/pork
Poultry
Eggs
Fish
Oils/fats/butter
Dairy (e.g., milk/yoghurt/cheese)
Condiments (e.g., spices/salt/pepper)
Kocho/Bula (enset)

Supplementary Table 4 Asset items for calculating material wellbeing

Asset
Bicycle
Cart (animal drawn)
Cart (hand pushed)
CD/VCD/DVD/Video Deck
Fixed line telephone
Gabi (blanket)
Gejera (machete)
Geso (pick axe)
Kerosene stove
Machid (sickle)
Mattress and/or bed
Mitad (flatbread stove)
Mobile telephone
Plough (modern)
Plough (traditional)
Radio
Satellite Dish
Shelf for storing goods
Sofa set
Television
Wardrobe
Water pump
Water storage pit
Wrist watch/clock

Supplementary Table 5 Covariates used for statistical matching relating to each directed acyclic graph (DAG) in Extended Data Fig 2 A and B. Data for all covariates resampled to 1km resolution for gridcell matches and to a 2km buffer around each household for household matches. Further information on the theory for including each covariate is included in Supplementary Table 6.

DAG	Covariate	Description	Data type	Unit	Data source
A & B	**ELEVATION**	Altitude	Continuous	m.a.s.l	Global 3- Arc-Second Elevation (GTOPO30) [4]
A & B	**SLOPE**	Slope	Continuous	Degrees	Global 3- Arc-Second Elevation (GTOPO30) [4]
A & B	**TEMPERATURE**	Average annual temperature (1981-2010)	Continuous	°C	Climatologies at high resolution for the earth's land surface areas (CHELSA) [5]
A & B	**PRECIPITATION**	Average annual rainfall (1981-2010)	Continuous	kg/m^2	Climatologies at high resolution for the earth's land surface areas (CHELSA) [5]
A & B	**AGRICULTURAL SUITABILITY**	Historical average suitability based on rainfed conditions (1980-2009)	Continuous		[35]
A	**ECOREGION**	Dominant ecoregion type	Categorical		[36]
A & B	**ETHNO-LINGUISTIC GROUPS**	First component of a PCA of proportion of people in each group	Continuous		[37]
A & B	**ACCESS**	Travel time to nearest city (>50,000 people) in 2000	Continuous	Minutes	Global Accessibility Map [3]
A & B	**POPULATION**	Population in 2000	Continuous	Number of people per 1km^2 grid cell	[1]
A	**FOREST**	Baseline forest cover in 2000	Continuous	%	[32]
A & B	**AGRICULTURE**	Baseline agricultural land in 2003	Continuous	%	Global Land Analysis and Discovery [2]
A	**GRASSLAND**	Baseline grassland in 2000	Continuous	%	MODIS V6 [38]
A	**LAND**	Majority land cover type in 2000	Categorical		MODIS V6 [38] – Reclassified into broader categories

Supplementary Table 6 Theory on how each confounding variable may influence both treatment and outcomes from literature review focused on the Ethiopian context. Darker colours indicate stronger expected impact on the outcome.

