Long-term community management of agrobiodiversity zones reduces agricultural expansion and natural cover loss.

Comacchio, A.[1], Tovar, C.[2], Jago, S.[2,3], Jones, S.K.[4], Carmona, N.E.[4], Fernández Huatalla, E.[5], Quintana Palacios, C. [5], Gutiérrez Reynoso D. [5], Medina Hinostroza, T.[6], Koechlin Cuba, A.M. [7], Olazábal, O. [7], Catpo, R.[7], Sotomayor, D. [8], Borrell, J.S. [2]*

[1] Imperial College London, Centre for Environmental Policy, London, United Kingdom
[2] Royal Botanic Gardens, Kew, Richmond, TW9 3AE
[3] Durrell Institute of Conservation and Ecology, University of Kent, Canterbury, CT2 7NR, United Kingdom
[4] Bioversity International, Montpellier, France
[5] Instituto Nacional de Investigación Agraria (INIA), Lima, Perú[6] Conservación Amazónica – ACCA, Cusco, Perú
[7] Ministerio del Ambiente, Lima, Perú
8 Department of Environmental Engineering, Universidad Nacional Agraria La Molina, Lima, Perú

*Corresponding author: James S. Borrell

Email: j.borrell@kew.org

ABSTRACT

1. Global food system resilience is weakened by over reliance on a narrow range of crops and the erosion of traditional farming knowledge. Agrobiodiversity Zones (ABDZs) in Peru represent a novel and globally unique, community-led legal instrument for *in situ* agrobiodiversity conservation. However, the long-term impact of community-led stewardship and associated traditional farming practices on landscape management has not been evaluated.
2. This study applies a counterfactual approach using high-resolution remote sensing data to characterise agricultural land use change between 2000 and 2022. We compare changes in agricultural expansion, natural cover loss, gross primary productivity (annual means and interannual variability) and mean field size between ABDZs and socio-ecologically matched control landscapes across the Peruvian Andes.
3. We find significantly less agricultural expansion and natural cover loss in ABDZs than in control areas, equivalent to ~3323 ha of avoided agricultural encroachment and ~3713 ha of avoided forest and grassland loss over the study period.
4. Field size remained stable, and gross primary productivity increased in both groups, but ABDZs showed significantly more interannual variability in gross primary productivity, suggesting divergence in agricultural management strategies.
5. These findings demonstrate that community-led area-based agrobiodiversity management can effectively limit agricultural land expansion and landscape simplification, providing a unique contribution to national food system and landscape management for wild and cultivated diversity conservation. The study provides a scalable, open-data-based framework for monitoring and evaluating area-based agrobiodiversity policy outcomes.

KEYWORDS

Peru; Land-use change; Agricultural intensification; Statistical matching; Impact Evaluation; Community-based conservation; Integrated Landscape Management.

MAIN TEXT

INTRODUCTION

Global reliance on a narrow range of high-yielding crops combined with the erosion of traditional farming knowledge has contributed to the decline of cultivated and co-dependent species diversity, termed agrobiodiversity (Zimmerer & Haan, 2017; Khoury et al., 2021, Jago et al., 2024). This weakens the resilience and sustainability of food systems under growing human and climate pressure (Jago & Borrell, 2024; Chaudhary et al., 2020; Kahane et al., 2013). Area-based agrobiodiversity conservation aims to mitigate these declines by designating landscapes explicitly for the maintenance of diverse traditional farming systems and the numerous cultivated and co-occurring wild species that they contain (Dawson et al., 2023; Jago et al., 2024). Conserving agrobiodiversity *in situ* is fundamental, since it enables the continued local adaptation of crops to changing conditions and ensures that species are co-located with the traditional ecological knowledge needed for their effective use, both now and in the future (Esquinas-Alcázar, 2005; Love & Spaner, 2007; Bellon, Gotor et al., 2017).

The Peruvian Andes is a globally important centre of crop domestication (De Haan et al., 2010; Navarrete et al., 2024) where long-term management of agrobiodiversity has generated a multitude of indigenous crop varieties adapted to a diverse range of local conditions (Zimmerer et al., 2019; Mathez Stiefel et al., 2017; Parra-Rondinel et al., 2021; Mariel et al., 2021). In 2017, to address the growing vulnerability of agrobiodiversity, the Peruvian government legally recognised a network of Agrobiodiversity zones (ABDZs) (D.S. Nº 020-2016-MINAGRI, 2016) located in the southern Peruvian Andes. This designation aims to support communities willing to voluntarily conserve indigenous crop diversity, traditional management practices, and other diversification strategies (Ruiz Muller, 2009), and safeguard the long-term viability of family farming systems while improving farmers' livelihoods and delivering environmental co-benefits (Sotomayor et al., 2020). To our knowledge, ABDZs constitute a globally unique country-led conservation instrument explicitly protecting agrobiodiversity *in situ;* an approach analogous to protected areas for wild biodiversity. However, while there is extensive literature on the effectiveness of protected areas for conserving wild biodiversity (Schleicher et al., 2017; Black & Anthony, 2022; Morgans et al., 2024), rigorous evaluation of how community-led management affects agricultural land use remains limited (Drucker et al., 2024; Jago et al. 2024; Bellon et al., 2014).

In Peru, agriculture remains a cornerstone of rural livelihoods, with approximately 2.2 million smallholder farmers (CENAGRO, 2012). Between 2000 and 2022, agriculture expanded by 4.4% in the southern Andes, growing from 3.36 to 3.51 million hectares (Supplementary figure S1). Production also grew through intensification and specialisation, evidenced by national average yields for potato (12 to >17 t/ha), cereals (3.0 to ~5.0 t/ha), and quinoa (1.0 to 1.4 t/ha) (Supplementary figure S2), with drivers including increased use of chemical fertilizers and pesticides (Supplementary figure S3), tillage tractors, and shortened fallow cycles (Zimmerer, 2013). While increased production through expansion, intensification and simplification has been pursued as a central strategy to ensure one dimension of food security, it often comes at the expenses of agency and sustainability and does not ensure access or stability (Clapp et al., 2022). Hence, if not carefully planned, agricultural development can be associated with environmentally damaging management techniques (Fonte et al., 2012) including expansion onto marginal lands and steeper slopes, increasing susceptibility to erosion (Kessler and Stroosnijder, 2006). In some cases, commercial agriculture can impact the rights of peasants and indigenous people and fail to ensure the right to food for everyone despite sufficient caloric production (Ramankutty et al., 2018; FAO et al., 2025). Importantly, landscape simplification and intensification can also be associated with the homogenisation of crop species diversity (Khoury et al., 2021), placing a growing number of underutilised crop species and varieties at risk of extinction as they are cultivated by fewer farmers (Velásquez-Milla et al., 2011; Parra-Rondinel et al., 2021; Gotor et al., 2017).

We use a suite of remotely sensed indicators, underpinned by extensive local knowledge, to evaluate the impact of long-term community-led management on comparable agricultural landscapes between 2000 and 2022. We note that while legal recognition of ABDZs is recent, communities that have applied for this status must have demonstrated a long-standing commitment to traditional landscape management, and it is the impact of this management that we seek to measure. Specifically, we use a counterfactual matching approach that compares land use change within Peru's ABDZs with "control" units outside the treatment area that have similar biophysical and socio-ecological context, but are characterised by more conventional agricultural development (Figure 1) (Schleicher et al., 2020; O'Garra et al., 2025). By selecting comparable control areas, we aim to reduce bias from confounding factors and approximate the counterfactual: what would have happened in the absence of long-term, community-led, agrobiodiversity-oriented management?

Previous counterfactual studies have successfully examined the impacts of protected areas on land use change, with metrics including deforestation rates or habitat intactness (Andam et al., 2008; Blackman, 2013; Eklund et al., 2019). Here we adapt this approach to evaluate patterns of agricultural expansion and intensification using a suite of variables encompassing agricultural and natural land use change, landscape heterogeneity and productivity. Finally, we explore how impact evaluation can strengthen Peru's ABDZs, improve monitoring and guide future efforts to deliver effective conservation of cultivated and wild biodiversity in unison.

METHODS

Study area and counterfactual rationale

This study focuses on 9 of the 10 Agrobiodiversity Zones (ABDZs) designated by the Peruvian government as of September 2025 (Figure 2, supplementary table S1). We did not include the Cotahuasi ABDZ as this is also a National Landscape Reserve with distinct management regulations. Together these ABDZs span ~2,143 km² across an elevation range of ~1,460–5,930 m.a.s.l. ABDZ designation provides national recognition of the existence of long-term community agrobiodiversity management, rather than denoting a change in management practices. Therefore, from a causal inference perspective, our treatment is long-term community land management, rather than ABDZ designation *per se*, which is recent (since 2017) and not expected to have substantially changed farming behavior (Supplementary figure S4).

ABDZ boundaries are based on the community's collective or private land tenure rights (Sotomayor et al. 2020). We define treatment landscape, the ABDZs boundaries plus a 5-km buffer to account for potential spillover effects, i.e. to encompass the immediate socio-economic influence of the communities on their close surroundings. We then apply a further 5-km buffer around treatment landscapes, excluded these areas from both treatment and control pools to prevent contamination between the two groups. All protected areas were excluded from the control pool to avoid biases associated with differing conservation regimes. We also excluded areas identified by Parra-Rondinel et al. (2021) as being under community-based agrobiodiversity management, as these may be future candidate ABDZs even though they have not been officially designated (Figure 2).

To delimit the study area from which to identify control sites (i.e. bioclimatically similar areas, not characterised by long-term community management), we first delineated a study area encompassing the Peruvian Andes. To justify this extent, we conducted a Principal Component Analysis (PCA) using key biophysical variables to characterize the environmental niche of the ABDZs (Supplementary figure S5). We randomly sampled 10,000 cropland pixels derived from Mapbiomas Peru, using the whole country extent (Mapbiomas, 2023). Eight environmental variables were extracted at 1 km spatial resolution, representing annual averages spanning the period 1979–2016: temperature range, precipitation, radiation, elevation, slope, soil water balance, humidity, and growing season length (Karger, Zimmermann and CHELSA Climate, 2023). Environmental variables were log-transformed where appropriate, mean-centered and scaled to unit variance prior to PCA (Abdi & Williams, 2010). PCA results confirmed that ABDZs occupy a distinct environmental space compared to the national average. Consequently, we used this Andean-specific polygon as our exclusive sampling frame to draw 1:1 matched control units, ensuring the counterfactual comparison was bioclimatically constrained. We additionally cross-checked the distribution of control units with local partners from the National Institute of Agricultural Innovation in Peru (INIA) who have field experience of these landscapes.

We assess outcomes (see next section and workflow in Figure 1) between early-2000s (baseline) and 2020s (endline), a decisive era of agricultural transformation, with growing interest for agrobiodiversity on one hand (Sayre et al., 2017; Sotomayor et al., 2020) (Sayre et al., 2017; Sotomayor et al., 2020) and growing commercial intensification on the other (Zimmerer, 2013; Arce et al., 2019) (supplementary figures S1-S3). We then estimate differences between treatment (ABDZs) and controls for clearly defined outcome variables and across time steps. Because matching balances observed covariates at the baseline (early 2000's) – e.g. variables that can influence both the treatment and our land-use and productivity outcomes - remaining differences can be interpreted as management-associated impacts, with the caveat that unobserved confounding variables may also exert an influence (an assumption which we later test the sensitivity of our results to; see *Sensitivity and Robustness checks*). These could include, for example, other market access dynamics beyond accessibility, strength of local governance or other target policies, and historical land use trajectories. Note that the time windows differ among outcome variables due to underlying dataset availability and, for interannual variability in Gross Primary Productivity, the requirement for sufficiently long time series to calculate the coefficient of variation (CV).

Indicators of agricultural intensification over time

Agricultural expansion and natural cover loss . We expect the legal figure and the long-term community-led commitment to have an impact on land use outcomes. Hence, we sourced land cover data were obtained from MapBiomas Peru, which provides 30-meter resolution historical land use classifications until 2022. We masked cloud (40%) and used the most frequent land cover class over 3-year intervals for 2000-2002 and 2020-2022, to reduce year-specific classification noise, image quality, or transient land use variation. To align these data with our socio-ecological matching covariates, we aggregated the 30 m resolution pixels to a 1 km² analysis grid. For each 1 km² unit, we calculated the 'cropland fraction' and 'natural cover fraction' as the percentage of 30 m pixels belonging to those respective classes within the grid cell. Change was then calculated as the percentage point difference between the baseline (2000-2002) and endline (2020-2022) periods. These unit-level percentage changes served as the primary outcomes for our matching and regression analysis.

Land cover data were obtained from MapBiomas Peru, which provides 30-meter resolution historical land use classifications until 2022 (Mapbiomas, 2023). We masked cloud (40%) and used the most frequent land cover class over 3-year intervals for 2000-2002 and 2020-2022, to reduce year-specific classification noise, image quality, or transient land use variation (Blackman, 2013). Land use and land cover classes aggregation are specified in supplementary material (Supplementary table S2), which includes land-use classes other than our focal outcomes (e.g. mining) to provide contextual information, but we did not treat these as formal outcome variables.

Gross primary productivity and interannial variability. Changes in annual mean Gross Primary Productivity (GPP) and interannual variability in GPP serve as proxies for crop yield and biomass production (Menefee et al., 2023; Nawaz Khan & Maimaitijiang, 2024). For annual mean GPP, a positive outcome for ABDZs is the maintenance of stable or increasing productivity, demonstrating that traditional management remains viable without transitioning to input-intensive intensification. In the context of ABDZs, a positive outcome is characterised by the maintenance of higher interannual variability compared to conventional systems. This reflects the ecological rhythms of traditional management, such as rotational fallows and diverse species polycultures, which naturally generate more biomass fluctuations than homogenised, intensified systems. But it could also result in higher crop losses and less stable yields in the short term. Conversely, a significant reduction in variability would indicate a shift toward simplified, input-intensive management—consistent with the use of external fertilizers, irrigation, and shortened fallow cycles—which aims to artificially stabilize yields at the cost of traditional agrobiodiversity.

Mean GPP and inter-annual variability were derived from MODIS annual GPP at 500 m resolution (Running et al., 2015) in Google Earth Engine for two seven-year periods—2001–2007 (baseline) and 2015–2021 (endline)—chosen to capture productivity trends and interannual fluctuations. For each year, we computed annual cumulative GPP (by summing all valid 8-day composites. To align these indicators with our socio-ecological matching covariates (Figure 1, supplementary table S3), we used a 1 km² unit as the primary analysis grid. The interaction between scales was managed through a nested, dynamic masking process: within each 1 km unit, the cropland extent was delineated at 30 m resolution using year-specific MapBiomas Perú (2023) data. This 30m high-resolution cropland mask was used to select those 500 m MODIS pixels whose GPP contributed to the unit-level mean, calculated as an area-weighted average based on the pixel-polygon overlap. This 30m high-resolution mask was used both to compute cropland area (for the cropland fraction) and to select those 500 m MODIS pixels whose annual cumulative GPP contributed to the unit-level mean. Specifically, the GPP for each 1 km unit was calculated as an area-weighted mean of the overlapping 500 m MODIS pixels, weighting the contribution of each pixel by its overlap with the 30 m cropland mask (details in supplementary methods S2). Interannual variability in GPP was measured with the coefficient of variation (CV) of cropland-only GPP within each period. Crucially, because the MapBiomas 'cropland' class includes both active cultivation and fallow periods, this metric captures the total 'all-crops' production and the distinct ecological rhythms of the landscape.

Mean cropland patch size. Changes in cropland mean patch size between 2000-2002 and 2020-2022 were used as an indicator of landscape simplification or structural consolidation, both common outcomes of agricultural intensification (Sirami et al., 2019). Enlarged patches are associated with mechanisation and input-intensive practices, while smaller, fragmented patches can reflect more traditional systems and less consolidated land. Using the terra package in R (Hijmans, 2025), we clipped the 30 m resolution cropland rasters to each 1 km2 unit. Within these units, individual cropland patches were identified using 8-cell neighborhood connectivity (queen's case). Mean patch size was then calculated as the average area (ha) of all 30 m patches identified within that specific 1km2 unit.". A limitation of this approach is potential artificial field-boundary fragmentation arising from computing mean patch size within fixed 1 km cells, which may slightly underestimate true field size but is expected to be approximately symmetric across treatment and control units. Given that typical field sizes in the Andes are on the order of 2–4 ha—substantially smaller than the 1 km^2 grid—most fields are fully contained within individual cells. We therefore interpret mean patch size as a reasonable proxy for local field size, and changes in mean patch size through time as indicative of field consolidation or fragmentation.

Spatial autocorrelation, covariate choice and statistical matching

To mitigate spatial autocorrelation and prepare the sample for matching, we applied a grid-based thinning procedure for each outcome indicator. We tested multiple sampling densities (Supplementary table S4) to identify the distance at which spatial autocorrelation was effectively minimized (4 km). Consequently, for agricultural expansion, natural cover loss, and mean field size, we sampled gridcells using a gridded sampling technique which ensured each gridcell was 4 km from another gridcell. Due to lower data coverage for GPP, minimum distance was retained at 2km. We checked for spatial autocorrelation in treatment units using semi-variograms. We addressed residual spatial correlation in GPP outcomes by employing 5-km cluster-robust standard errors in the regression analysis, accounting for remaining autocorrelation after the 2-km thinning procedure (Devenish et al., 2022).