Covariate	Potential Effect on Treatment Selection	Potential effect on environmental outcomes			Potential effect on wellbeing outcomes		
		Forest Cover Change	Agricultural Land Cover Change	Grassland Cover Change	Months of Adequate Household Food Provisioning Change	Household Dietary Diversity Change	Asset Ownership Change
Elevation	PA locations are often biased towards high elevation areas, as this land is often less accessible and less able to be used for human settlement and agriculture [39]. Joppa and Pfaff [40] found elevation to be a significant and positive factor explaining protected area locations in Ethiopia.	Moderate impact. Higher elevations may have some protective effect for forest due to being less accessible for logging or less suitable for agriculture, but this varies based on local practices [41]. In coffee growing regions, deforestation is greater at high elevations as they are not suitable for coffee growth, while lower elevations are somewhat protected due to providing shade for coffee plants [42].	Moderate impact. Lower elevations are often preferred for agriculture [43] due to improved soil conditions and access to markets so agricultural expansion may be more likely.	Minimal impact. Grasslands at lower elevations may be more vulnerable to conversion to agriculture [43].	Minimal impact. Households at higher elevations are likely to have greater travel time to markets and fewer alternative livelihood options, which may impact food provisioning [44].	Moderate impact. Farm crop composition and diversity has been shown to be influenced by elevation, and this is likely to be closely related household dietary diversity, particularly in rural areas where subsistence farming is a common livelihood [45].	Minimal impact. Households at higher elevations are likely to have greater travel time to markets and fewer alternative livelihood options, which may impact how much income they can generate for asset accumulation [44].
Slope	PAs are also often biased towards steeper slopes as these areas are often less accessible and have fewer opportunity costs for alternative uses such as agriculture [40].	Moderate impact. Steep slopes resist deforestation due to difficulty in clearing; low slopes are more easily converted to other land uses and preferable for agriculture [41,42].	Moderate impact. Steep slopes limit agriculture and grazing due to reduced accessibility, reducing expansion [43].	Minimal impact. Flat terrain may promote grassland conversion for agricultural purposes [43].	Moderate impact. Slope has been shown to impact soil nutrients in Southern Ethiopia with significantly lower organic carbon on total nitrogen in lower slopes [46]. This in turn influences food production and food security.	Minimal impact. Farmer decisions regarding on farm crop diversity are influenced by slope [45].	Minimal impact. Slope has been shown to impact soil nutrients in Southern Ethiopia with significantly lower organic carbon on total nitrogen in lower slopes [46]. This in turn influences food production and production income.
Precipitation (1981-2010)	Areas with high precipitation tend to support denser forests and biodiversity which may make them more likely to be established as PAs [39]. Species richness was found to be significantly positively associated with PA placement in Ethiopia [40].	Moderate impact. Wetness influences agricultural suitability which in turn can influence likelihood of forest clearance for agriculture [41], particularly as much forest disturbance is driven by smallholder agriculture which is more reliant on rain [47].	Strong impact. Wetness influences agricultural suitability which in turn can influence likelihood of agricultural expansion [41], particularly as subsistence farming is the most common livelihood in Ethiopia and is more reliant on rain [47].	Moderate impact. Grasslands in moderately wet regions may be targeted for agriculture, while very arid areas are less likely to be converted [41,48].	Moderate impact. Higher precipitation can increase crop productivity, improving food provisioning particularly as the majority of agriculture in Ethiopia is rain-fed [49].	Moderate impact. Higher historical average rainfall is positively correlated with crop diversity on Ethiopian farms [50] which impacts dietary diversity	Minimal impact. Higher precipitation can increase crop productivity, improving yields and available product to sell for additional income [49].
Temperature (1981-2010)	Temperature influences vegetation types as well as suitability of areas for agriculture. Both of these are likely to influence whether a PA is designated in the area [39].	Moderate impact. In Ethiopia, extreme high temperatures are associated with crop damage and a farmer response to deforest and expand agriculture for food security [51].	Moderate impact. Where high temperatures reduce crop yield, agricultural expansion may occur to maintain food production levels [51,52].	Minimal impact. Temperatures will impact suitability for cropland expansion, and so areas with temperatures more suited for agriculture may be more likely to be converted from grassland to agriculture [53].	Moderate impact. Extreme high temperatures in Ethiopia have been found to be associated with increase crop damage and reduced crop production and value [51].	Minimal impact. historical mean temperatures are associated with lower crop diversity on Ethiopian farms [50] which in turn influences dietary diversity.	Minimal impact. Higher temperatures have been shown to have a negative relationship with agricultural yields and income [54].
Agricultural Suitability	PAs are often biased towards areas less suitable for agriculture as there are fewer opportunity costs for alternative uses [40].	Moderate impact. Greater agricultural suitability can influence the likelihood of forest clearance for agriculture [41].	Strong impact. Agricultural suitability can influence likelihood of agricultural expansion [41].	Moderate impact. Greater agricultural suitability can influence the likelihood of grassland conversion to agriculture [41].	Strong impact. Agricultural suitability takes into account a variety of soil properties. Households living in areas with soil fertility are more likely to be able to produce adequate food for consumption [55].	Moderate impact. Soil fertility (an important component of agricultural suitability) has a statistically significant negative relationship with crop diversification in Ethiopia, with farmers more likely to have more diverse crops on more degraded less suitable land [56].	Moderate impact. suitability takes into account a variety of soil properties. Rural households living in areas with soil fertility are more likely to be able to produce higher yields which may increase the amount of products that can be sold on the market to generate additional income [57]. People leaving in areas with low agricultural potential have also been found to be more marginalised [58].

Ecoregion	Certain ecoregions (e.g., forests) may be prioritised in PA designation due to their respective conservation value. High biodiversity areas are a priority in Ethiopia's NBSAP [59].	Moderate impact. An area dominated by a non-forest ecoregion type at baseline is less likely to experience changes in forest cover.	Moderate impact. Ecoregion type affects suitability for agriculture conversion [60].	Moderate impact. Ecoregion type influences how likely it is an area can convert to or from grassland. E.g., savanna/ or shrubland is more associated with grassland changes [60].	Minimal impact.	Minimal impact.	Minimal impact.
Ethnolinguistic group	Ethiopia's ethnolinguistic groups have generally determined administrative region borders. Many of Ethiopia's protected areas are managed by regional rather than federal authorities. Regional authorities can request designation of new protected areas, and therefore locations may depend on priorities of different ethnolinguistic groups.	Moderate impact. Different groups have different cultural practices - e.g. pastoralism, strong or weak utilisation from the forest. Regional states have their own proclamations related to forestry and its sustainable use and conservation [59]	Moderate impact. Different groups have different cultural practices - e.g. pastoralism, strong or weak utilisation from the forest. Regional policies can influence expansion. For example land rental duration and size depends on the laws of the respective regional state [61].	Moderate impact. Different groups have different cultural practices - e.g. pastoralism, strong or weak utilisation from the forest. According to Ethiopia's NBSAP [59] several regions are integrating measures to rehabilitate degraded montane grasslands.	Moderate impact. Different ethnolinguistic groups in Ethiopia have different indigenous agrisystems and cultures relating to food production, which can have impacts on food security [62]. For example, households in enset-based agrisystems have been found to be less impacted by drought and receive less food aid than other farming systems in Ethiopia [63,64].	Moderate impact. Ethiopia's ethnolinguistic groups closely align with administrative regions. Dietary diversity has been shown to significantly differ across regions which may be related to access to diverse food markets, employment opportunities of cultural habits for consuming diverse foods [65].	Moderate impact. Ethnic diversity and ethnicity have been found to be important factors in explaining differences in wealth [66]. Additionally, hotspots of marginality in Ethiopia are more homogenous in terms of ethnic group [58].
Access (travel time to major city, 2000)	Remote areas are more likely to be protected due to lower economic opportunity costs. Joppa and Pfaff [40] found distance to urban areas to be significantly positively associated with PA placement in Ethiopia.	Strong impact. More accessible areas often experience more deforestation due to reduced travel time to markets which can boost agriculture conversion and logging [47].	Strong impact. Better access can promote expansion of large scale agriculture as it reduces transportation costs to markets and less accessible areas may have higher costs of clearing the land therefore reducing agricultural expansion [52].	Moderate impact. Accessible grasslands may be at risk of conversion, but this depends on local demand for land [67].	Moderate impact. Access to towns in Ethiopia is negatively associated with total cultivated area which is likely to impact food provisioning ability [68]. Remote areas might also experience reduced food provisioning due to limited market access [44].	Minimal impact. Limited access to urban markets in remote areas has been shown to reduce dietary diversity in Ethiopia [44].	Strong impact. Positive relationships between access to markets and household wellbeing have been found in Ethiopia [44].
Population (2000)	Areas with high human populations are generally more developed with land dedicated to alternative uses making them less likely to be established as protected areas due to opportunity costs and social conflicts [39].	Strong impact. Higher population densities are often in towns and cities with greater possibilities to generate income through non-farming related jobs so are less associated with forest clearance for agriculture [42]. Lower population densities were found to lead to higher forest loss in the Albertine rift [69].	Strong impact. Population density is likely to affect the demand for farmland [52]. In areas close to cities it may reduce agricultural expansion as people switch to alternative livelihoods, whereas in less accessible areas it may lead to expansion to meet subsistence demands [42].	Moderate impact. High population densities are likely to be associated with increased livestock grazing promoting bush encroachment on grasslands [70].	Moderate impact. In rural areas of Ethiopia, higher population density is associated with smaller farm sizes and lower farm income per hectare [71] which is likely to reduce food security.	Minimal impact. High populations are often found in urban areas. Living in an urban area has been found to be positively associated with household dietary diversity in Ethiopia [72].	Moderate impact. High population areas are often found in urban locations, and poverty status and change are driven by different factors in urban compared to rural areas in Ethiopia [73].
Baseline Forest Cover (2000)	High baseline forest cover areas may be prioritised for protection to conserve forest ecosystems, biodiversity, and carbon stocks and are considered priorities for conservation in Ethiopia's National Biodiversity Strategic Action Plan [59].	Moderate impact. More intact forest is likely to be less accessible and therefore less targeted for logging and clearance for agricultural activities [47].	Moderate impact. Lower baseline forest cover may indicate fragmented landscapes which are more likely to be targeted for agricultural expansion [74].	Minimal impact. Areas with high baseline forest cover are unlikely to undergo grassland changes.	Minimal impact.	Minimal impact.	Minimal impact.
Baseline Grassland Cover (2001)	Grassland-rich areas may be chosen for PAs to preserve unique ecosystems and biodiversity.	Minimal impact.	Moderate impact. Higher baseline grassland cover may indicate greater suitability of land for agriculture conversion [75].	Moderate impact. Baseline grassland cover affects how much grass can be gained/lost.	Minimal impact.	Minimal impact.	Minimal impact.
Baseline Agriculture (2000)	Areas with minimal agriculture are more likely to be established as PAs to avoid disrupting land use and economic opportunities. Joppa and Pfaff [40] found agricultural suitability to be significantly negatively associated with PA placement in Ethiopia.	Minimal impact. Forest areas fragmented with agriculture are more likely to be targets for further conversion to agriculture [74].	Strong impact. Baseline agricultural land coverage affects how much agricultural expansion can occur.	Minimal impact. Areas with high baseline agriculture may have more potential for grassland restoration.	Moderate impact. Areas under large scale farming have been shown to reduce local household food security in several regions of Ethiopia due to limiting land available for smallholders, outsourcing of employees and export of food into national and international markets [76,77].	Minimal impact. Small (less intensive) farms have been shown to have higher crop richness than larger farms, which may affect dietary diversity [78].	Moderate impact. Village level crop areas in Ethiopia are positively correlated with farm-related income which will impact asset accumulation [79].

Supplementary Table 7 Semivariance produced at different sampling densities for gridcells

Distance between sampled units (km)	Mean semivariance	Maximum semivariance	Minimum semivariance
0	24.34	51.59	2.46
2	2.09	3.30	2.58
4	2.97	3.21	2.45
6	3.13	3.34	2.65

Supplementary Table 8 Involvement of external project funding or non-governmental organisations (NGOs) with protected areas. This compiles accessible information available for each protected area on whether it was associated with any external funding between 2000 and 2020.

Protected Area	NGO present	NGO names
Abasheba Demero	No	
Abjata Shala Lakes	Yes	Farm Africa; Wetlands International; United Nations Development Program (Global Environment Fund)
Abune yosef Zigit Abohoy Gara	No	
Adaba Dodola	Yes	GIZ
Afdem-Gewane	No	
Alitash	Yes	United Nations Development Program (Global Environment Fund)
Aluto	No	
Amibera-Melika sadi	No	
Anole Amude	No	
Arba Gugu	No	
Arsi Mountains	Yes	Climate Chance, Rufford Foundation
Asibahri Kebena	No	
Awash	Yes	United Nations Development Program (Global Environment Fund), GIZ
Babile Elephant	Yes	United Nations Development Program (Global Environment Fund)
Bakusa	No	
Bale Mountains	Yes	United Nations Development Program (Global Environment Fund); Frankfurt Zoological Society; Ethiopian Wolf Conservation Programme
Bejmiz	No	
Beroye	No	
Besemena Odo-bulu	No	
Billen-Hertale	No	
Borena	Yes	SOS Sahel International
Borena sayint Worehimano	Yes	Ethiopian World Conservation Programme
Chebera Churchura	Yes	GIZ; Global Environment Fund
Chelbi	No	
Chifra	No	
Choke Mountain	Yes	Global Environment Fund
Deddessa	No	
Dembel Ayisha Adigala	No	
Dhati Welel	No	
Dindin	No	
Erer-Gota	No	
Gambella	Yes	United Nations Development Program (Global Environment Fund); African Parks
Gara Gumbi	No	
Gara Meti	No	
Gassera Wabe	No	
Gelila Dura	No	
Geralle	Yes	United Nations Development Program (Global Environment Fund);