We used a comprehensive set of biophysical and socioeconomic covariates for matching (Supplementary table S3), comprising elevation, slope, annual precipitation, annual temperature, population density, accessibility (e.g. travel time to major cities), distance to roads, and income (weighted average of monthly per capita income per district - the smallest standard administrative unit in Peru) as main variables identified in the literature driving agricultural intensification and expansion (Fonte et al, 2012). For natural cover loss and agricultural expansion, we also used baseline landcover percentages (cropland, forests, grassland). For GPP indicators and changes in mean field size we used percentage cropland cover only. Finally, for changes in mean field size we additionally included baseline mean cropland patch size.

For each outcome, we tested three matching algorithms: propensity score matching (PSM) with and without a caliper of 0.2, and Mahalanobis distance matching, using the *MatchIt* package in R (Ho et al., 2011). We retained only 1:1 matched pairs so that each treated unit is matched to one control. We assessed model performance and covariate balance using standardized mean differences (SDM), love plots, and summary balance statistics (mean and median absolute SMD). For each outcome, we selected the final matching specification that minimized overall covariate imbalance while maximising the proportion of treated units maintained.

Statistical inference

We estimated the Average Treatment Effect on the Treated (ATT) for each outcome using a covariate-adjusted OLS regression on the matched dataset. This approach mitigates residual bias, particularly where minor covariate imbalance remains (Rubin, 1979; Andam et al., 2008; Stuart 2010; Ferraro & Hanauer, 2014). The same set of socio-ecological covariates used in the matching procedure were included in the post-matching regression to ensure consistency in adjustment and interpretability (Supplementary table S3). We expressed the ATT as an absolute change (% point difference). For agricultural expansion and natural cover loss, we also estimated the total change across all ABDZs by multiplying the ATT by the total number of treated cells, producing impact estimates in square kilometres.

Finally, we applied causal mediation analysis using the mediation package in R (Tingley et al., 2014) to assess whether the effect of protection on natural cover loss was mostly mediated by the reduction in agricultural expansion. We used the mediate() function to estimate the ACME—i.e., the indirect effect of treatment on natural cover loss through agricultural expansion—and the ADE—i.e., the portion of the effect not transmitted through the mediator. This is done by extracting repeated samples from the estimated distributions of the regression coefficients based on their standard errors. The mediation analysis is run on the matched sample of treated and control units used to compute agricultural expansion (the mediator) and natural cover loss (outcome).

Sensitivity and robustness checks

To evaluate sensitivity of our outcomes to potential unobserved confounding, we applied the sensemakr package to assess the sensitivity of OLS-based treatment effects to potential omitted variable bias (Cinelli & Hazlett, 2020). This approach estimates the strength an unobserved confounder required to render the results statistically insignificant.

To ensure the robustness of the significant findings in estimating treatment effects on the outcome variables against several arbitrary modelling decisions—many of which can influence the results—we conducted comprehensive robustness checks using different alternative matching combinations, following and adapting the framework consolidated by Devenish et al. (2022). For any assessed outcomes, we ran permutation tests over many different specifications, looped with three different matching approaches and several combinations of covariates and subsequent significance testing to confirm whether results remained consistent (see supplementary method S4 and Figure S7). To estimate the treatment effect within each combination of matched samples, we used an OLS regression with cluster error when needed.

RESULTS

Across Andean agricultural areas, principal component analysis showed that ABDZs tend to occupy landscapes with more heterogeneous topography, higher elevation, and lower temperatures (Figure 3). Nevertheless a considerable number of cropland pixels outside of the ABDZs share similar environmental characteristics, justifying the surrounding Peruvian Andes biome (excluding Protected Areas and indigenous agricultural areas that may be candidate ABDZs) as an appropriate area from which to draw control sites for comparison. Counterfactual matching between treatment and control landscapes across all outcome variables achieved covariate balance with standardised mean differences <0.1 (supplementary figure S6). and retained more than 90% of treatment units for all outcome variables.

ABDZs have lower agricultural expansion and natural cover loss. At baseline (2000–02), agricultural land use in Agrobiodiversity Zones (ABDZs) was 13.9% (95% CI: 12.2–15.5%). By 2020–22, this remained essentially unchanged at 13.9% (95% CI: 12.3–15.4%), indicating long-term landscape stability. In contrast, matched control landscapes showed a significant increase from 14.6% (95% CI: 12.6–16.7%) to 15.9% (95% CI: 13.8–17.9%) agricultural cover.

Adjusting for socio-ecological covariates, this stability resulted in a significant negative treatment effect for agricultural expansion (ATT = -1.39 percentage points, 95% CI: -2.30 to -0.48; $p = 0.0029$) and natural cover loss (ATT = -1.55 percentage points, 95% CI: -2.58 to -

0.52; $p = 0.0032$) compared to the counterfactual. This corresponds to a net stabilization of agricultural land in ABDZs (a nominal decrease of 41 ha when scaled to the 239,234 ha network). Consequently, we estimate that community management avoided approximately 3,323 ha of cropland expansion and 3,713 ha of natural cover loss over the two decades, indicating that agricultural expansion was over 80-fold higher in landscapes undergoing a conventional management pathway compared to the stability observed under community-led stewardship.

Causal mediation analysis confirms that this preservation of natural cover was primarily driven by the suppression of agricultural expansion seen in control groups (ACME = -1.34 percentage points, 95% CI: -2.27 to -0.38; $p = 0.004$). The direct effect unrelated to expansion was nonsignificant (ADE = -0.22 percentage points, $p = 0.47$), confirming that constrained conversion is the primary mechanism of impact. Beyond preventing loss, land-cover transition matrices (Supplementary table S6) suggest a restorative component: when grassland changed within ABDZs, it was significantly more likely than in controls to shift into native forest (4.5% vs 2.8%). This indicates that treatment both reduces agricultural conversion and facilitates native forest recovery, distinct from plantation forestry which is identified with a dedicated binary classifier. Thus, the observed forest gains mainly reflect recovery of native or secondary forest rather than expansion of plantation forestry, although some residual misclassification is still possible. For context, changes in other land cover types were relatively minor (Figure 4). Mining expanded slightly in both groups, by +0.21 percentage points in ABDZs (95% CI: −0.20 to 0.62) and +0.05 percentage points in controls (95% CI: −0.04 to 0.14), with no significant difference between groups (ATT = 0.19 percentage points, 95% CI: −0.22 to 0.61; $p = 0.36$).

ABDZs have greater changes in annual mean Gross Primary Productivity (GPP) and higher interannual variability in GPP. Both treatment and control landscapes experienced modest increases in annual mean gross primary productivity (GPP). The average change in mean GPP (ΔMean) was 41.7 g C m^{-2} yr^{-1} in control areas and 43.6 g C m^{-2} yr^{-1} in treated areas, with no significant difference between groups (ATT = –4.6 g C m^{-2} yr^{-1}, 95% CI [–27.9 to +18.7 g C m^{-2} yr^{-1}], $p = 0.70$; (Figure 5). Similarly, both landscapes exhibited declines in the interannual variability of GPP, however the decline was significantly smaller in treated units (−0.27) compared to controls (−1.04) (ATT = +0.76 percentage points, 95% CI [+0.10 to +1.42], $p < 0.02$; (Figure 6).

ABDZs have smaller changes in cropland patch size. In treatment landscapes, mean patch size declined from 1.91 ha to 1.86 ha, a loss of 0.049 ha (–2.6%). In matched control areas, mean patch size for cropland rose from 1.56 ha to 1.92 ha, a gain of 0.365 ha (+23.4%). The covariate-adjusted OLS on the matched sample estimated an average treatment effect of –0.297 ha (ATT = –0.297 ha; 95% CI: –0.723 to 0.129; $p = 0.172$; $n = 828$), indicating that, on average, mean cropland patch size in ABDZs remains stable while it increases in matched controls, but the difference is not statistically significant.

Robustness and sensitivity checks

We assessed several alternative matching specifications for each outcome variable (Supplementary figure S7). Across the 89 valid matching specifications - defined as those achieving good (SMD < 0.1) or moderate (0.1 ≤ SMD < 0.25) covariate balance and excluding the models with poor balance (SMD > 0.25), the mean ATT from OLS was –1.17 percentage points for agricultural expansion and –1.32 percentage points for natural cover loss. For agricultural expansion, 55% (49/89) of regressions were statistically significant at $p < 0.05$, while for natural cover loss, 58% (52/89) were significant. Importantly, all valid models estimated treatment effects in the expected negative direction for both outcomes, demonstrating high sign-consistency.

For GPP variability (ΔCV), we tested 191 valid matching specifications across 5-, 6-, and 7-year windows, excluding the one specification that resulted in poor balance. Across these models, 54% of OLS regressions were statistically significant at $p < 0.05$, and all significant effects were in the expected positive (treatment-increasing) direction. For mean GPP and mean field size, fewer than 10% of valid specifications produced significant ATT estimates, in line with our main model results. Moreover, these estimates were not consistent in direction, illustrating a lack of detectable effects for these variables.

Using robustness values (RV) from sensemakr, we assessed how strong an unobserved confounder would need to be to nullify the significant treatment effects after adjusting for observed covariates (Table 2). For agricultural expansion, the RV was 9.76%; for natural cover loss, 9.43%; and for GPP variability (ΔCV), 11.98%—meaning a confounder would need to explain roughly 10–12% of the residual variance in both treatment and outcome to eliminate the estimated effects. Relative to precipitation (our benchmark covariate for ΔCV), this implies an omitted confounder would need to be ≥10× more predictive of treatment than precipitation (and comparably predictive of ΔCV) to overturn the ΔCV result. Overall, only confounders with explanatory power far exceeding the observed covariates (e.g., precipitation) could plausibly overturn these findings (Cinelli & Hazlett, 2020).

DISCUSSION

We evaluated change in five indicators of agricultural expansion and intensification over two decades in the Peruvian Andes, comparing the impact of traditional community-managed agricultural landscapes with carefully matched controls encompassing a diversity of conventional and increasingly intensive agricultural management. We show that traditionally managed landscapes, now recognised as ABDZs, and their immediate surroundings experienced significantly lower agricultural expansion and natural cover loss than comparable landscapes outside these areas. Scaled to the total treatment area of the ABDZ network, these effects equate to ~3323 ha of avoided agricultural encroachment and ~3713 ha of avoided forest and grassland loss over the study period, an 80-fold difference between ABDZs and control landscapes. By comparing a wide range of matching specifications, we are confident that these results are robust to arbitrary modelling choices.

Notably, this level of stability in natural cover within ABDZs is comparable to the effectiveness of many formal Protected Areas (PAs) in the tropics, which have been shown to reduce forest loss by approximately 0.5–10% compared to their own counterfactuals (Schleicher et al., 2017; Andam et al., 2008; Bowker et al., 2017). Similarly, many protected areas seek to avoid agricultural expansion and encroachment (Rodrigues & Cazalis, 2020). Ethiopia's protected area network for example, achieved a 73% reduction in agricultural expansion between 2000-2019 (Jago et al 2026 *in press*). Importantly, however, in ABDZs the mechanisms of stabilising land use are inclusive, rather than exclusive of people (Geldmann, 2024). Our findings suggest that while ABDZs are designed to support active agricultural practices rather than excluding them, they can be as effective as formal PAs at stabilising land use conversion.

We used mean annual GPP, interannual variation in GPP and mean field size to capture complementary dimensions of intensification — productivity, temporal stability and landscape heterogeneity. Overall, in both treatment and control landscapes GPP increased and became less variable over time, indicative of efforts to promote yield stability (Ray et al., 2015; Manenti et al., 2023). However, decline in interannual variability in GPP was significantly greater in control areas. This may reflect traditional, rotational, and more diverse agricultural systems in ABDZs, resulting in spatial heterogeneity and more variable interannual biomass production compared to more intensively manage systems where we see trends towards reduced variability. It may also reflect higher crop losses, or fewer resources to mitigate those losses, related to stronger exposure to climate variability, as traditionally managed zones tend to rely on rainfed, lower-input systems (Perez et al., 2010; Ray et al., 2015). By contrast, introduction of irrigation, fertilisation, and mechanisation in more intensive systems aim to buffer crops against weather shocks that can affect productivity (Lobell and Field; Ray et al., 2015). This suggests that long-term community management within Peru's ABDZs has successfully decoupled agricultural activity from landscape degradation over the last two decades. While field sizes remained statistically stable in both groups, the observed divergence in Gross Primary Productivity (GPP) variability suggests that ABDZs have resisted the trend toward input-driven homogenisation seen in control landscapes.Evidence from ABDZ case studies — Parque de la Papa, Cuyocuyo, and Huancavelica — provides insights on the management activities that corroborate our findings. For example, traditional agricultural practices use crop–fallow rotations, reciprocal manual labour systems, and collective land organisation. These practices combined with labour shortages may limit agricultural expansion and field consolidation, maintaining heterogeneity (Swiderska & Argumedo, 2022; WCS Peru, 2019; Arce et al., 2019; Altieri & Koohafkan, 2008; Graddy, 2013; Rolando et al., 2017; INIA, n.d.). For example, Arce et al. (2019) found that Huancavelica (an ABDZ) is characterised by diversified, low-input, rainfed systems compared to the surrounding Eastern Andean slope region, which is increasingly market-oriented and input-intensive with larger fields and shorter rests. Similarly, Zimmerer (2013) shows that maize cultivation in the nearby Bolivian Andes intensified between 2000 and 2010 through mechanised tillage, synthetic fertilisers, and dam-fed irrigation, alongside shorter traditional maize–fallow rotations. This mirrors processes likely occurring in our control landscapes.

A limitation of our study is that our control landscapes do not represent a single “conventional agriculture” pathway (Schleicher et al., 2020). Instead, they exhibit a variety of management approaches and thus the true treatment effect, for example compared to commercial agriculture, is likely to be different (almost certainly stronger). In addition, because each outcome variable was estimated using a different matched dataset, this makes it inappropriate to generalise about our control group landscapes undergoing both expansion and intensification concurrently. Furthermore, while the 2000 baseline captures a decisive era of agricultural transformation, it is important to note that community-led management in these areas predates the study period. Consequently, our baseline metrics likely reflect landscapes that were already differentiated by long-standing traditional practices, and we cannot fully account for divergent land-use trajectories that may have occurred prior to 2000. Finally, while important aspects of agrobiodiversity are likely correlated with our indicators (e.g. crop diversity, traditional knowledge), there remains a need to validate our remotely sensed findings at the field scale. Critically, monitoring should also capture human outcomes of agrobiodiversity conservation — livelihood security, income dynamics, dietary diversity, and market access (Bellon, Gotor & Caracciolo, 2014) — to evaluate whether these zones are meeting their dual goal of improving environmental sustainability and human wellbeing.

CONCLUSIONS

Long-term community management of agricultural landscapes has resulted in significantly less agricultural expansion, significantly less natural land cover loss, and less landscape homogenisation, compared to carefully matched control landscapes. These findings demonstrate that community-led, area-based stewardship can locally decouple increased national agricultural productivity from landscape simplification and loss of traditional farming practices—a level of effectiveness often reserved for formal protected areas. Beyond agrobiodiversity, the patterns we observe have broader biodiversity and socio-economic relevance: lower expansion and slower intensification help maintain more heterogeneous, semi-natural habitat structures associated with higher wild beta-diversity and species persistence across connected landscapes (Estrada-Carmona et al., 2022, Mohamed et al., 2024).

A highly policy relevant question is whether these data support wider adoption of agrobiodiversity zones, or similar area-based agrobiodiversity conservation strategies? This depends on whether these landscape indicators are correlated with the biological assets that ABDZs intend to conserve: agrobiodiversity and traditional knowledge. This can be tested through corroboration with household and farm surveys. Equally important is the conviction that preserving traditional agricultural systems should not be achieved at the cost of socio-economic development for rural farmers. Over time, the benefits of ABDZs may accrue nationally and internationally (conservation of globally valuable agrobiodiversity), but the costs may be disproportionately local (opportunity costs of lower or more variable production). Tools to mitigate these tradeoffs range from compensation mechanisms (Narloch, Drucker & Pascual, 2011) to international recognition of the contribution of these landscapes to global conservation targets (Jago et al., 2024; Kahane et al., 2013). In this context, Peru's efforts are especially timely: as countries work toward protecting 30% of land and water by 2030, he transition of ABDZs into the international conservation framework is already underway. In December 2025, ABDZs in Cuzco and Puno have been officially recognised as OECMs (INIA, 2025) marking them the first Agrobiodiversity Zones in Peru to directly contribute to the Global

Biodiversity Framework's '30x30' target. Such recognition validates community-led agrobiodiversity management as a primary vehicle for meeting area-based conservation targets while elevating the largely under-recognised biodiversity value of managed agricultural landscapes.

TABLES

Table 1. Summary of outcome variables used to evaluate land-use change and agricultural intensification in Agrobiodiversity Zones. For each variable we report the spatial resolution of the underlying data, the primary data source, the calculation used to derive the metric at the analysis unit, the time window considered, and the expected direction of the treatment effect relative to matched control areas. All outcome variables are calculated as a change over their corresponding time period. Expectation refers to the expected direction of change for PAs compared to matched counterfactuals.