Gewane	Yes	CARE climate change
Gibe Sheleko	No	
Godebie	No	
Guna Mountain	Yes	Global Environment Fund
Hadar	No	
Hallaydeghe-Asebot	Yes	United Nations Development Program (Global Environment Fund); KFW
Hanto	No	
Haro Aba Diko	No	
Hurufa-Soma	No	
Jibat	No	
Kafa	Yes	NABU
Kafta Sheraro	Yes	United Nations Development Program (Global Environment Fund)
Liban Plain	No	
Loka Abaya	Yes	SOS Sahel International
Mago	Yes	Global Environment Fund
Mahbere Silasie	No	
Majang	Yes	Swedish International Development Cooperation Agency (Farm Africa, TechnoServe and MELCA-Ethiopia)
Mao-Komo	No	
Maze	No	
Melka Guba	No	
Menze Guassa	No	
Milleserdo	No	
Munessa Ambagoda-Sade	No	
Munessa Kuke	No	
Murulle	No	
Nanigadhera	No	
Nech Sar	Yes	United Nations Development Program (Global Environment Fund); GIZ
Omo	Yes	United Nations Development Program (Global Environment Fund)
Senkele Swaynes Hartebeast	Yes	United Nations Development Program (Global Environment Fund), Farm Afric;
Shedeme Berbere	No	
Sheka	Yes	NABU
Shinele Meto	No	
Simien Mountains	Yes	United Nations Development Program (Global Environment Fund;, KFW; AWF
Sororo Torgam Gara Muktar	No	
Tama	No	
Tana	Yes	NABU
Telalak Dewe	No	
Tulu Lafto-Sedden	No	
Urgan-Bula	No	
Weyib Valley	No	
Yangudi Rassa	Yes	United Nations Development Program (Global Environment Fund)
Yayu	Yes	Critical Ecosystem Partnership Fund (CEPF); NABU

Supplementary Table 9 Demographic information for questionnaire respondents. N is number of respondents and % is the percentage of respondents.

Demographic	N	%
Age		
<21	0	0.0
21-30	1	2.7
31-40	15	40.5
41-50	11	29.7
51-60	9	24.3
61-70	0	0.0
>70	1	2.7
Sex		
Male	32	86.5
Female	5	13.5
Education		
Primary	1	2.7
Secondary	0	0.0
Bachelors	6	16.2
Masters	21	56.8
PhD	9	24.3
Organisation		
Research	5	11.6
NGO	6	14.0
Private	2	4.7
Government	30	69.8

Supplementary Table 10 Updated full list of protected areas and associated metadata. Earliest year represents the earliest record (to the best of the Ethiopian Wildlife Conservation Authorities knowledge) of the protected area either regionally or nationally, including if the area used to be under a different type of protection or different name, rather than the date it was designated on the World Database of Protected Areas. Budget group indicates whether the budget fell within the bottom quartile (Low), interquartile range (Mid) or upper quartile (High). True budget data can be obtained from the Ethiopian Wildlife Conservation Authority. This dataset represents the protected area shapefile in September 2024, this is continually being updated.

Name	Designation	IUCN	Area (km^2)	Earliest Year	Budget
Abasheba Demero	Control Hunting Area	VI	178	1994	Low
Abjata Shala Lakes	National Park	II	813	1963	High
Abune yosef Zigit Abohoy Gara	Community Conservation Area	VI	81	2014	Low
Adaba Dodola	Control Hunting Area	VI	514	2000	High
Afdem-Gewane	Control Hunting Area	VI	4718	1973	Low
Alitash	National Park	II	2667	1997	High
Aluto	Control Hunting Area	VI	89	2006	Low
Amibera-Melika sadi	Control Hunting Area	VI	111	1973	Low
Anole Amude	Control Hunting Area	VI	102	1973	Low
Arba Gugu	Control Hunting Area	VI	338	1995	Low
Arsi Mountains	National Park	II	930	1973	Mid
Asibahri Kebena	Control Hunting Area	VI	167	1973	Low
Awash	National Park	II	590	1958	High
Babile Elephant	Sanctuary	IV	8804	1962	High
Bakusa	National Park	II	518	2012	Mid
Bale Mountains	National Park	II	2148	1962	High
Bejmiz	National Park	II	1836	2015	Low
Beroye	Control Hunting Area	VI	356	2013	Low
Besemena Odo-bulu	Control Hunting Area	VI	242	1930	Mid
Billen-Hertale	Control Hunting Area	VI	825	1973	Low
Borena	National Park	II	3724	1966	High
Borena sayint Worehimano	National Park	II	152	1930	High
Chebera Churchura	National Park	II	1265	1997	High
Chelbi	Wildlife Reserve	IV	4303	1973	Low
Chifra	Control Hunting Area	VI	545	1998	Low
Choke Mountain	Community Conservation Area	VI	60	2011	Low
Deddessa	National Park	II	2343	1970	Low
Dembel Ayisha Adigala	Control Hunting Area	VI	908	2010	Low
Dhati Welel	National Park	II	1040	2010	Mid
Dindin	Control Hunting Area	VI	286	1992	High
Erer-Gota	Control Hunting Area	VI	2630	1973	Low
Gambella	National Park	II	4621	1966	High
Gara Gumbi	Open Hunting Area	VI	49	1973	Low
Gara Meti	Open Hunting Area	VI	319	1973	Low
Gassera Wabe	Control Hunting Area	VI	230	1964	Low
Gelila Dura	Open Hunting Area	VI	52	1973	Low
Geralle	National Park	II	1767	1974	High
Gewane	Wildlife Reserve	IV	3008	1973	Low
Gibe Sheleko	National Park	II	321	1930	Low
Godebie	National Park	II	187	2016	Mid

Guna Mountain	Community Conservation Area	VI	46	2016	Mid
Hadar	Control Hunting Area	VI	377	1973	Low
Hallaydeghe-Asebot	National Park	II	1099	1973	Mid
Hanto	Control Hunting Area	VI	206	1991	Mid
Haro Aba Diko	Control Hunting Area	VI	244	2000	Low
Hurufa-Soma	Control Hunting Area	VI	231	2000	High
Jibat	Control Hunting Area	VI	367	1988	Mid
Kafa	Biosphere Reserve	VI	7406	1973	Low
Kafta Sheraro	National Park	II	2196	1999	High
Liban Plain	Sanctuary	IV	97	1930	Low
Loka Abaya	National Park	II	546	2001	Low
Mago	National Park	II	1870	1971	Mid
Mahbere Silasie	Community Conservation Area	VI	191	2016	Mid
Majang	Biosphere Reserve	VI	2258	1973	Mid
Mao-Komo	National Park	II	2320	2016	Low
Maze	National Park	II	202	1983	High
Melka Guba	National Park	II	547	1930	Low
Menze Guassa	Community Conservation Area	VI	77	1600	Mid
Milleserdo	Wildlife Reserve	IV	7305	1973	Low
Munessa Ambagoda-Sade	Control Hunting Area	VI	163	1963	Mid
Munessa Kuke	Control Hunting Area	VI	110	1993	High
Murulle	Control Hunting Area	VI	504	1973	Low
Nanigadhera	Control Hunting Area	VI	192	2018	Low
Nech Sar	National Park	II	415	1966	High
Omo	National Park	II	5160	1959	Mid
Senkele Swaynes Hartebeast	Sanctuary	IV	53	1964	High
Shedeme Berbere	Control Hunting Area	VI	184	1988	Mid
Sheka	Biosphere Reserve	VI	2334	1973	Mid
Shinele Meto	Control Hunting Area	VI	641	2000	Low
Simien Mountains	National Park	II	411	1959	High
Sororo Torgam Gara Muktar	Control Hunting Area	VI	73	2000	Mid
Tama	Community Conservation Area	IV	1948	1973	High
Tana	Biosphere Reserve	VI	6972	2011	Mid
Telalak Dewe	Control Hunting Area	IV	503	1972	Low
Tulu Lafto-Sedden	Sanctuary	IV	563	1988	Mid
Urgan-Bula	Control Hunting Area	VI	78	2000	Low
Weyib Valley	Control Hunting Area	VI	350	2013	Low
Yangudi Rassa	National Park	II	3047	1969	Mid
Yayu	Biosphere Reserve	VI	1670	1988	High

Supplementary Table 11 Number of species with range overlapping each protected area

Protected area	Birds	Herptiles	Mammals	Plants	Total
Abasheba Demero	369	51	83	217	720
Abjata Shala Lakes	476	58	90	277	901
Abune Yosef Zigit Abohoy Gara	278	29	58	121	486
Adaba Dodola	340	63	88	237	728
Afdem-Gewane	443	57	86	222	808
Alitash	298	29	67	121	515
Aluto	449	54	88	259	850
Amibera-Melika sadi	438	57	87	204	786
Anole Amude	455	58	91	274	878
Arba Gugu	375	56	80	237	748
Arsi Mountains	465	70	107	302	944
Asibahri Kebena	416	49	84	168	717
Awash	457	63	85	229	834
Babile Elephant	373	77	80	257	787
Bakusa	306	29	66	116	517
Bale Mountains	393	69	94	242	798
Bejmiz	312	29	68	120	529
Beroye	370	54	87	202	713
Besemena Odo-bulu	361	52	85	220	718
Billen-Hertale	427	50	83	183	743
Borena	468	78	94	291	931
Borena sayint Worehimano	320	36	66	138	560
Chebera Churchura	429	62	99	287	877
Chelbi	459	78	116	243	896
Chifra	295	30	53	121	499
Choke Mountain	320	45	74	144	583
Deddessa	386	55	89	222	752
Dembel Ayisha Adigala	321	69	52	159	601
Dhati Welel	331	43	74	173	621
Dindin	378	57	77	215	727
Erer-Gota	411	57	74	230	772
Gewane	355	44	77	151	627
Gambella	348	68	95	169	680
Gara Gumbi	430	56	81	210	777
Gara Meti	459	60	87	239	845
Gassera Wabe	374	48	73	218	713
Gelila Dura	327	36	73	131	567
Geralle	304	76	62	185	627
Gibe Sheleko	421	56	78	253	808
Godebie	272	26	53	117	468
Guna Mountain	309	35	65	134	543
Hadar	285	33	59	115	492
Hallaydeghe-Asebot	444	60	88	208	800
Hanto	350	55	82	215	702
Haro Aba Diko	360	55	86	224	725
Hurufa-Soma	356	56	87	221	720
Jibat	407	55	80	252	794
Kafa	457	74	109	335	975
Kafta Sheraro	327	29	58	147	561
Liban Plain	323	59	62	211	655
Loka Abaya	472	63	98	270	903