Outcome variables	**Resolution**	**Source**	**Calculation**	**Time**	**Outcome expected**
Change in agricultural expansion	30m	MapBiomas Peru, 2023	Percentage change in agricultural cover between 2000-2002 and 2020-2022 for each 1 km² pixel, later averaged for all control and treatment	2000-2002 vs 2020-2022	Less expansion in treatment
Change in Natural Cover Loss	30m	MapBiomas Peru, 2023	Percentage combined decrease in forest and grassland cover over 2000-2002 and 2020-2022 for each 1 km² pixel.	2000-2002 vs 2020-2022	Less natural cover loss in treatment
Change in mean GPP over cropland	500m	Running et al. 2015	Difference in mean GPP between early (2001–2003) and late (2019–2021) period for each pixel.	2001-2003 vs 2019-2021 (GPP datasets only starts in 2001)	Less increase in treatment
Change in GPP interannual variability (IAV) over cropland	500m	Running et al. 2015	Change in interannual GPP variability using the coefficient of variation (CV) between early (2001–2007) and late (2015–2021) periods for each pixel.	2001-2007 vs 2015-2021 (big enough window to look at interannual variability)	Higher variability in treatment
Change in cropland mean patch size	30m	MapBiomas Peru, 2023	Mean size (in hectares) of contiguous agricultural	2000-2002 to 2020-2022	Smaller field size increase in treatment

	patches per 1 km² pixel in 2000–2002 and 2020-2022, calculated using connected 30mt pixels.	

Table 2. Robustness of treatment effect estimates to unobserved confounding for each significant outcome variables. RV (Robustness value) is the percentage of residual variance of treatment and outcome which a hidden confounding variable needs to explain to nullify the effect or to make it insignificant compared to a significant "benchmark" covariate. As the assumed strength of the hidden confounder increases, the adjusted estimates decrease.

Outcome variable	RV (%) to bring regression estimate to 0	RV (%) to lose significance	Benchmark covariate [R^2 %]	Explanatory power required by hidden covariate to overturn effect
Agricultural expansion	9.76	5.3	Temperature (0.7)	>9×
Natural cover loss	9.43	3.3	Temperature (0.6)	>9×
GPP Interannual variability (CV)	11.98	1.5	Precipitation (0.2)	>9x

FIGURES

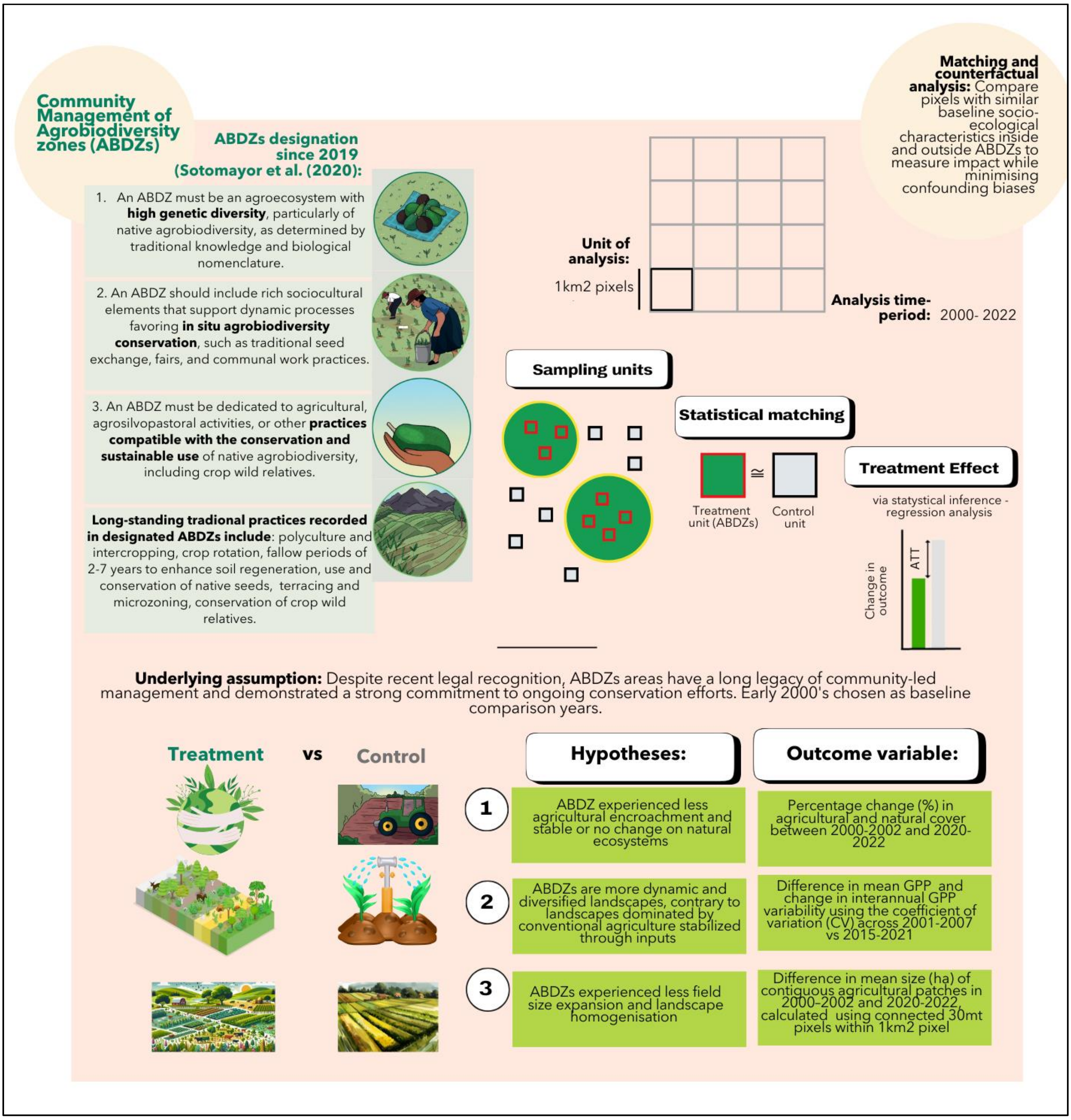


Figure 1. Conceptual overview of the study rationale and design, illustrating the counterfactual approach used to assess land use change and agricultural intensification differences between putative ABDZs and matched control areas. Images rights: INIA. Zonas de Agrobiodiversidad (Peru) (2024).

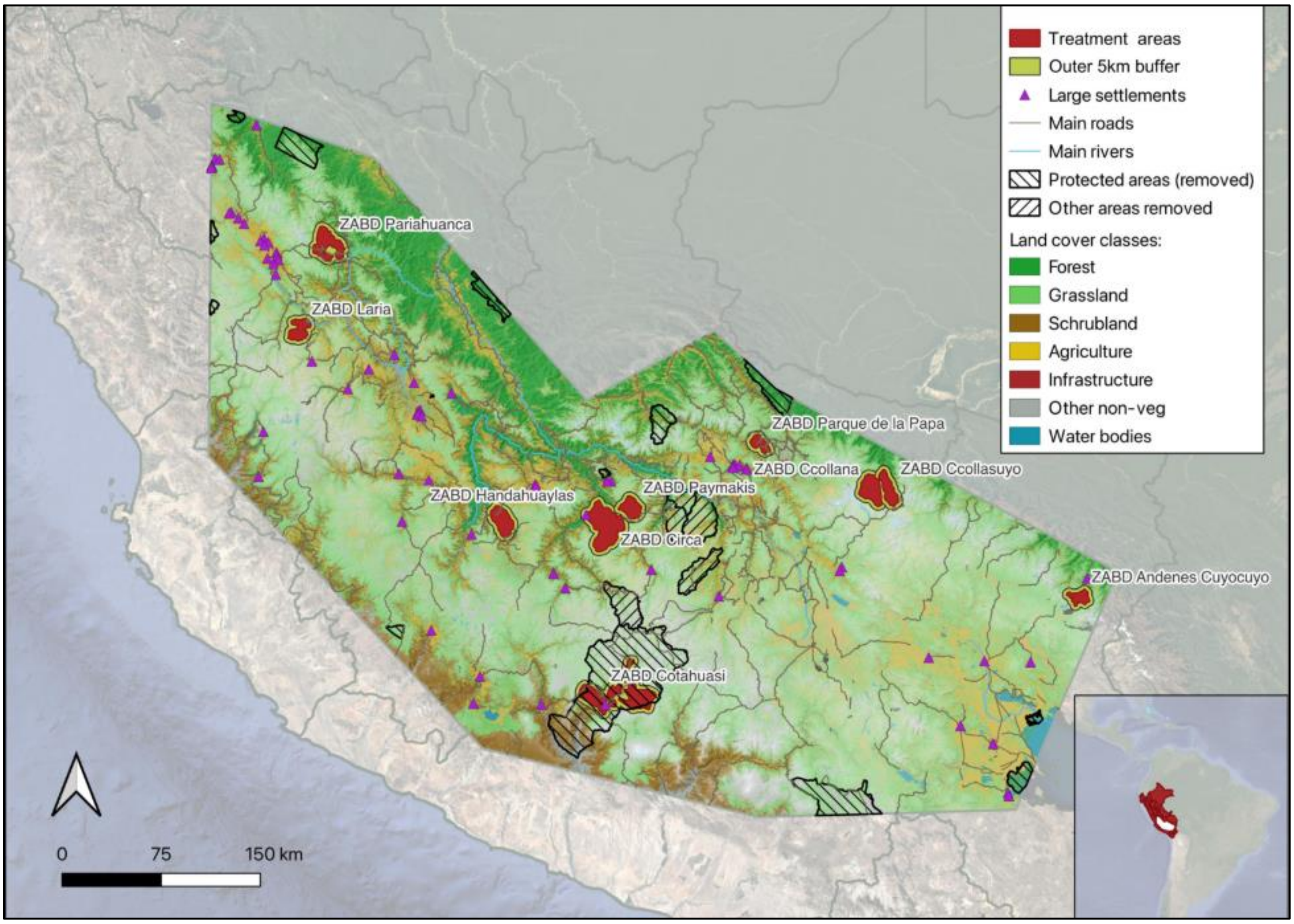


Figure 2. Study area map covering all 10 ABDZs (treatment areas), the buffers and the bounding box from where the control pool was selected. Cotahuasi was removed from ABDZs because it overlapped with a designed protected area. Other PAs and areas known to be managed as ABDZs though not yet designated are also excluded from the control pool (UNEP–WCMC & IUCN, 2025a; Parra Rondinel 2021). Land cover classification obtained from Mapbiomas Peru (2023).

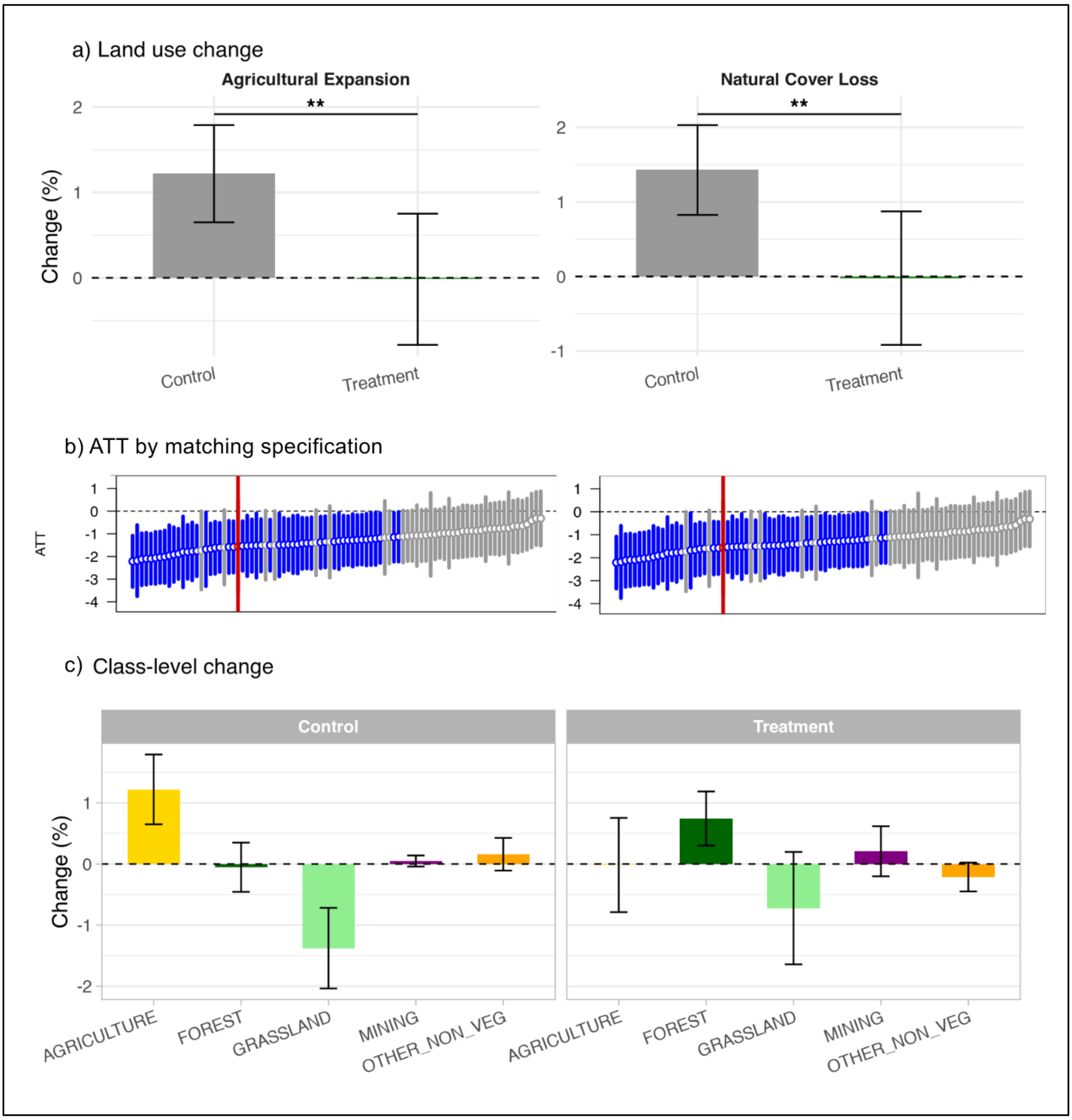


Figure 3. a) Agricultural expansion and natural cover loss (2000–02 to 2020–22) in ABDZs versus control sites, with means and 95% confidence intervals; and b) sensitivity of the estimated average treatment effect (ATT) on both outcomes across alternative matching models. Red marker indicates the main model specification estimates. c) Net change in land cover classes per 1 km² pixel, with 95% CIs.

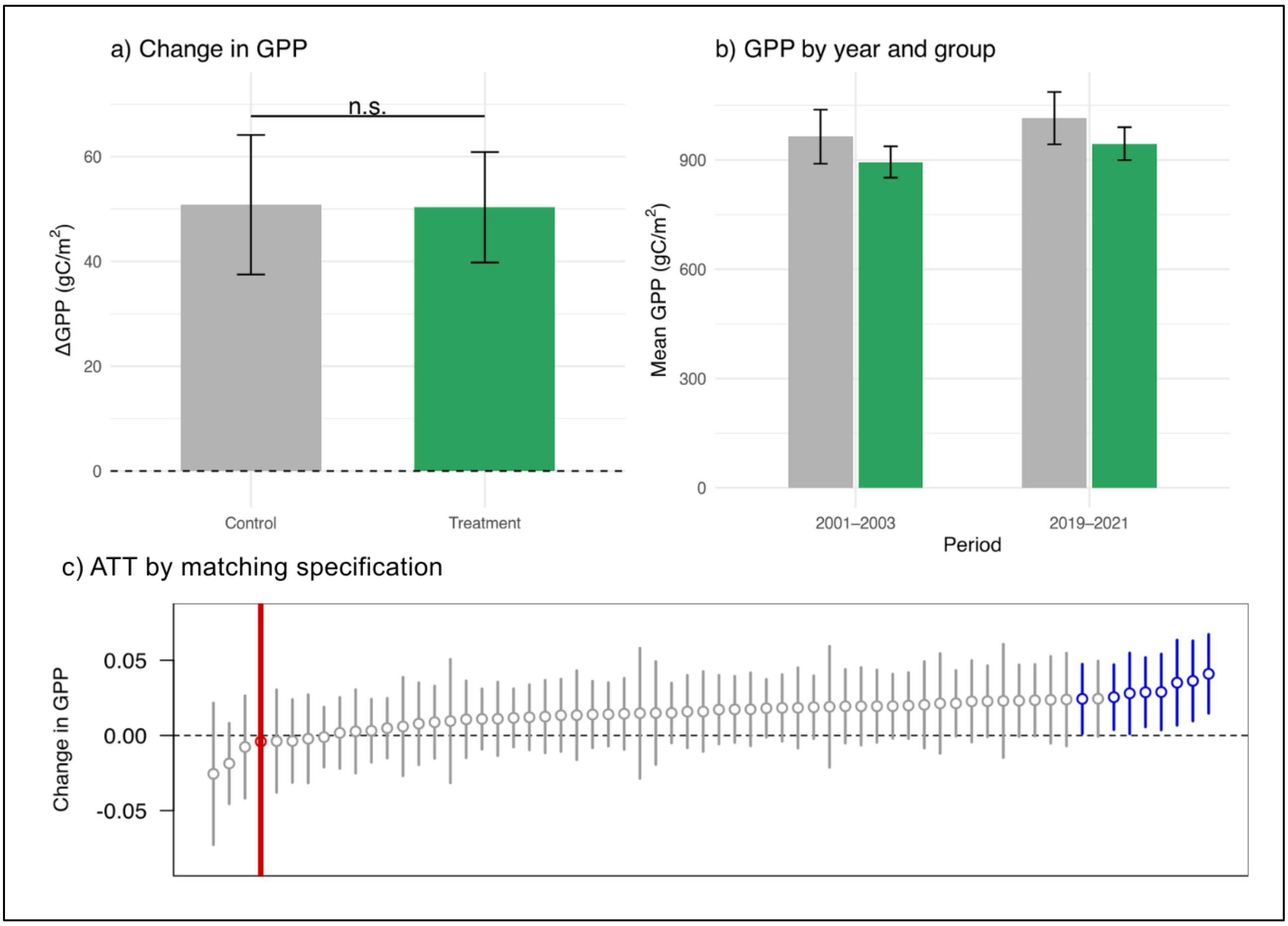


Figure 4. (a) Change in Gross Primary Productivity (GPP) between early (2001-2003) and late (2019–2021) period Bars show mean change and 95% CIs; b) Mean GPP for both time periods; c) robustness analysis of the estimated average treatment effect (ATT) on mean field size across alternative matching model specifications. The main model specification estimate is highlighted in red.