Mago	445	73	117	225	860
Mahbere Silasie	319	29	55	130	533
Majang	403	61	100	236	800
Mao-Komo	327	46	74	156	603
Maze	424	65	97	246	832
Melka Guba	354	68	63	208	693
Menze Guassa	326	33	67	139	565
Milleserdo	312	38	61	121	532
Munessa Ambagoda-Sade	433	54	93	269	849
Munessa Kuke	391	55	86	265	797
Murulle	403	71	108	181	763
Nanigadhera	343	50	71	215	679
Nech Sar	472	72	102	264	910
Omo	463	75	117	228	883
Senkele Swaynes Hartebeast	443	58	89	246	836
Shedeme Berbere	371	51	85	219	726
Sheka	412	67	99	273	851
Shinele Meto	367	59	64	221	711
Simien Mountains	343	37	67	179	626
Sororo Torgam Gara Muktar	355	59	71	202	687
Tama	464	71	119	258	912
Tana	433	55	81	184	753
Telalak Dewe	306	33	63	127	529
Tulu Lafto-Sedden	371	48	86	240	745
Urgan-Bula	345	55	80	237	717
Weyib Valley	367	54	77	213	711
Yangudi Rassa	311	37	66	124	538
Yayu	382	60	91	250	783

Supplementary Table 12 Matching is robust to the presence of an unobserved confounding variable. Outputs from sensitivity analyses conducted using the R package *Sensemakr* for each outcome variable in each matching group. The robustness value (RV) represents the percentage of the residual variance of both the treatment and the outcome that an unobserved confounder would need to explain to bring the estimated effect to zero. This is then compared to a benchmark covariate, for environmental outcomes we used population size as the benchmark, and for social outcomes we used agricultural suitability. We only tested these bounds up to 9 times the strength of the benchmark.

Matching group	**Outcome variable**	**RV (%)**	**Benchmark covariate [RV (%)]**	**Explanatory power required by unobserved covariate to bring the outcome to zero, compared to the observed power of the benchmark**
Strict	Forest	2.81	Population [0.04]	> 9x
	Grassland	6.40		> 9x
	Agriculture	8.04		> 9x
Less Strict	Forest	NA	Population [0.08]	NA (effect is already zero)
	Grassland	3.37		> 9x
	Agriculture	8.84		> 9x
Household	Months of adequate food	2.35	Agricultural suitability [0.01]	> 9x
	Dietary diversity	NA		NA (effect is already zero)
	Material wellbeing	13.31		> 9x

Supplementary Table 13 Individual protected area environmental outputs showing the average treatment effect on the treated (ATT), t-statistic (t) and significance (p); significant p-values are shown in bold. For forest and grassland, a positive ATT indicates better performance while for agriculture a negative ATT indicates better performance.