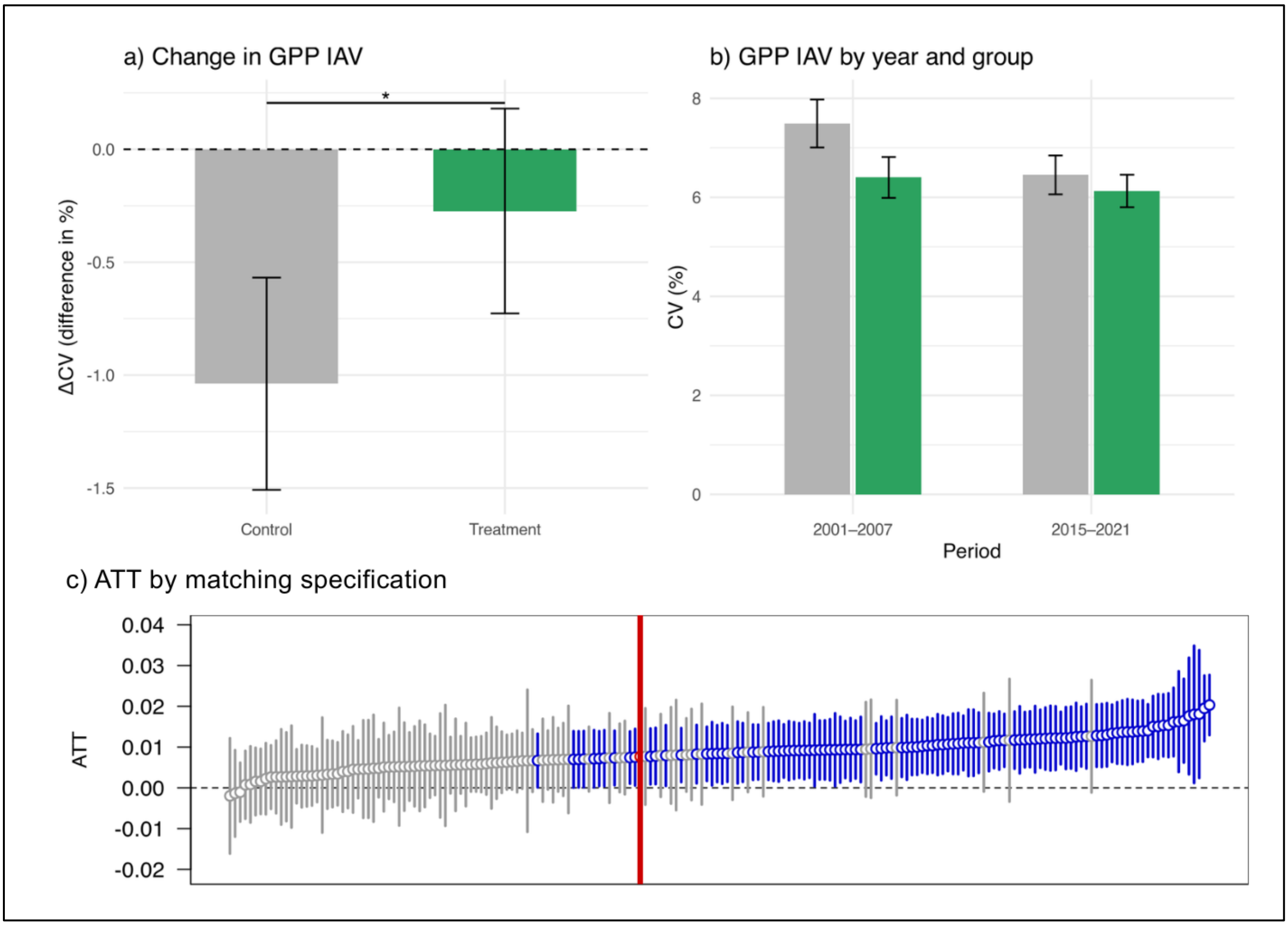


Figure 5. a) Change in interannual GPP variability (ΔCV) between early (2001-2007) vs late period (2015-2021); b) Mean interannual GPP variability for both time periods; c) Robustness analysis with different time windows (bottom). Bars show mean change and 95% CIs; with robustness analysis of the estimated average treatment effect (ATT) on mean field size across alternative matching model specifications. The main model specification estimate is highlighted in red.

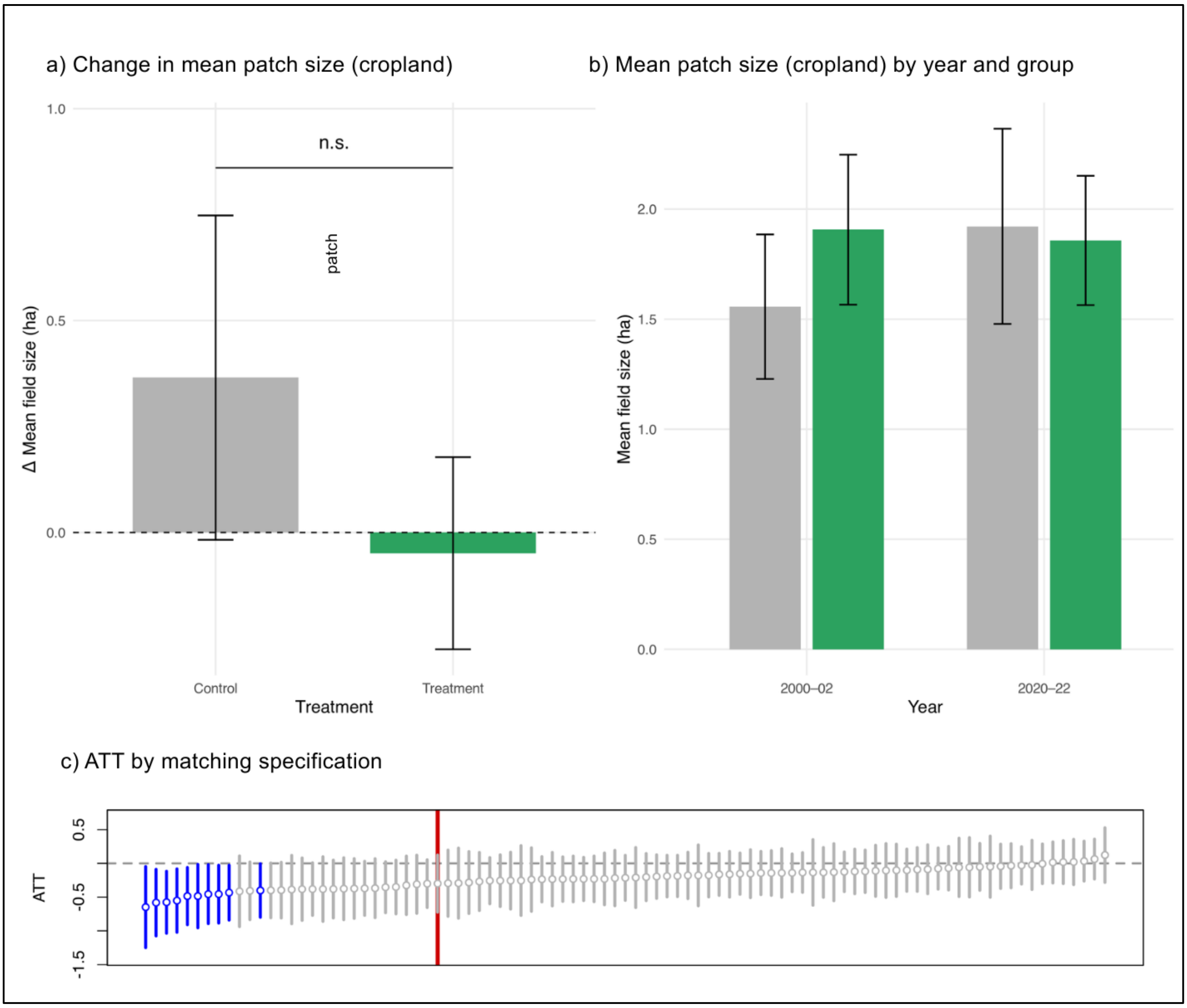


Figure 6. a) Change in mean patch size (in ha per 1 km² pixel) in treatment and matched control areas between the years 2000–2002 and 2020–2022. b) mean field size for both time periods. Bars show group means 95% confidence intervals, with robustness analysis of the estimated average treatment effect (ATT) on mean field size across alternative matching model specifications. The main model specification estimate is highlighted in red.

AUTHOR CONTRIBUTION

JB and CT conceptualised the original idea for research and methodology. AC contributed to the ideation and development of indicators, manuscript outline and content. AC conducted the literature review and analysis, with support from all authors. All authors contributed to the editing and revision of the manuscript.

CONFLICT OF INTEREST STATEMENT

No competing interests are declared.

STATEMENT ON INCLUSION

This study was developed through a multidisciplinary collaboration with Peruvian and international academics, with inputs from the Peruvian Ministry of Agriculture Innovation (INIA), and locally active NGO. The research team therefore includes diverse perspectives from those directly involved in empowering communities to manage Agrobiodiversity Zones (ABDZs).

The research design acknowledges ABDZs as community-led legal instruments for *in situ* conservation, rooted in long-term indigenous stewardship and traditional farming practices.

All processed datasets are made available to ensure the findings remain accessible for future community-led monitoring and independent policy evaluation.

DATA AVAILABILITY STATEMENT

Processed datasets and codes required to reproduce all results are included in the Github archive.

Primary data used in this study are available from the following public repositories:

- **Land-use and land-cover data (Collection 3)**: MapBiomas Perú (2023) via https://peru.mapbiomas.org/.
- **Gross Primary Productivity (MOD17A2H)**: NASA LP DAAC (2015) https://doi.org/10.5067/MODIS/MOD17A2H.006.
- **Bioclimatic variables (CHELSA v2.1)**: Swiss Federal Institute for Forest, Snow and Landscape Research (WSL).
- **Elevation data (GTOPO30):** U.S. Geological Survey (2018) https://doi.org/10.5066/F7DF6PQS.
- **Population**: WorldPop (2018) https://doi.org/10.5258/SOTON/WP00675.
- **Accessibility data**: Global map of travel time to major cities (2008) , available from the Joint Research Centre (JRC) and World Bank via https://forobs.jrc.ec.europa.eu/products/gam/.
- **Income**: Instituto Nacional de Estadística e Informática (INEI), Encuesta Nacional de Hogares (ENAHO) 2002–2004, available via the INEI repository at https://proyectos.inei.gob.pe/microdatos/

ACKNOWLEDGEMENTS

We thank the late Marleni Ramirez for encouraging this manuscript, and for bringing energy, enthusiasm and clarity to agrobiodiversity conservation.

REFERENCE LIST (FORMATTED)

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(4), 433–459. https://doi.org/10.1002/wics.101

Altieri, M. A., & Koohafkan, P. (2008). *Enduring farms: Climate change, smallholders and traditional farming communities*. ResearchGate. Available at: https://www.researchgate.net/publication/252167278_Enduring_Farms_Climate_Change_Smallholders_and_Traditional_Farming_Communities (Accessed 7 January 2025).

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences*, 105(42), 16089–16094. https://doi.org/10.1073/pnas.0800437105

Arce, A., de Haan, S., Juarez, H., Burra, D., Plasencia, F., Ccanto, R., Polreich, S., & Scurrah, M. (2019). The spatial–temporal dynamics of potato agrobiodiversity in the highlands of central Peru: A case study of smallholder management across farming landscapes. *Land*, 8(11), 169. https://doi.org/10.3390/land8110169

Beillouin, D., Ben-Ari, T., Malézieux, E., Seufert, V., & Makowski, D. (2021). Positive but variable effects of crop diversification on biodiversity and ecosystem services. *Global Change Biology*, 27(19), 4697–4710. https://doi.org/10.1111/gcb.15747

Bellon, M. R., Gotor, E., & Caracciolo, F. (2014). Conserving landraces and improving livelihoods: How to assess the success of on-farm conservation projects? *International Journal of Agricultural Sustainability*, 13(2), 167–182. https://doi.org/10.1080/14735903.2014.986363

Black, B., & Anthony, B. P. (2022). Counterfactual assessment of protected area avoided deforestation in Cambodia: Trends in effectiveness, spillover effects and the influence of establishment date. *Global Ecology and Conservation*, 38, e02228. https://doi.org/10.1016/j.gecco.2022.e02228

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics*, 34, 1–16. https://doi.org/10.1016/j.forpol.2013.04.006

Bowker, J. N., De Vos, A., Ament, J. M., & Cumming, G. S. (2017). Effectiveness of Africa's tropical protected areas for maintaining forest cover. *Conservation Biology*, 31(3), 559–569. https://doi.org/10.1111/cobi.12851

Chaudhary, P., Bhatta, S., Aryal, K., Joshi, B., & Gauchan, D. (2020). Threats, drivers, and conservation imperative of agrobiodiversity. *Journal of Agriculture and Environment*, 21, 44–61. https://doi.org/10.3126/aej.v21i0.38441

Cinelli, Carlos, et al. “Sensemakr: Sensitivity Analysis Tools for OLS in R and Stata.” SSRN Electronic Journal, 2020, https://doi.org/10.2139/ssrn.3588978

Clapp, J., Moseley, W.G., Burlingame, B. & Termine, P. (2022) The case for a six-dimensional food security framework. *Food Policy*. 106 (102164), 1–10. https://doi.org/10.1016/j.foodpol.2021.102164

Dawson, T., Juárez, H., Maxted, N. & de Haan, S. (2023) Identifying priority sites for the on-farm conservation of landraces and systematic diversity monitoring through an integrated multi-level hotspot analysis: the case of potatoes in Peru. Frontiers in conservation science. 4. https://doi.org/10.3389/fcosc.2023.1130138.

De Haan, S., Núñez, J., Bonierbale, M., & Ghislain, M. (2010). Multilevel agrobiodiversity and conservation of Andean potatoes in central Peru. *Mountain Research and Development*, 30(3), 222–231. https://doi.org/10.1659/MRD-JOURNAL-D-10-00020.1

Devenish, K., Desbureaux, S., Willcock, S., & Jones, J. P. G. (2022). On track to achieve no net loss of forest at Madagascar’s biggest mine. *Nature Sustainability*, 5, 1065–1075. https://doi.org/10.1038/s41893-022-00850-7

Drucker, A.G., Arpazi-Valero, K., Ramírez, M., Medina, T., Álvarez-Alonso, J., Amanzo, J. & Quijandría-Acosta, G. (2024) Attaining conservation goals for quinoa: Implications for public policy in Peru and beyond. Ambio. 54 (3), 566–576. https://doi.org/10.1007/s13280-024-02097-2

Eklund, J., Coad, L., Geldmann, J., & Cabeza, M. (2019). What constitutes a useful measure of protected area effectiveness? A case study of management inputs and protected area impacts in Madagascar. *Conservation Science and Practice*, 1(10), e107. https://doi.org/10.1111/csp2.107

Esquinas-Alcázar, J. (2005). Protecting crop genetic diversity for food security: Political, ethical and technical challenges. *Nature Reviews Genetics*, 6(12), 946–953. https://doi.org/10.1038/nrg1729

Estrada-Carmona, N., Sánchez, A. C., Remans, R., & Jones, S. K. (2022). Complex agricultural landscapes host more biodiversity than simple ones: A global meta-analysis. *Proceedings of the National Academy of Sciences*, 119(38), e2203385119. https://doi.org/10.1073/pnas.2203385119

FAO, IFAD, UNICEF, WFP and WHO (2025) *The State of Food Security and Nutrition in the World 2025 – Addressing high food price inflation for food security and nutrition*. Rome: FAO. https://doi.org/10.4060/cd6008en

Ferraro, P. J., & Hanauer, M. M. (2014). Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the National Academy of Sciences*, 111(11), 4332–4337. https://doi.org/10.1073/pnas.1307712111

Fonte, S. J., Vanek, S. J., Oyarzún, P. J., Parsa, S., Quintero, D. C., Rao, I. M., & Lavelle, P. (2012). Pathways to agroecological intensification of soil fertility management by smallholder farmers in the Andean highlands. *Advances in Agronomy*, 116, 125–184. https://doi.org/10.1016/B978-0-12-394277-7.00004-X

Geldmann, J. (2024). Protected areas: Biodiversity or people — or both? Current Biology. 34 (13), R633–R635. doi:https://doi.org/10.1016/j.cub.2024.05.040.

Gotor, E., Bellon, A., Polar, V., & Caracciolo, F. (2017). Assessing the benefits of Andean crop diversity on farmers' livelihood: Insights from a development programme in Bolivia and Peru. *Journal of International Development*, 29(7), 877–898. https://doi.org/10.1002/jid.3270

Graddy, T. G. (2013). Regarding biocultural heritage: In situ political ecology of agricultural biodiversity in the Peruvian Andes. *Agriculture and Human Values*, 30(4), 587–604. https://doi.org/10.1007/s10460-013-9428-8

Hijmans, R. (2025). *terra: Spatial data analysis* (R package version 1.8-29) [Computer software]. https://CRAN.R-project.org/package=terra

Ho, D., Imai, K., King, G., & Stuart, E. (2011). MatchIt: Nonparametric preprocessing for parametric causal inference. *Journal of Statistical Software*, 42(8), 1–28. https://doi.org/10.18637/jss.v042.i08

Instituto Nacional de Innovación Agraria (INIA). (2025). *Zonas de Agrobiodiversidad de Cusco y Puno son reconocidas como áreas de conservación de la agrobiodiversidad a nivel mundial*. Plataforma Digital Única del Estado Peruano. https://www.gob.pe/institucion/inia/noticias/1322617-zonas-de-agrobiodiversidad-de-cusco-y-puno-son-reconocidas-como-areas-de-conservacion-de-la-agrobiodiversidad-a-nivel-mundial

Instituto Nacional de Investigación Agraria (INIA). (2007). *Los cultivos nativos en las comunidades del Perú*. https://repositorio.inia.gob.pe/items/3dc3584b-f4ca-48c7-85b9-f6a4aa2d41dd

Instituto Nacional de Innovación Agraria (INIA). (n.d.). *Zonas de Agrobiodiversidad del Perú (ZABD Perú)*. Available at: https://zabdperu.inia.gob.pe/Front/ (Accessed 27 June 2025).

Instituto Nacional de Estadística e Informática (INEI). (2012). IV Censo Nacional Agropecuario 2012: Resultados Definitivos. Lima, Perú: INEI. Available at: https://censos.inei.gob.pe/Cenagro/redatam/

Jago, S., & Borrell, J. S. (2024). Agrobiodiversity conservation enables sustainable and equitable land sparing. *Trends in Ecology & Evolution*, 39(10), 877–880. https://doi.org/10.1016/j.tree.2024.08.009

Jago, S., Elliott, T., Tovar, C., Gomez, M. S., Starnes, T., Comacchio, A., Catpo, R., Girón Aguilar, C., Medina Hinostroza, T., Koechlin Cuba, A. M., Olazábal, O., Quintana Palacios, C., Sotomayor, D., Jones, S. K., Estrada-Carmona, N. and Borrell, J. S. (2024) 'Adapting wild biodiversity conservation approaches to conserve agrobiodiversity', *Nature Sustainability*, 7(11), pp. 1324–1334. https://www.nature.com/articles/s41893-024-01427-2

Jago, S.C., Gizaw, G., Genanaw, B., Langley, J.F., Lulekal, E., White, J.D.M., Rowlands, A.N., Geda, T., Wakjira, K., Regassa, F., Demissew, S., Woldeyes, F., Abebe, W., Jones, J.P.G., Smith, R.J. & Borrell, J. S. (2025) Trade-offs between nature and people reveal challenges in translating global conservation targets into national realities. 28 July 2025. Ecoevorxiv.org. https://ecoevorxiv.org/repository/view/9756/

Jones, S. K., Estrada-Carmona, N., Juventia, S. D., Dulloo, M. E., Laporte, M.-A., Villani, C., & Remans, R. (2021). Agrobiodiversity Index scores show agrobiodiversity is underutilized in national food systems. *Nature Food*, 2(9), 712–723. https://doi.org/10.1038/s43016-021-00344-3

Kahane, R., Hodgkin, T., Jaenicke, H., Hoogendoorn, C., Hermann, M., Dyno, Keatinge, J. D. H., d'Arros Hughes, J., Padulosi, S., & Looney, N. (2013). Agrobiodiversity for food security, health and income. *Agronomy for Sustainable Development*, 33(4), 671–693. https://doi.org/10.1007/s13593-013-0147-8

Karger, D. N., Zimmermann, N. E., & CHELSA Climate. (2023). *CHELSA v2.1 bioclimatic variables* [Dataset]. Swiss Federal Institute for Forest, Snow and Landscape Research (WSL). Available at: https://chelsa-climate.org/ (Accessed 14 May 2025).

Kessler, C. A., and L. Stroosnijder. "Land Degradation Assessment by Farmers in Bolivian Mountain Valleys." Land Degradation & Development, vol. 17, no. 3, 2006, pp. 235–248, https://doi.org/10.1002/ldr.699.

Khoury, C. K., Brush, S., Costich, D. E., Curry, H. A., Haan, S., Engels, J. M. M., Guarino, L., Hoban, S., Mercer, K. L., Miller, A. J., Nabhan, G. P., Perales, H. R., Richards, C., Riggins, C., & Thormann, I. (2021). Crop genetic erosion: Understanding and responding to loss of crop diversity. *New Phytologist*, 233(1), 84–118. https://doi.org/10.1111/nph.17733

Lobell, David B, and Christopher B Field. “Global Scale Climate–Crop Yield Relationships and the Impacts of Recent Warming.” Environmental Research Letters, vol. 2, no. 1, Mar. 2007, p. 014002, https://doi.org/10.1088/1748-9326/2/1/014002.

Love, B., & Spaner, D. (2007). Agrobiodiversity: Its value, measurement, and conservation in the context of sustainable agriculture. *Journal of Sustainable Agriculture*, 31(2), 53–82. https://doi.org/10.1300/J064v31n02_05

Manenti, L., Macholdt, J., Garcia, F. O., & Rubio, G. (2023). Resilience of maize, wheat, and soybean cropping systems as affected by fertilization: Analysis of a long-term field network. *Agronomy Journal*, 115(4), 2017–2029. https://doi.org/10.1002/agj2.21325

MapBiomas Peru Project. (2023). *Collection 3 of the annual land cover and land use series for Peru* [Dataset]. Available at: https://peru.mapbiomas.org/coleccion-3/descarga (Accessed 3 May 2025).

Mariel, J., Carrière, S. M., Penot, E., Danthu, P., Rafidison, V. M., & Labeyrie, V. (2021). Exploring farmers’ agrobiodiversity management practices and knowledge in clove agroforests of Madagascar. *People and Nature*, 3(4), 914–928. https://doi.org/10.1002/pan3.10238

Mathez Stiefel, S., Peralvo, M., Báez, S., Rist, S., Buytaert, W., Cuesta, F., Fadrique, B., Feeley, K. J., Aaron, M., Homeier, J., Llambí, L. D., Locatelli, B., Malizia, A., & Young, K. R. (2017). Research priorities for the conservation and sustainable governance of Andean forest landscapes. *Mountain Research and Development*, 37(3), 323–339. https://doi.org/10.2307/90013240

Menefee, D., Lee, T. O., Flynn, K. C., Chen, J., Abraha, M., Baker, J., & Suyker, A. (2023). Machine learning algorithms improve MODIS GPP estimates in United States croplands. *Frontiers in Remote Sensing*, 4, 1240895. https://doi.org/10.3389/frsen.2023.1240895

Ministerio de Agricultura y Riego. (2016, 14 de diciembre). Decreto Supremo Nº 020-2016-MINAGRI. Aprueban el Reglamento sobre Formalización del Reconocimiento de Zonas de Agrobiodiversidad orientadas a la conservación y uso sostenible de especies nativas cultivadas por parte de pueblos indígenas. *Diario Oficial El Peruano*. https://news.ycombinator.com/item?id=15912706

Mohamed, A., DeClerck, F., Verburg, P.H., Obura, D., Abrams, J.F., Zafra-Calvo, N., Rocha, J., Estrada-Carmona, N., Fremier, A., Jones, S.K., Meier, I.C. & Stewart-Koster, B. (2024) Securing Nature’s Contributions to People requires at least 20%–25% (semi-)natural habitat in human-modified landscapes. One Earth. 7 (1), 59–71. https://doi.org/10.1016/j.oneear.2023.12.008

Morgans, C. L., Jago, S., Andayani, N., Linkie, M., Lo, M. G. Y., Mumbunan, S., St. John, F. A. V., Supriatna, J., Voigt, M., Winarni, N. L., Santika, T., & Struebig, M. J. (2024). Improving well-being and reducing deforestation in Indonesia's protected areas. *Conservation Letters*. https://doi.org/10.1111/conl.13010

Narloch, U., Drucker, A.G. & Pascual, U. (2011) Payments for agrobiodiversity conservation services for sustained on-farm utilization of plant and animal genetic resources. Ecological Economics. 70 (11), 1837–1845. https://doi.org/10.1016/j.ecolecon.2011.05.018

Navarrete, I., Parra-Rondinel, F., Scurrah, M., Bonifacio, A., & Andrade-Piedra, J. L. (2024). Recent developments for robust potato seed systems through agrobiodiversity and farmers' engagement in the Andes. *Current Opinion in Environmental Sustainability*, 69, 101454. https://doi.org/10.1016/j.cosust.2024.101454

Nawaz Khan, S., Li, D., & Maimaitijiang, M. (2024). Using gross primary production data and deep transfer learning for crop yield prediction in the US Corn Belt. *International Journal of Applied Earth Observation and Geoinformation*, 131, 103965. https://doi.org/10.1016/j.jag.2024.103965

O'Garra, T., Martin, R., Pynegar, E., Polo-Urrea, C., & Eklund, J. (2025). Selecting among counterfactual methods to evaluate conservation interventions. *Conservation Science and Practice*. https://doi.org/10.1111/csp2.70066

Parra-Rondinel, F., Casas, A., Begazo, D., Paco, A., Márquez, E., Cruz, A., Segovia, J., Torres-García, I., Zarazúa, M., Lizárraga, L., & Torres-Guevara, J. (2021). Natural and cultural processes influencing gene flow among wild (*atoq papa*), weedy (*araq papa* and *k'ipa papa*), and crop potatoes in the Andean region of southern Peru. *Frontiers in Ecology and Evolution*, 9, 617969. https://doi.org/10.3389/fevo.2021.617969

Perez, C., Nicklin, C., Gallardo, O., & Chevarría, D. (2010). Climate change in the High Andes: Implications and adaptation strategies for small-scale farmers. *The International Journal of Environmental, Cultural, Economic and Social Sustainability: Annual Review*, 6(5), 71–88. https://doi.org/10.18848/1832-2077/CGP/v06i05/54835

Ramankutty, N., Mehrabi, Z., Waha, K., Jarvis, L., Kremen, C., Herrero, M. & Rieseberg, L.H. (2018) Trends in Global Agricultural Land Use: Implications for Environmental Health and Food Security. Annual Review of Plant Biology. 69 (1), 789–815. https://doi.org/10.1146/annurev-arplant-042817-040256

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications*, 6, 5989. https://doi.org/10.1038/ncomms6989

Rodrigues, A.S.L. & Cazalis, V. (2020) The multifaceted challenge of evaluating protected area effectiveness. Nature Communications. 11 (1). https://doi.org/10.1038/s41467-020-18989-2

Rolando, J.L., Turin, C., Ramírez, D.A., Mares, V., Monerris, J. & Quiroz, R. (2017) Key ecosystem services and ecological intensification of agriculture in the tropical high-Andean Puna as affected by land-use and climate changes. Agriculture, Ecosystems & Environment. 236, 221–233. https://doi.org/10.1016/j.agee.2016.12.010

Rubin, D. B. (1979). Using multivariate matched sampling and regression adjustment to control bias in observational studies. *Journal of the American Statistical Association*, 74(366), 318–328. https://doi.org/10.1080/01621459.1979.10482513

Ruiz Muller, M., & Bioversity International. (2009). *Las zonas de agrobiodiversidad y el registro de cultivos nativos: Aprendiendo de nosotros mismos*. Available at: https://www.researchgate.net/publication/33554522_Las_zonas_de_agrobiodiversidad_y_el_registro_de_cultivos_nativos_Aprendiendo_de_nosotros_mismos (Accessed 20 June 2025).

Running, S., Mu, Q., Zhao, M., & MODAPS SIPS – NASA. (2015). *MOD17A2H MODIS/Terra Gross Primary Productivity 8-Day L4 Global 500 m SIN Grid* [Dataset]. NASA LP DAAC. https://doi.org/10.5067/MODIS/MOD17A2H.006 (Accessed 7 July 2025).

Sayre, M., Stenner, T., & Argumedo, A. (2017). You can't grow potatoes in the sky: Building resilience in the face of climate change in the Potato Park of Cuzco, Peru. *Culture, Agriculture, Food and Environment*, 39(2), 100–108. https://doi.org/10.1111/cuag.12100

Schleicher, J., Eklund, J., Barnes, M., Geldmann, J., Oldekop, J. A., & Jones, J. P. G. (2020). Statistical matching for conservation science. *Conservation Biology*, 34(3), 538–549. https://doi.org/10.1111/cobi.13448

Schleicher, J., Peres, C. A., Amano, T., Llactayo, W., & Leader-Williams, N. (2017). Conservation performance of different conservation governance regimes in the Peruvian Amazon. *Scientific Reports*, 7, 11318. https://doi.org/10.1038/s41598-017-10736-w

Sirami, C., Gross, N., Baillod, A. B., Bertrand, C., Carrié, R., *et al.* (2019). Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. *Proceedings of the National Academy of Sciences*, 116(33), 16442–16447. https://doi.org/10.1073/pnas.1906419116

Smith, R. G., Menalled, F. D., & Robertson, G. P. (2007). Temporal yield variability under conventional and alternative management systems. *Agronomy Journal*, 99(6), 1629–1634. https://doi.org/10.2134/agronj2007.0096

Sotomayor, D., Carrillo, F., Becerra, R., Roldan, A., Amasifuen, C., & Guerrero, J. (2020). *Guía para el reconocimiento de zonas de agrobiodiversidad en el Perú*. Instituto Nacional de Innovación Agraria (INIA). ISBN: 978-9972-44-055-7. https://repositorio.inia.gob.pe/handle/20.500.12955/1111

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, 25(1), 1–21. https://doi.org/10.1214/09-STS313

Swiderska, K., & Argumedo, A. (2022). Indigenous seed systems and biocultural heritage: The Andean Potato Park's approach to seed governance. In Y. Nishikawa & M. Pimbert (Eds.), *Seeds for diversity and inclusion*. Palgrave Macmillan. https://doi.org/10.1007/978-3-030-89405-4_4

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). *mediation*: R package for causal mediation analysis. *Journal of Statistical Software*, 59(5), 1–38. https://doi.org/10.18637/jss.v059.i05

UNEP–WCMC and IUCN. (2025). *The World Database on Protected Areas (WDPA), November 2025 release* [Dataset]. Cambridge, UK: UNEP–WCMC and IUCN. Available at: https://www.protectedplanet.net/ (Accessed 21 June 2025).

Velásquez-Milla, D., Casas, A., Torres-Guevara, J., & Cruz-Soriano, A. (2011). Ecological and socio-cultural factors influencing *in situ* conservation of crop diversity by traditional Andean households in Peru. *Journal of Ethnobiology and Ethnomedicine*, 7(1), 40. https://doi.org/10.1186/1746-4269-7-40

WCS Peru. (2019, October 17). “Andenes de Cuyocuyo”: Primera zona de Agrobiodiversidad del Perú. Available at: https://peru.wcs.org/es-es/WCS-Peru/Noticias/articleType/ArticleView/articleId/13202/Andenes-de-Cuyocuyo-Primera-zona-de-Agrobiodiversidad-del-Peru.aspx (Accessed 21 August 2025).

Zimmerer, K. S. (2013). The compatibility of agricultural intensification in a global hotspot of smallholder agrobiodiversity (Bolivia). *Proceedings of the National Academy of Sciences*, 110(8), 2769–2774. https://doi.org/10.1073/pnas.1216294110

Zimmerer, K. S., & de Haan, S. (2017). Agrobiodiversity and a sustainable food future. *Nature Plants*, 3(4), 17047. https://doi.org/10.1038/nplants.2017.47

Zimmerer, K. S., de Haan, S., Jones, A. D., Creed-Kanashiro, H., Tello, M., Carrasco, M., Meza, K., Plasencia Amaya, F., Cruz-Garcia, G. S., Tubbeh, R., & Jiménez Olivencia, Y. (2019). The biodiversity of food and agriculture (agrobiodiversity) in the Anthropocene: Research advances and conceptual framework. *Anthropocene*, 25, 100192. https://doi.org/10.1016/j.ancene.2019.100192

1. SUPPLEMENTARY MATERIALS FOR

Long-term community management of Agrobiodiversity Zones reduces agricultural expansion and natural cover loss.