Protected area	Forest			Agriculture			Grassland		
	ATT	t	p	ATT	t	p	ATT	t	p
Abasheba Demero (LS)	2.78	5.36	**<0.001**	-0.89	-0.26	0.796	-0.54	-0.12	0.906
Abjata Shala Lakes (S)	-0.20	-1.63	0.103	7.78	2.08	**0.038**	11.95	1.90	0.058
Adaba Dodola (LS)	-1.25	-2.14	**0.033**	-1.82	-1.48	0.138	-2.48	-0.59	0.558
Afdem Gewane (LS)	-0.02	-0.29	0.771	-0.35	-1.67	0.096	0.43	0.31	0.759
Alitash (S)	0.03	0.38	0.706	-0.08	-0.24	0.813	46.99	18.73	**<0.001**
Amibera Melika sadi (LS)	-0.42	-3.37	**0.001**	-0.56	-1.89	0.059	-54.63	-3.72	**<0.001**
Anole Amude (LS)	0.67	2.30	**0.022**	-1.54	-0.60	0.550	7.09	1.79	0.074
Arba Gugu (LS)	-0.28	-0.53	0.596	-2.67	-1.25	0.212	13.04	3.10	**0.002**
Arsi Mountains (S)	0.15	0.76	0.447	3.68	1.88	0.060	0.54	0.08	0.933
Asibahri Kebena (LS)	-0.59	-4.30	**<0.001**	-0.71	-1.87	0.061	8.38	2.45	**0.015**
Awash (S)	-0.06	-1.44	0.150	-0.19	-0.65	0.519	4.85	1.96	0.050
Babile Elephant (LS)	0.10	2.43	**0.015**	-2.76	-8.99	**<0.001**	3.43	4.11	**<0.001**
Bale Mountains (S)	0.52	0.58	0.564	1.96	1.42	0.155	7.56	3.03	**0.003**
Besemena Odo bulu (LS)	1.88	4.03	**<0.001**	-3.26	-2.72	**0.007**	-2.44	-0.61	0.540
Billen Hertale (LS)	-0.29	-2.76	**0.006**	-0.48	-2.00	**0.046**	5.41	2.31	**0.021**
Borena (S)	-0.18	-1.43	0.152	-0.38	-0.76	0.445	5.34	3.03	**0.002**
Chebera Churchura (S)	1.10	4.83	**<0.001**	-2.19	-2.70	**0.007**	-4.51	-2.10	**0.036**
Chelbi (LS)	-0.62	-4.95	**<0.001**	-2.17	-4.83	**<0.001**	1.69	1.13	0.258
Chifra (LS)	0.10	1.83	0.067	-0.56	-2.86	**0.004**	7.49	10.23	**<0.001**
Deddessa (S)	0.53	2.00	**0.046**	-2.99	-4.24	**<0.001**	-5.13	-3.24	**0.001**
Dindin (LS)	0.93	2.49	**0.013**	-7.22	-3.11	**0.002**	11.29	1.67	0.095
Erer Gota (LS)	0.09	1.21	0.225	-0.57	-3.21	**0.001**	7.11	5.10	**<0.001**
Gambella (S)	-0.21	-2.20	**0.028**	-0.09	-0.46	0.645	-3.68	-1.27	0.204
Gara Gumbi (LS)	-0.56	-4.05	**<0.001**	-1.46	-1.40	0.160	-31.48	-3.07	**0.002**
Gara Meti (LS)	0.36	2.62	**0.009**	-0.10	-0.17	0.862	-5.93	-0.99	0.324
Gassera Wabe (LS)	-1.07	-2.42	**0.016**	-1.36	-0.95	0.341	-13.80	-2.53	**0.011**
Gelila Dura (LS)	-0.17	-0.68	0.498	-0.49	-0.76	0.445	2.64	0.34	0.732
Geralle (S)	0.02	0.51	0.608	-0.60	-1.90	0.057	-4.82	-1.33	0.183
Gewane (LS)	-0.39	-4.14	**<0.001**	-0.30	-1.36	0.173	7.22	7.67	**<0.001**
Gibe Sheleko (S)	-0.17	-0.95	0.342	-7.00	-2.37	**0.018**	-18.67	-3.73	**<0.001**
Hadar (LS)	-0.42	-3.96	**<0.001**	-0.30	-1.12	0.263	7.22	9.49	**<0.001**
Hallaydeghe Asebot (S)	-0.09	-1.62	0.105	-0.22	-0.72	0.469	6.79	3.35	**0.001**
Hanto (LS)	1.24	2.62	**0.009**	-1.52	-1.11	0.267	-6.56	-1.13	0.259
Haro Aba Diko (LS)	-1.24	-0.87	0.382	1.68	0.61	0.543	0.43	0.26	0.796
Hurufa Soma (LS)	-1.39	-1.82	0.069	-1.71	-1.94	0.052	1.27	0.90	0.370
Jibat (LS)	0.51	1.37	0.171	-4.45	-2.64	**0.008**	-4.81	-2.47	**0.014**
Kafa (LS)	-0.39	-1.56	0.119	-0.45	-0.80	0.422	6.06	5.59	**<0.001**
Kafta Sheraro (S)	-0.07	-1.17	0.244	-0.68	-2.28	**0.023**	-4.63	-1.24	0.217
Liban Plain (LS)	0.20	1.36	0.174	11.27	0.91	0.364	0.92	0.15	0.880
Mago (S)	-0.07	-0.71	0.476	-0.61	-1.44	0.151	0.28	0.09	0.931
Majang (LS)	-0.88	-1.48	0.138	-0.24	-0.49	0.622	1.93	1.95	0.051
Maze (S)	-0.92	-1.22	0.221	-1.26	-0.96	0.339	31.95	3.25	**0.001**

Melka Guba (S)	0.03	0.48	0.634	0.70	1.66	0.097	-20.50	-3.70	**<0.001**
Menze Guassa (LS)	0.51	0.96	0.335	-8.33	-1.36	0.172	9.53	1.76	0.078
Milleserdo (LS)	-0.12	-3.06	**0.002**	0.33	1.73	0.084	-4.01	-3.79	**<0.001**
Munessa Ambagoda Sade (LS)	-1.44	-3.14	**0.002**	10.87	2.53	**0.011**	0.64	0.07	0.946
Munessa Kuke (LS)	-1.83	-0.70	0.481	6.19	0.95	0.345	10.55	1.31	0.189
Murulle (LS)	-0.31	-2.14	**0.033**	-2.11	-3.73	**<0.001**	14.57	6.88	**<0.001**
Nech Sar (S)	0.20	1.36	0.175	-1.08	-1.39	0.165	-24.96	-2.95	**0.003**
Omo (S)	0.13	1.37	0.170	-2.31	-4.69	**<0.001**	-2.09	-1.00	0.316
Senkele Swaynes Hartebeast (LS)	0.57	1.30	0.193	-1.89	-0.96	0.338	17.41	6.00	**<0.001**
Shedeme Berbere (LS)	0.02	0.05	0.961	-2.13	-2.78	**0.006**	-4.38	-2.05	**0.040**
Sheka (LS)	-0.72	-1.58	0.114	-0.50	-0.60	0.548	3.97	2.32	**0.020**
Shinele Meto (LS)	0.29	3.02	**0.003**	-0.30	-0.97	0.331	-11.42	-3.78	**<0.001**
Simien Mountains (S)	-0.35	-1.10	0.271	7.04	1.48	0.139	21.34	2.08	**0.038**
Sororo Torgam Gara Muktar (LS)	2.19	4.87	**<0.001**	-21.69	-1.67	0.095	8.43	0.72	0.470
Tama (LS)	0.16	1.00	0.316	-3.18	-5.38	**<0.001**	-5.74	-3.05	**0.002**
Telalak Dewe (LS)	-0.36	-3.48	**<0.001**	0.60	1.98	**0.048**	3.37	1.28	0.202
Tulu Lafto Sedden (LS)	-2.08	-2.33	**0.020**	-1.83	-1.90	0.057	-2.34	-2.01	**0.045**
Urgan Bula (LS)	0.21	0.50	0.617	-3.03	-1.60	0.109	-0.45	-0.03	0.976
Yangudi Rassa (S)	-0.03	-0.64	0.522	0.63	2.64	**0.008**	3.70	2.16	**0.031**
Yayu (LS)	2.03	8.56	**<0.001**	-2.46	-3.25	**0.001**	-1.94	-2.42	**0.016**

Supplementary Table 14 Individual protected area social wellbeing outputs showing the average treatment effect on the treated (ATT), t-statistic (t) and significance (p); significant p-values are shown in bold. A positive ATT indicates better performance.