Comacchio, A.[1], Tovar, C.[2], Jago, S.[2,3], Jones, S.K.[4], Carmona, N.E.[4], Fernández Huatalla, E.[5], Quintana Palacios, C. [5], Gutiérrez Reynoso D. [5], Medina Hinostroza, T.[6], Koechlin Cuba, A.M. [7], Olazábal, O. [7], Catpo, R.[7], Sotomayor, D. [8], Borrell, J.S. [2]*

[1] Imperial College London, Centre for Environmental Policy, London, United Kingdom
[2] Royal Botanic Gardens, Kew, Richmond, TW9 3AE
[3] Durrell Institute of Conservation and Ecology, University of Kent, Canterbury, CT2 7NR, United Kingdom
[4] Bioversity International, Montpellier, France
[5] Instituto Nacional de Investigación Agraria (INIA), Lima, Perú
[6] Ministerio del Ambiente, Lima, Perú
[7] Conservación Amazónica – ACCA
8 Department of Environmental Engineering, Universidad Nacional Agraria La Molina, Lima, Perú

*Corresponding author: James S. Borrell

Email: j.borrell@kew.org

TABLE OF CONTENT

SUPPLEMENTARY MATERIAL

Method S1: Baseline choice and long-term ABDZs commitment

The creation of Peru's ABDZs is the result of decades of dialogue, citizen mobilization, and action research, rooted in previous projects and efforts working with communities on in-situ conservation, traditional seed systems and diversified farming strategies (Sayre, Stenner & Argumedo, 2017). The ABDZ concept emerged from earlier grassroots and institutional efforts—such as the Parque de la Papa, the In Situ Conservation Project of Native Crops and Wild Relatives (2001–2006), and national debates shaped by the Convention on Biological Diversity—which positioned multiple Peruvian regions as "hotspots" of domesticated genetic diversity sustained through complex and dynamic cultural practices. The early 2000s saw the implementation of important initiatives, including the INIA in-situ conservation programme, reflecting growing institutional recognition of their ecological and cultural value (Instituto Nacional de Investigación Agraria, 2007; Drucker, Ramirez & Medina, 2024). Taken together, this pre-2017 history underscores that ABDZs are the product of long-standing, locally rooted conservation strategies rather than solely a recent legal designation. Since the official recognition, communities have increasingly and voluntarily requested that their landscapes be designated as Agrobiodiversity Zones.

While traditional practices have long sustained agricultural resilience in the Andes, they are increasingly challenged by environmental degradation, changes in land-use patterns and land scarcity, poor socio-economic conditions, and climate change (Boillat & Berkes, 2013; Tovar et al., 2013: Aguilar-Luis et al., 2024). This is likely to be exacerbated in the future, with climate models projecting higher frequency of extreme precipitation and droughts (Potter et al., 2023).

Method S2: Additional method section for GPP extraction

Because ABDZs are characterised by overlapping planting/harvest calendars and widespread intercropping within small, heterogeneous parcels, we summarised productivity using annual calendar-year mean of GPP rather than imposing a single growing season and is thus a proxy for “all-crops” production. To limit contamination from non-cropland and mixed 1km units, all calculations were restricted to cropland using the year-specific MapBiomas Perú cropland mask (including agricultural mosaic) at 30 m. Within each 1 km analysis unit we computed cropland-only annual GPP as an area-weighted mean of constituent units, weighting by the pixel–polygon overlap area and the per-pixel cropland fraction. This approach allows intercropped parcels to contribute in proportion to their cropped area down-weighting signal from natural cover, but including fallow periods usually categorised as cropland or mosaic in Mapbiomas class legend.

Method S3: Matching and collider bias

Statistical matching for counterfactual analysis consists of matching treatment units with units outside the treatment area (ABDZs) that share similar biophysical and socio-ecological conditions and it is used as a pre-processing step to construct a balanced sample of treated and control units, thereby reducing confounding and improving the validity of causal comparisons.

A recommended cautious approach if there's uncertainty about the potential of a variable to act as a potential confounder is to include it as a covariate in the matching process in any case, while excluding those variables that may have been affected by the outcome itself and therefore potentially introducing collider bias (Stuart 2010; Schleicher et al., 2020). Although distance to road is measured using post-2000 spatial data given limited availability, we do not expect this to introduce collider bias in the counterfactual analysis, as cautioned by Geldmann et al. (2025). This is because road construction is not plausibly influenced by ABDZs, which encompass multiple communities and inhabited areas. These are not protected areas and have no legal status that would affect infrastructure planning. We included this covariate in the matching as we considered it an important confounder (road proximity can in turn influence agricultural expansion or intensification) and used the robustness check, to assess whether the inclusion or exclusion of this covariate influenced the results.

Method S4: robustness check to different matching model specifications

To ensure the robustness of the significant findings in estimating treatment effects on the outcome variables against several arbitrary modelling decisions – many of which can influence the results – We conducted comprehensive robustness checks using different alternative matching combinations, following and adapting the framework consolidated by Devenish et al. (2022). For any assessed outcomes, we ran permutation tests over many different specifications, looped with 3 different matching approaches and several combinations of co-variates variables and subsequent significant testing to confirm whether results remained consistent (see supplementary method section). Each specification included a consistent set of core covariates. We then varied the inclusion of additional covariates considered less crucial or slightly correlated with the main variables, testing all non-empty combinations.

For each covariate configuration, we applied three matching approaches, i.e. Mahalanobis distance, propensity scores estimated via logit model caliper 0.2, and propensity scores estimated using a random forest model (Devenish et al. 2022). For GPP interannual variability, we also added a variation across time periods - by shifting or removing a year from the time windows - ensuring that patterns hold across various temporal scales. To estimate the treatment effects within each combination of matched samples, for example, for the main testing method, OLS regression was employed in robustness checks across multiple matching specifications.

Table S1: Agrobiodiversity zones

ABDZ	Department	ha	Altitude range
Andenes de Cuyocuyo	Puno	6,554	2,850 – 4,395
Parque de la Papa	Cusco	7,238	3,475 – 4,500
Ccollasuyo	Cusco	14,240	2,330 – 5,575
Marcapata-Ccollana	Cusco	~15,000	3,130 – 5,930
Pariahuanca	Junín	23,136	1,460 – 5,000
Paymakis	Apurímac	14,261	2,840 – 4,910
Laria	Huancavelica	13,742	3,050 – 4,620
Cotahuasi (excluded from the analysis because of overlapping with PA)	Arequipa-Ayacucho	45,766	2,195 – 5,445
Circa	Apurímac	53,454	1,965 – 4,855
Andahuaylas	Apurímac	20,923	2,330 – 4,300

Table S2: Land cover class aggregation

For land use change outcomes, the 12 original land cover classes present in the area were aggregated into five categories as shown below: agricultural land, forest, grassland, other non-vegetation, and mining. Agricultural expansion includes cropland, agricultural mosaic, and managed pasture. Natural cover loss encompasses loss of native forests and grasslands not under active management. Importantly, fallow fields, which are common in rotational systems, are typically retained in class 18 (cropland) or class 21 (agricultural mosaic) in MapBiomas, ensuring they are not misclassified as natural vegetation.

Aggregated class	**Original Mapbiomas class**	**Code**
Agricultural land	Cropland	18
Agricultural land	Agricultural mosaic	21
Agricultural land	Managed pasture	15
Forest (natural cover)	Forest	3
Grassland (natural cover)	Grassland	12
Other non-vegetation	Infrastructure Bare rock Glacier Water	24 25 34 33
Mining	Mining	30

Table S3. Covariates choice. Covariates used for statistical matching and regression models. Data for all covariates resampled to 1km resolution for gridcell matches and reprojected to UTM 18S.

Covariate	Rationale	Source and Reference	Native Resolution	Unit	Data type
Elevation	Influences crop types, climate, productivity; mountainous vs flat areas differ in land use.	Global 3- Arc-Second Elevation (GTOPO30) (EROS, 2017)	~90 m	m.a.s.l.	Continuous
Slope	Steeper areas are less likely to be farmed intensively; affects access and erosion.	Global 3- Arc-Second Elevation (GTOPO30) (EROS, 2017)	~90 m	Degrees	Continuous
Temperature (mean diurnal range)	Determines climate suitability for crops, vegetation productivity.	Climatologies at high resolution for the earth's land surface areas (CHELSA) (Karger et al., 2017)	1 km	°C	Continuous
Precipitation (average annual rainfall)	Affects water availability and rainfall variability critical for agriculture.	Climatologies at high resolution for the earth's land surface areas (CHELSA) (Karger et al., 2017)	1 km	kg/m^2	Continuous
Accessibility to Cities	Proximity to markets influences land-use decisions and economic pressures.	Global Accessibility Map (Nelson, 2008)	1 km	Minutes	Continuous
Distance to Roads	Roads influence intensification and ease of agricultural expansion.	OpenStreetMap	Vector	m (Euclidian distance)	Continuous

Income	Income level influence land use decision such as need for agricultural land, mining or development infrastructure	National dataset ENAHO 2002-4 (Encuesta Nacional de Hogares 2002-4)	District level aggregation	m (Euclidian distance)	Continuous
Land Cover (2000 baseline)	Starting proportions: forest, grassland, agricultural land, cropland-only proportions influence future land change trajectories.	MapBiomas Peru	30 m	as % area	Continuous
Population Density in 2000	Reflects human pressure and demand for land conversion.	WorldPop (2020)	1 km	Number of people per 1km^2 grid cell	Continuous

Table S4. Semivariance analysis and spatial autocorrelation. a) A**gricultural expansion, b) natural cover loss, c) mean GPP and d) mean patch size at different sampling densities. Values** represent the mean semivariance (pp) derived from the empirical variogram. The 0.0 km distance represents the global variance of the unthinned dataset, serving as the theoretical sill for the landscape.

a)

Distance between sampled units (km)	Mean Semivariance
0.0 (Global Variance)	**53.69**
2.0	32.60
4.0 (Selected Spacing)	**41.19**
5.6	44.19
7.9	46.65

b)

Distance between sampled units (km)	Mean Semivariance
0.0 (Global Variance)	**73.51**
2.0	37.43
4.0 (Selected Spacing)	**54.16**
5.6	56.95
7.9	61.22

c)

Distance between sampled units (km)	Mean Semivariance
0.0 (Global Variance)	**124.50**
2.0 (Selected Spacing) **	**72.10**
4.0	91.45
5.6	98.12
7.9	105.30

** choice made in order to keep a reasonable sample size (5km cluster-robust standard Error was applied in the regression to account for the remaining SAC).

d)

Distance between sampled units (km)	Mean Semivariance
0.0 (Global Variance)	**18.90**
2.0	9.45
4.0 (Selected Spacing)	**14.20**
5.6	14.80
7.9	15.95

Table S5. Covariate-adjusted OLS ATT estimates on matched samples for each outcome, with N, ATT, 95% CI, and p-value. Negative ATTs for agricultural expansion, natural cover loss, and field size indicate reductions in ABDZs vs. controls; GPP mean shows no difference; positive ΔCV indicates smaller decline (higher interannual variability) in ABDZs. Units as shown.

Outcome	N total	Average Treatment Effect (ATT)	95% CI	p-value
Agricultural Expansion	900	−1.39%	−2.30% to −0.48%	0.0029
Natural Cover Loss	900	−1.55%	−2.58% to −0.52%	0.0032
GPP Mean	538	−0.0046 kg C m^{-2} yr^{-1}	−0.0279 to +0.0187	0.70
GPP Variability (ΔCV)	476	+0.76 %	+0.10 to +1.42	<0.02
Mean Field Size	828	−0.297 ha	−0.723 to +0.129	0.172

Table S6. Land cover transition matrices. a) Agrobiodiversity Zones and b) Matched controls. Values represent the percentage of the total landscape area transitioning between land cover classes from baseline (2000–02) to endline (2020–22). Rows indicate the initial state (2000); columns indicate the final state (2022).

a) Treatment

From (2000) \ To (2022)	AGRICULTURE	FOREST	GRASSLAND	MINING	OTHER_NON_VEG
AGRICULTURE	4.606	1.727	7.125	0.000	0.426
FOREST	1.466	8.035	4.088	0.000	0.384
GRASSLAND	7.363	4.542	45.402	0.205	3.325
MINING	0.000	0.000	0.000	0.001	0.000
OTHER_NON_VEG	0.432	0.412	3.500	0.004	6.956

b) Matched control landscape

From (2000) \ To (2022)	AGRICULTURE	FOREST	GRASSLAND	MINING	OTHER_NON_VEG
AGRICULTURE	7.168	1.173	5.641	0.002	0.659
FOREST	1.274	6.933	2.717	0.000	0.087
GRASSLAND	6.688	2.772	49.161	0.043	4.203
MINING	0.000	0.000	0.004	0.001	0.000

OTHER_NON_VEG	0.733	0.080	3.968	0.009	6.684

Figure S1. Net agricultural expansion in the Andes and within the Area of Interest (AOI).

Change in total agricultural area (ha) comparing the baseline period (2000–2002) to the endline period (2020–2022). The data indicates a total growth of +4.4%, increasing from 3,364,494 ha to 3,510,874 ha over the two-decade observation period. Agriculture is defined as a composite of cropland (annual and perennial crops), managed pasture, and agricultural mosaics where small-scale farming and grazing land are interspersed. This trend highlights the background pressure of agricultural expansion in the region, against which the Agrobiodiversity Zones (ABDZs) were evaluated. Data derived from MapBiomas Perú.

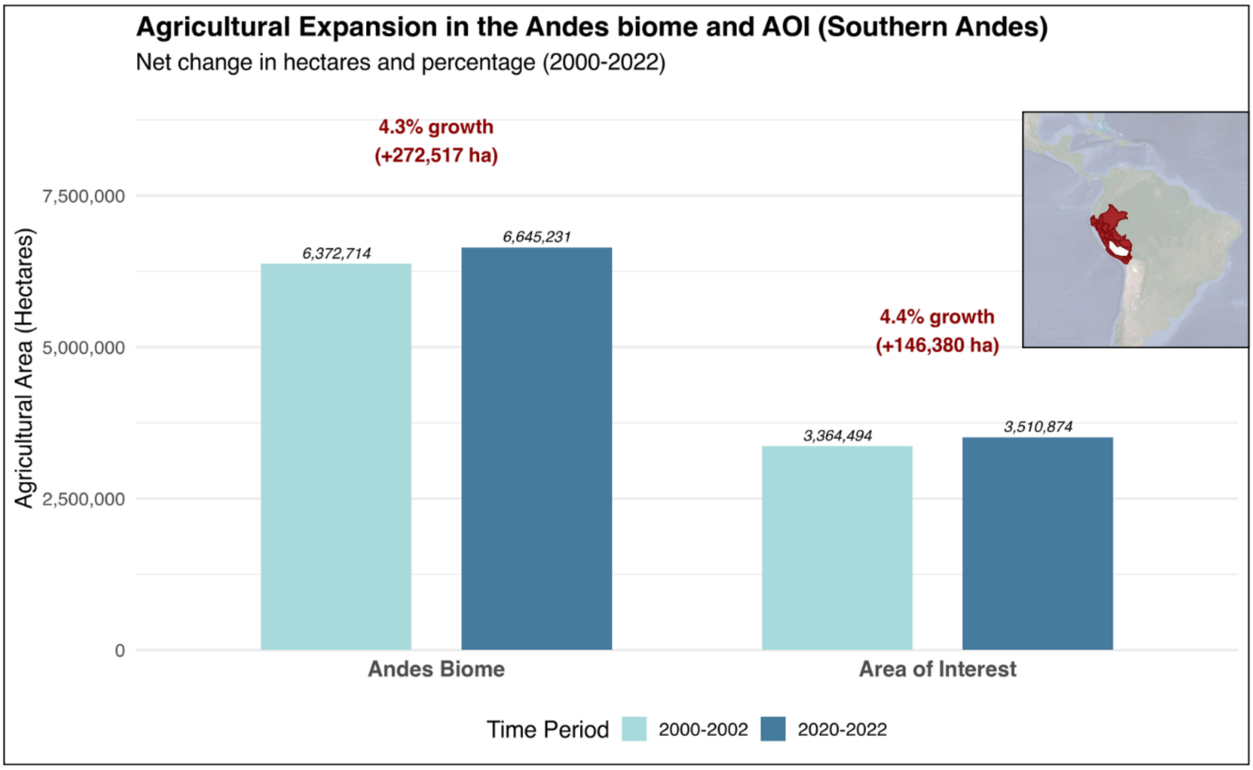


Figure S2. Trends in agricultural intensification in Peru: yields.

A) Arable land required to produce a fixed quantity of crops calculated as arable land divided by the crop production index. **B)** Comparative yield trajectories (tonnes per hectare) for key staples: Quinoa, Roots/Tubers, Potato, and Corn. Data sources: Food and Agriculture Organization of the United Nations and Our World in Data.