Protected area	Months of adequate food			Dietary diversity			Material wellbeing		
	ATT	t	p	ATT	t	p	ATT	t	p
Abasheba Demero (LS)	-0.73	-2.36	**0.019**	0.23	0.34	0.733	-0.15	-0.14	0.893
Amibera Melika sadi (LS)	-1.61	-3.26	**0.001**	2.01	2.16	**0.031**	1.20	1.30	0.195
Asibahri Kebena (LS)	-8.30	-6.03	**<0.001**	1.13	1.63	0.104	0.35	0.49	0.625
Babile Elephant (LS)	-2.87	-3.05	**0.002**	-0.65	-1.00	0.320	-0.66	-2.25	**0.025**
Bale Mountains (S)	-2.29	-3.17	**0.002**	0.34	0.36	0.719	-1.10	-1.80	0.073
Billen Hertale (LS)	-5.75	-2.31	**0.021**	-0.18	-0.15	0.879	2.59	1.74	0.083
Borena (S)	1.26	2.36	**0.019**	2.66	4.08	**<0.001**	0.51	1.28	0.201
Borena sayint Worehimano (S)	0.04	0.07	0.943	-0.74	-0.76	0.448	-3.23	-3.71	**<0.001**
Chebera Churchura (S)	-0.81	-2.26	**0.024**	-1.90	-3.12	**0.002**	-12.75	-5.10	**<0.001**
Chifra (LS)	-2.83	-3.05	**0.002**	0.45	0.74	0.459	1.04	1.87	0.062
Dindin (LS)	-4.16	-3.05	**0.002**	-2.29	-1.71	0.089	1.67	1.36	0.173
Erer Gota (LS)	0.13	0.41	0.679	1.53	2.17	**0.030**	0.54	0.90	0.370
Gambella (S)	0.39	1.88	0.061	1.43	2.44	**0.015**	-2.43	-0.91	0.365
Gara Gumbi (LS)	-5.89	-7.86	**<0.001**	2.47	7.59	**<0.001**	0.11	0.33	0.745
Gara Meti (LS)	-2.77	-3.20	**0.001**	1.06	1.23	0.218	1.11	1.58	0.116
Gibe Sheleko (S)	-0.02	-0.04	0.968	2.10	3.37	**0.001**	0.59	0.77	0.440
Kafa (LS)	-0.68	-2.60	**0.010**	-0.20	-0.50	0.614	0.28	0.69	0.488
Kafta Sheraro (S)	0.80	1.10	0.272	-1.49	-1.74	0.083	2.02	2.51	**0.012**
Majang (LS)	0.14	0.53	0.593	1.25	1.52	0.129	1.78	3.53	**<0.001**
Melka Guba (S)	1.75	2.96	**0.003**	-0.62	-0.94	0.346	1.41	2.04	**0.042**
Munessa Kuke (LS)	0.56	0.97	0.331	-1.17	-1.77	0.077	-0.01	-0.02	0.986
Sheka (LS)	0.46	1.19	0.235	0.36	0.54	0.589	-0.30	-0.48	0.635
Shinele Meto (LS)	-6.56	-6.15	**<0.001**	2.21	3.34	**0.001**	1.78	2.44	**0.015**
Simien Mountains (S)	-0.83	-1.59	0.112	-2.36	-2.98	**0.003**	-0.80	-3.01	**0.003**
Sororo Torgam Gara Muktar (LS)	-1.28	-2.29	**0.023**	0.64	0.98	0.327	-1.63	-3.62	**<0.001**
Yayu (LS)	-0.62	-1.79	0.075	2.77	3.87	**<0.001**	-0.50	-1.88	0.061

Supplementary Table 15 Model averaged predictors of protected area environmental and wellbeing performance across models where ($\Delta AIC < 2$) demonstrate significant predictors for environmental performance are area-adjusted budget, precipitation and agricultural suitability, while for wellbeing performance none are significant.

Response	Predictor	Estimate (full)	Adjusted S.E	z-value	p-value
Environmental performance	Budget (area-adjusted)	0.54	0.14	3.78	<0.001
	Precipitation	-1.34	0.33	4.07	<0.001
	Agricultural suitability	-0.42	0.18	2.27	0.02
	Agricultural land	-0.08	0.15	0.53	0.60
	Strictness (strict)	0.14	0.33	0.41	0.68
Wellbeing performance	Agricultural suitability	0.65	0.57	1.39	0.17
	Access	-0.06	0.20	0.32	0.75
	Population	0.07	0.25	0.29	0.77
	Agricultural land	0.06	0.21	0.27	0.79

Supplementary Table 16 Changes from grassland to savanna and shrubland are associated with bush encroachment. Results from a linear regression with cattle, sheep and goat densities as predictors of cells which change from grassland to savanna or shrubland (Adjusted $R^2 = 0.006$, $F_{(3, 4836)} = 4.12$, $p = 0.006$)

Predictor	Estimate	S.E	t-value	p-value
Cattle density	7.65×10^{-6}	2.21×10^{-6}	3.47	<0.001
Sheep density	-6.41×10^{-6}	3.15×10^{-6}	-2.04	0.042
Goat density	-2.31×10^{-6}	2.38×10^{-6}	-0.97	0.333

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