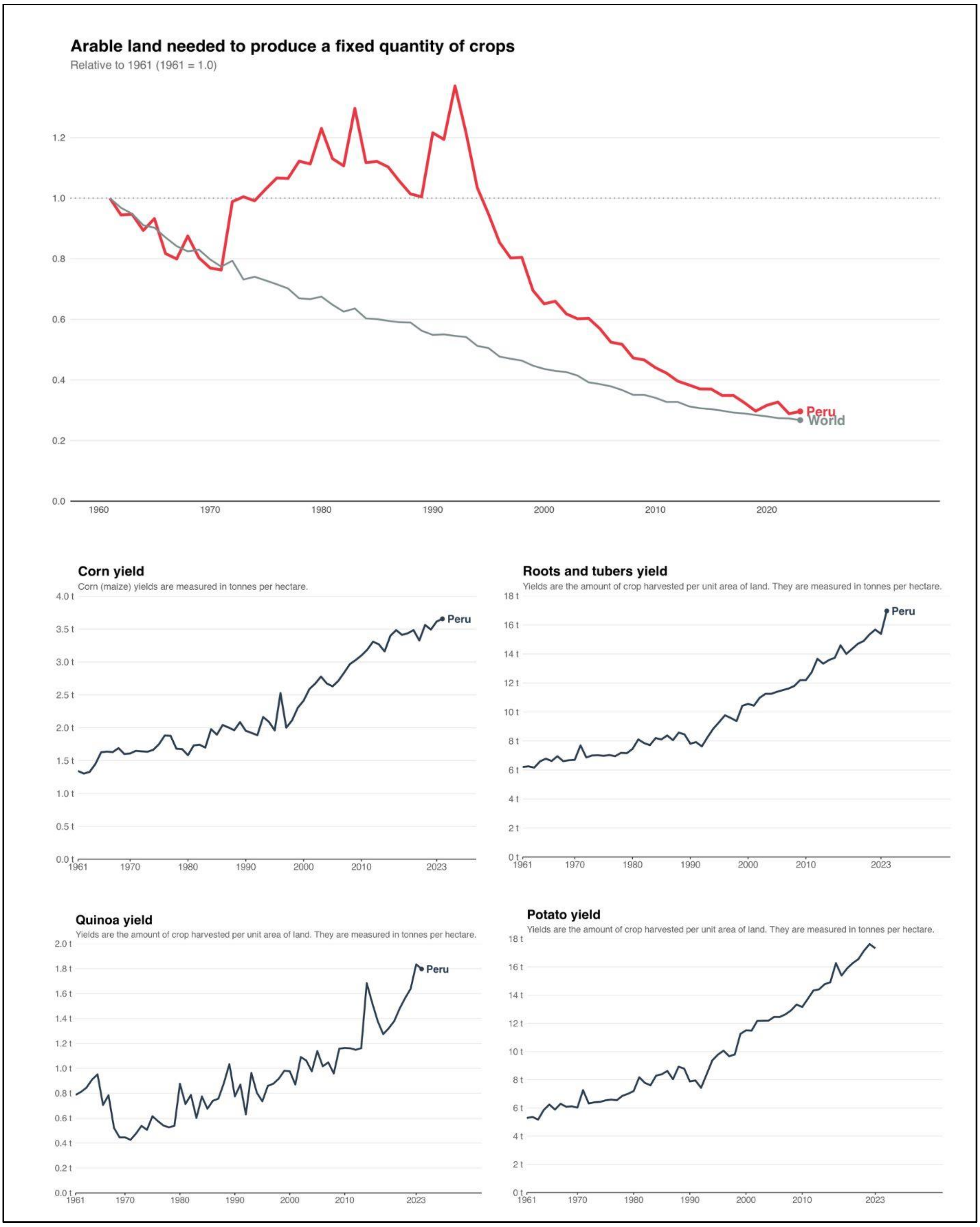


Figure S3. Trends in agricultural intensification in Peru: pesticides and fertilizer use. **(A)** Total fertilizer consumption (nitrogen, potassium, phosphorus, and organic inputs) from 1961 to 2022. **(B)** Total pesticide use measured in tonnes per year from 1990 to 2022.

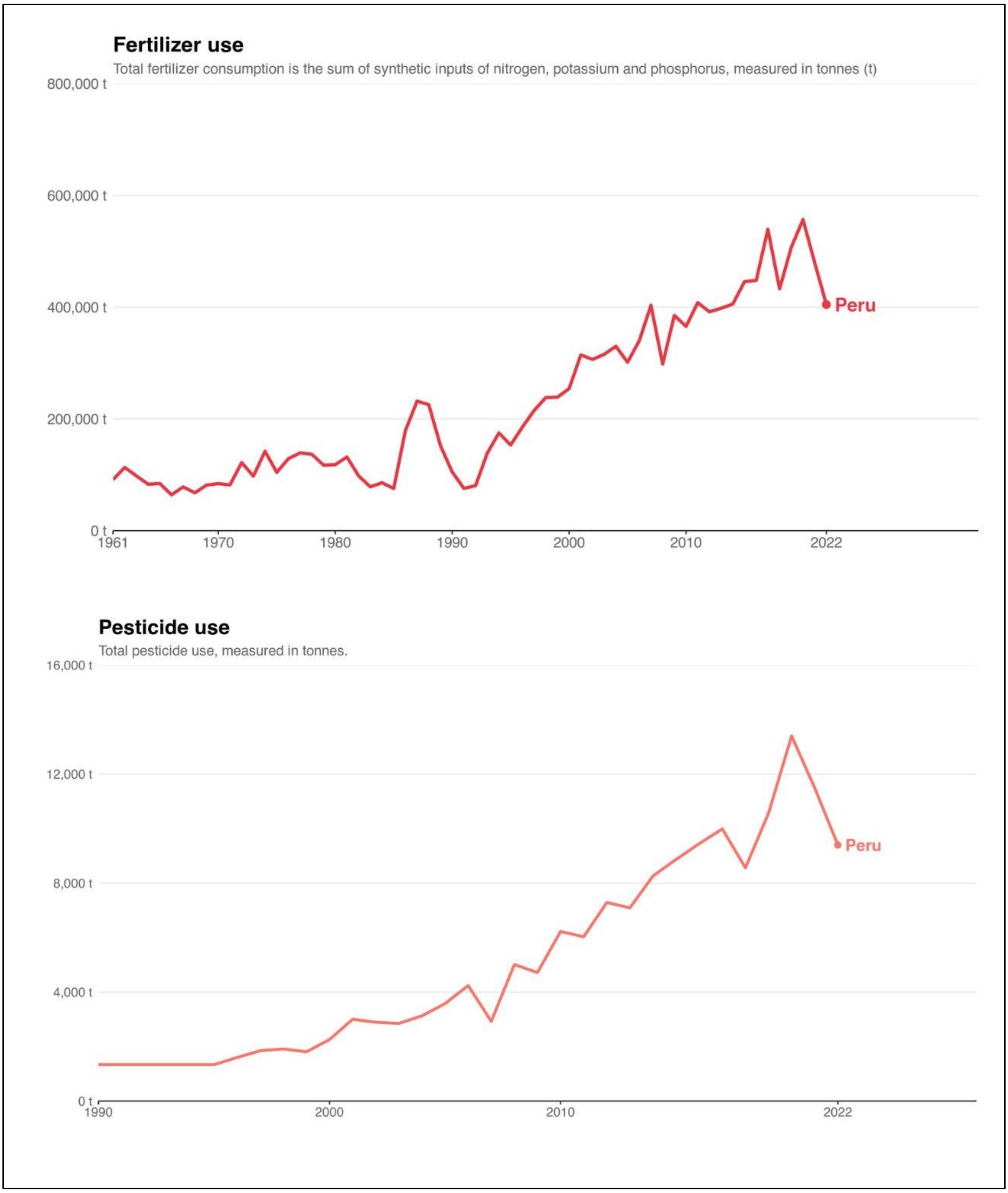


Figure S4. Directed Acyclic Graph (DAG) illustrating the quasi-experimental design and causal assumptions. The diagram maps the hypothesized causal pathway connecting the treatment—Long-term community management of agrobiodiversity zones (ABDZs)—to conservation outcomes. Biophysical Confounders (elevation, slope, temperature, precipitation) and Socio-economic

Confounders (population density, income, market access) are accounted for via statistical matching to isolate the treatment effect. Intermediate Mechanisms include intercropping, reciprocal labor, and crop-fallow rotation. These mechanisms drive the observed Outcomes: reductions in agricultural expansion, natural cover loss, and intensification. The model assumes that matching on baseline (early 2000s) confounders effectively controls for pre-existing landscape configurations and structural drivers of change.

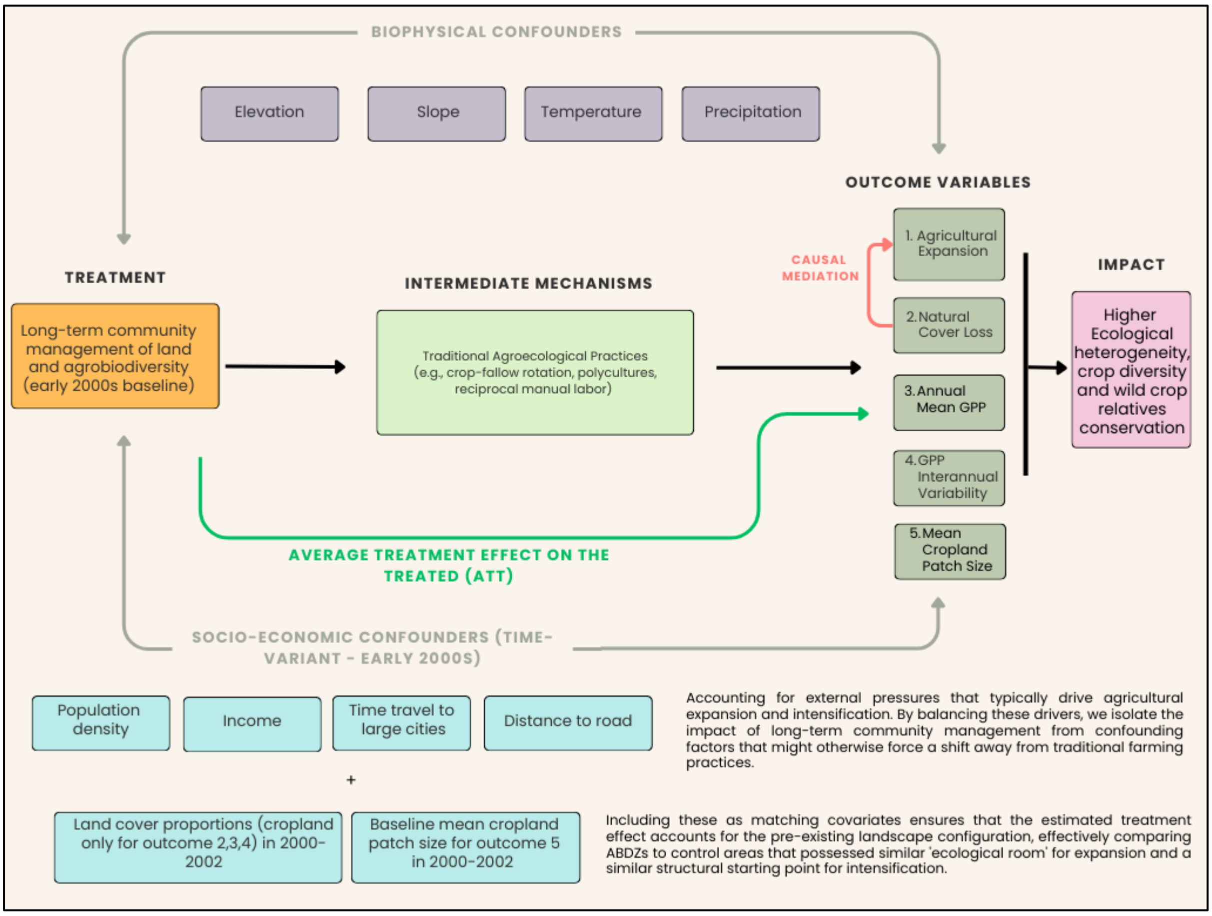


Figure S5. Principal Component Analysis (PCA). PCA of environmental variables for agricultural areas in Peru. Ellipses show 95% confidence intervals around the ABDZ and control area clusters.

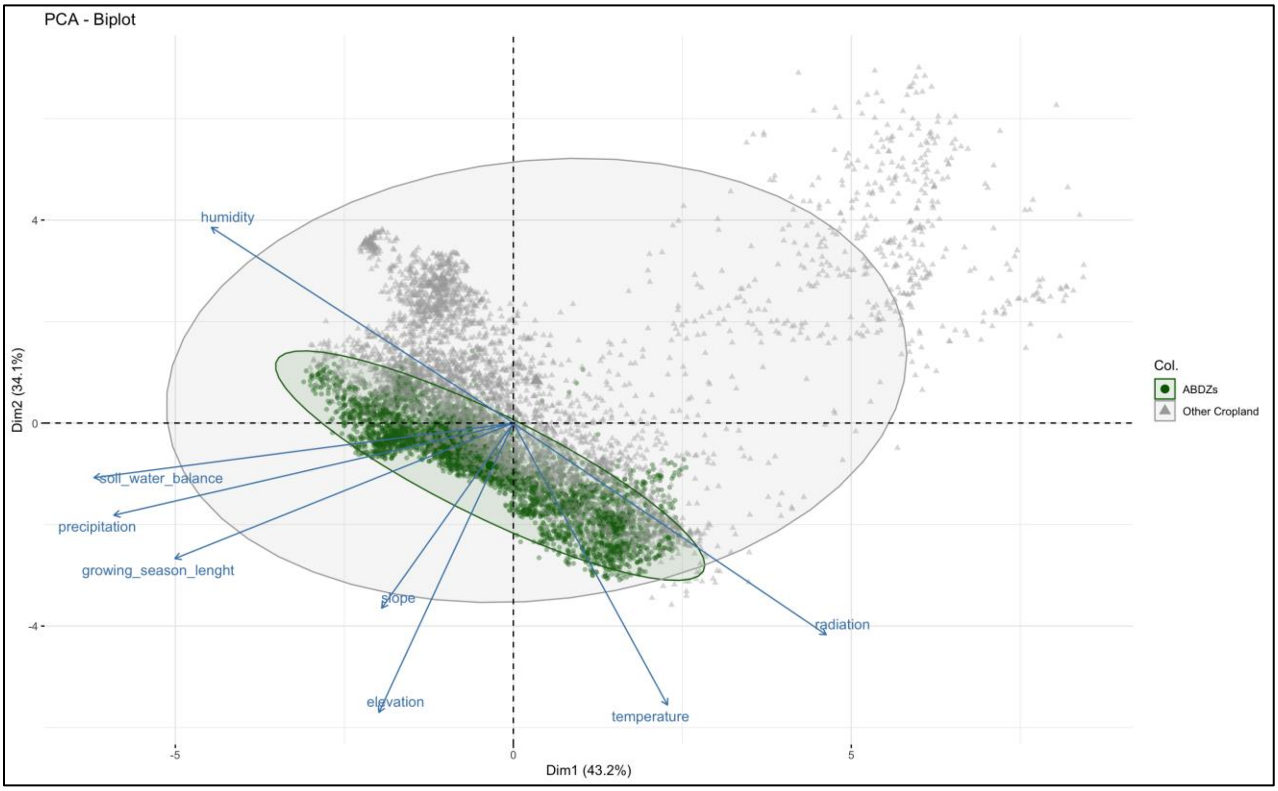


Figure S6. Covariate balance (loveplots). Loveplots for the three matched samples using propensity score caliper = 0.2 or malanahobis. Points show standardized mean differences (SMD) between ABDZs and control before matching (red) and after matching (blue). Dashed lines are my ±0.10 SMD threshold.

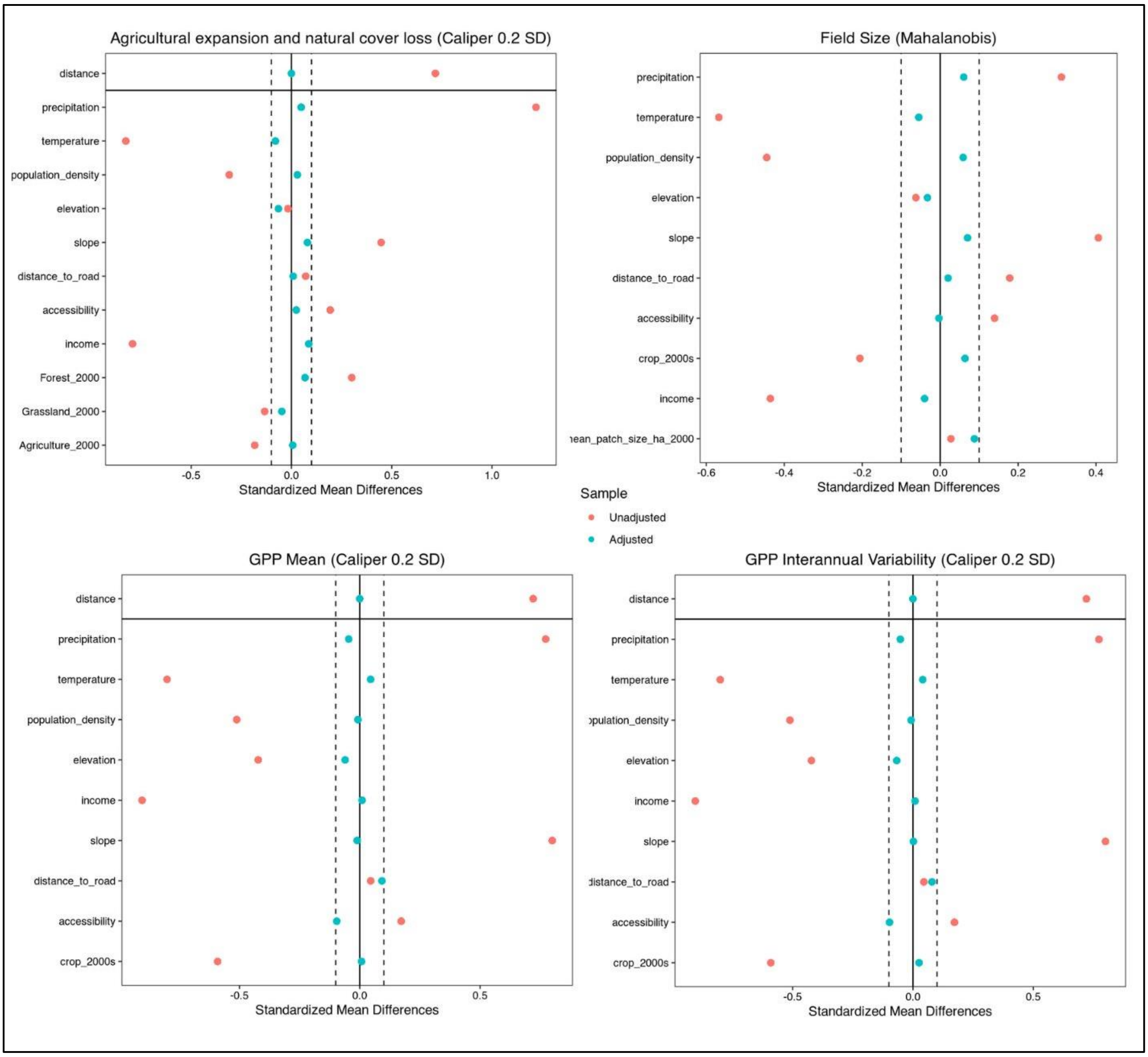
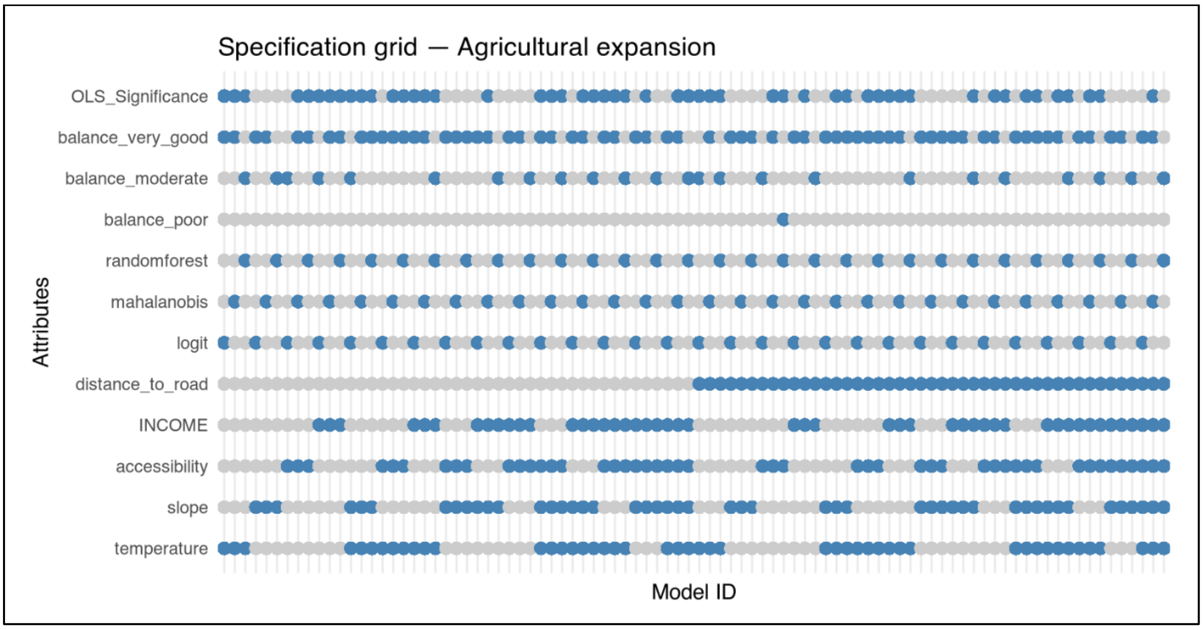
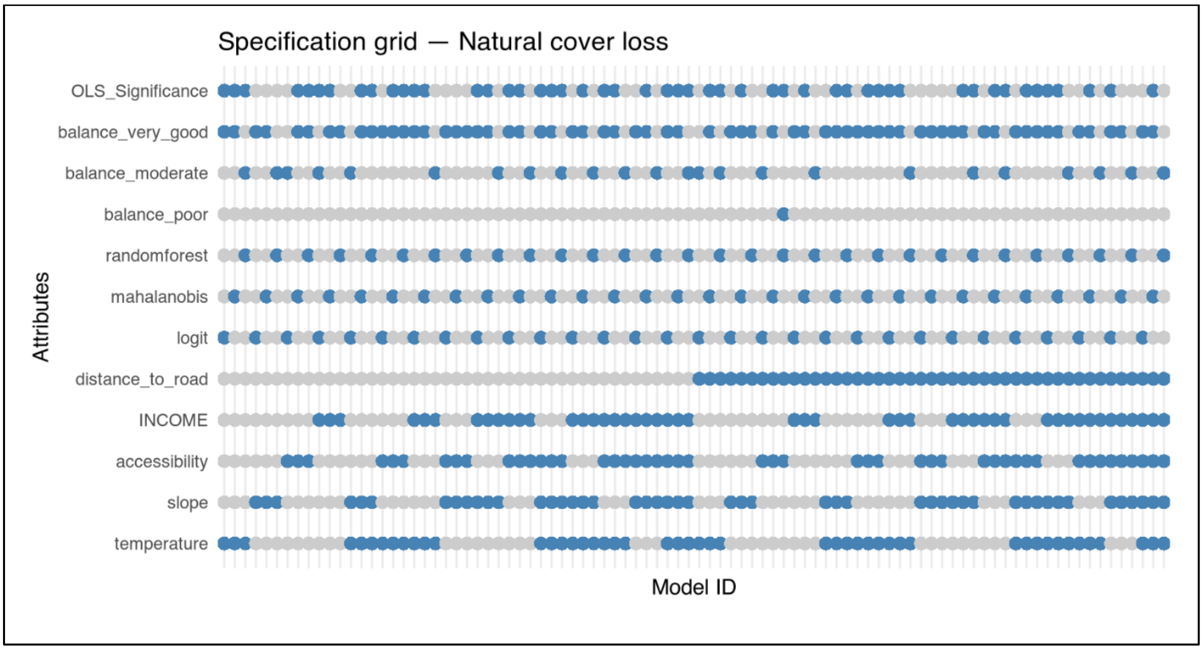


Figure S7. Specification grids to different matching combinations. Grids showing the sensitivity of estimated treatment effects across all outcome variables to design choices: covariate inclusion/exclusion, matching algorithm (logit PS, random forest PS, Mahalanobis), and moving time windows. Points indicate model specifications; color marks statistical significance; rows denote features (covariates, method, balance tier).

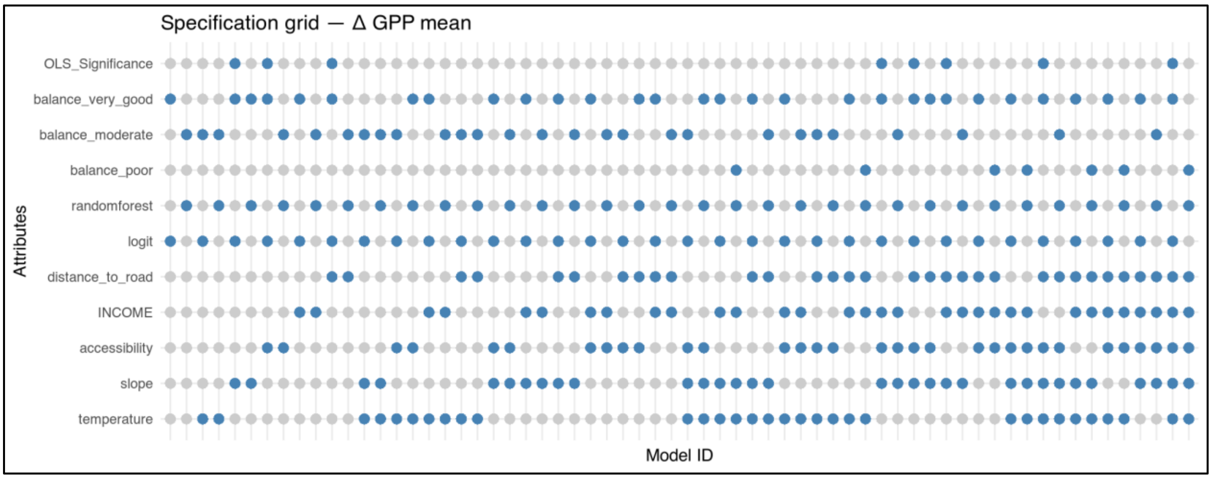
a)



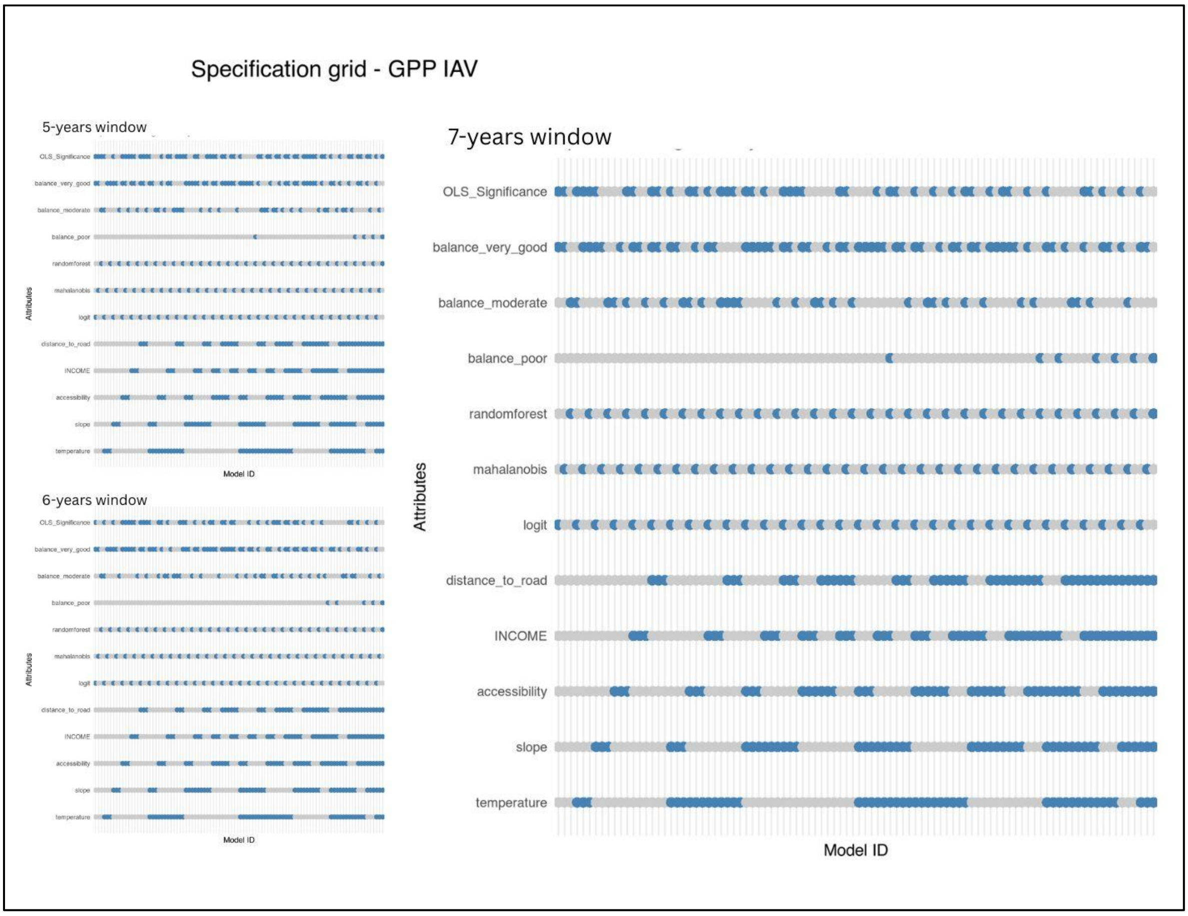
b)



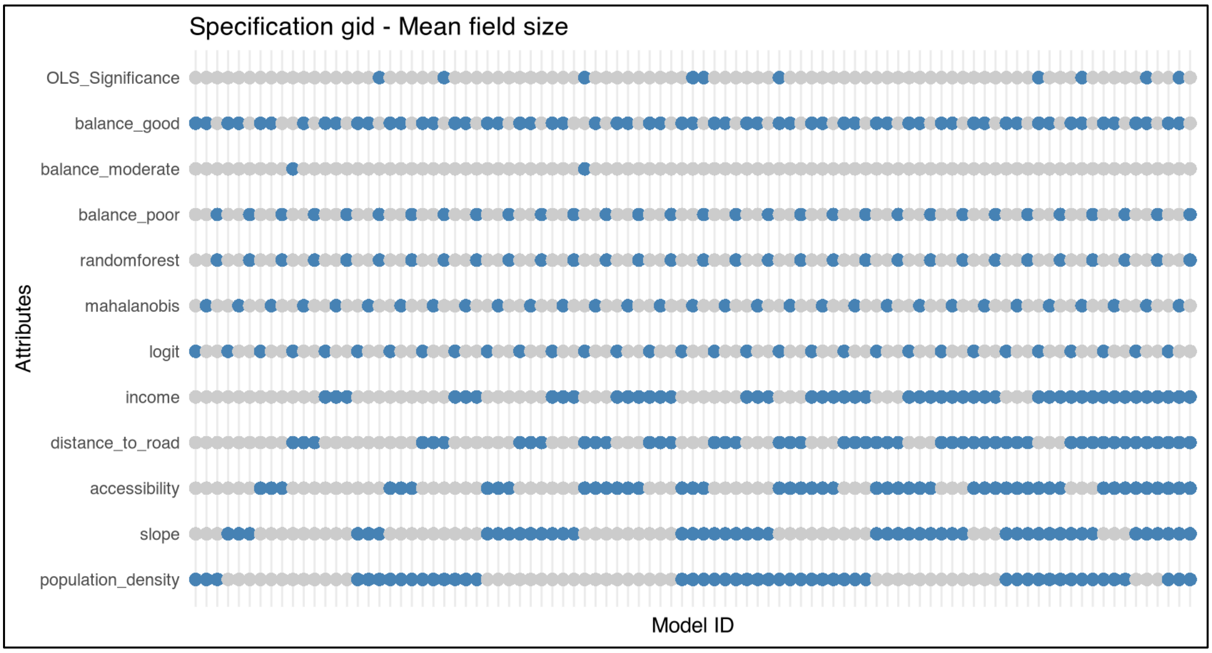
c)


Specification grid — Δ GPP mean
OLS_Significance
balance_very_good
balance_moderate
balance_poor
randomforest
logit
distance_to_road
INCOME
accessibility
slope
temperature
Attributes
Model ID

d)


Specification grid - GPP IAV
5-years window
6-years window
7-years window
OLS_Significance
balance_very_good
balance_moderate
balance_poor
randomforest
mahalanobis
logit
distance_to_road
INCOME
accessibility
slope
temperature
Attributes
Model ID

e)


Specification gid - Mean field size
OLS_Significance
balance_good
balance_moderate
balance_poor
randomforest
mahalanobis
logit
income
distance_to_road
accessibility
slope
population_density
Attributes
Model ID

ADDITIONAL REFERENCES (SUPPLEMENTARY MATERIAL)

Blackman, A. (2013). Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *Forest Policy and Economics*, 34, 1–16. https://doi.org/10.1016/j.forpol.2013.04.006

Devenish, K., Desbureaux, S., Willcock, S., & Jones, J. P. G. (2022). On track to achieve no net loss of forest at Madagascar's biggest mine. *Nature Sustainability*, 5, 1065–1075. https://doi.org/10.1038/s41893-022-00850-7

Ferraro, P. J., & Hanauer, M. M. (2014). Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the National Academy of Sciences*, 111(11), 4332–4337. https://doi.org/10.1073/pnas.1307712111

Geldmann, J., Jones, J. P. G., Wauchope, H., & Ferraro, P. J. (2025b). Causal claims, causal assumptions and protected area impact. *Nature*. https://doi.org/10.1038/s41586-024-08512-8 *(please verify authors/DOI match your intended citation)*

Instituto Nacional de Estadística e Informática (INEI). (2004). *Encuesta Nacional de Hogares 2004 (ENAHO 2004)* [Dataset]. ILO Survey Catalogue. Available at: **https://webapps.ilo.org/surveyLib/index.php/catalog/6815**

Nelson, A. (2008). *Travel time to major cities: A global map of accessibility*. Office for Official Publications of the European Communities. https://doi.org/10.2788/95835

OpenStreetMap contributors. (2025). *OpenStreetMap* [Dataset]. OpenStreetMap Foundation. Available at: https://www.openstreetmap.org/ (Accessed 21 April 2025).

Rubin, D. B. (1979). Using multivariate matched sampling and regression adjustment to control bias in observational studies. *Journal of the American Statistical Association*, 74(366), 318–328. https://doi.org/10.1080/01621459.1979.10482513

SERNANP. (2025). *Mapa oficial de las Áreas Naturales Protegidas* [Web map]. Available at: https://www.gob.pe/institucion/sernanp/informes-publicaciones/2560576-mapa-oficial-de-las-areas-naturales-protegidas (Accessed 20 April 2025).

U.S. Geological Survey. (2018). *Global 30 Arc-Second Elevation (GTOPO30)* [Dataset]. Earth Resources Observation and Science (EROS) Center. https://doi.org/10.5066/F7DF6PQS

WorldPop; School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville;

Département de Géographie, Université de Namur; & Center for International Earth Science Information Network (CIESIN), Columbia University. (2018). *Global High Resolution Population Denominators Project* [Dataset]. https://doi.org/10.5258/SOTON/WP00675