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LETTER

Private protected areas exhibit greater bias towards unproductive land compared to public protected areas

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Abstract

Globally, private protected areas (PPAs) have become an important tool for biodiversity conservation. While they are expanding in size and number, there is limited evidence on their potential impact on avoiding biodiversity loss, and how this impact compares to the public protected areas (public PAs). The impact of protection is measured as the actual biodiversity outcome within the area protected relative to the hypothetical outcome without protection. To maximise this positive impact, PAs need to be placed strategically on land that both harbours biodiversity and would be at risk of losing some of the biodiversity if it were not protected. We evaluate and compare the locations of PPAs and public PAs relative to random sites of similar governance type, and a range of covariates that capture biodiversity and the risk of biodiversity loss. We utilised data from a national PA database, and high-resolution data on nationally significant threatened species and indicators that capture risk of biodiversity loss at a continental scale in Australia. We find that PPAs tend to target areas of high threatened species richness. However, on average, PPAs are placed in areas that have lower risk of being cleared compared to randomly selected private land. We observe that this bias towards unproductive land is more prominent in PPAs when compared to public PAs. As nations work towards effectively conserving and managing at least 30% of the world's lands by 2030 under the new Kunming-Montreal Global Biodiversity Framework, it becomes essential to prioritise PAs and PPAs that deliver impacts on avoiding biodiversity loss rather than solely focusing on areas that represent biodiversity.

1. Introduction

Biodiversity is declining worldwide due to the conversion of natural habitat from anthropogenic activities (Brondizio *et al* 2019). To address this, protected areas (PAs) have become a common policy response internationally (Juffe-Bignoli *et al* 2014). PAs are defined as designated spaces with the goal of conserving nature and its associated ecosystem services and cultural values, through legal or other means (IUCN 2007). Since the World Parks Congress in 1982, countries have worked to expand the area of PAs. Currently, PAs cover close to 15% of the Earth's land surface, almost meeting the Aichi Target of protecting 17% by 2020 (CBD, 2020). Historically, PAs were established primarily on public land or land that was converted to public ownership. However, many areas important to biodiversity exist outside PAs located on private, community, or Indigenous people's land (Dinerstein *et al* 2017). As a result, privately owned protected areas, known as private protected areas (PPAs), have emerged as a more recent conservation tool (Mitchell *et al* 2018). There has been a significant increase in their establishment worldwide, as of 2018, the World Database on Protected Areas (WDPA) have reported 13,250 PPAs (Palfrey *et al* 2022). Many countries, including Australia, Chile, Finland, and the United States, have implemented voluntary agreements and land acquisitions to establish PPAs (UNEP-WDPA 2019). The Convention on Biological Diversity (CBD) aims to increase PAs and other effective area-based conservation measures to cover at least 30% of the planet by 2030 under the Kunming-Montreal Global Biodiversity Framework (CBD, 2022). This target emphasises the crucial role of area-based protection in preserving habitats and species.

Despite being a cornerstone of biodiversity conservation, PAs have been widely criticised for being on marginal lands thus not having a large enough impact, i.e., failing to deliver appropriate reductions in biodiversity loss (Venter *et al* 2018). Here, 'impact' refers to the reduction in biodiversity loss that can be attributed to a PA and is measured as the difference between biodiversity outcomes under protection and the hypothetical scenario of no protection (the 'counterfactual'). One measure of impact on biodiversity is the estimate of how much vegetation clearing has been avoided due to protection, which is referred to as 'avoided [or averted] loss'. The avoided loss metric is perhaps the most important measure of impact given that a major threat to biodiversity is habitat degradation and clearing (Curtis *et al* 2018). Therefore, to maximise avoided loss, PAs need to be established in locations that (i) contain high levels of biodiversity; (ii) would have a high level of certainty of being cleared. Previous studies have found that PAs are disproportionately located in 'residual areas'—marginal lands where anthropogenetic threats to biodiversity are low, and thus are unlikely to be cleared without protection (Joppa and Pfaff 2009, Venter *et al* 2018). They may, for example, have been established in locations with steep slopes, high elevation, infertile land, or in remote locations with low conversion value.

Understanding the location biases of both PPAs and public PAs is crucial for effective conservation planning and management of protected areas. Previous studies like Joppa and Pfaff (2009) and Venter *et al* (2018) primarily focused on public PAs. Whether PPAs show a similar or different level of bias, currently remains an open question. Moreover, these global studies have treated the surrounding unprotected landscape as uniform, not differentiating between public and private unprotected land. Such kinds of studies require random sampling from unprotected areas to create background sample, sampling over all unprotected areas without the differentiation of private and public land, may lead to biased background samples undermining conclusions of these studies. Indeed, such land tenure data is not easily obtainable for many countries, making this challenging for studies conducted at a global level. We aim to fill this gap by examining the distribution of public PAs and in Australia. Australia provides a good case for this analysis given that the country has one of the highest deforestation rates in the world (Pacheco *et al* 2021), combined with a large number of PPAs and public PAs spread throughout the country (UNEP-WCMC and IUCN 2023). Moreover, detailed data, such as the extent of public and private land that allows for appropriate comparisons, is available in Australia (ABARES 2021). Around 30% of the total land in Australia is freehold land (ABS, 2016): given the conversion potential of this land to intensive land uses, there is a unique opportunity for the Australian PPAs to protect biodiversity, which establishes an additional case for conducting this study.

In Australia, PPAs encompass a diverse range of conservation mechanisms tailored to various ownership and management arrangements. One common type involves conservation covenants or agreements (similar like easements in USA), where landowners voluntarily establish legally binding arrangements with governments or non-governmental organisations (NGOs) to manage their land for conservation purposes while retaining ownership. These agreements often allow landowners to continue using the land for non-conservation activities, such as residential use, provided they align with conservation objectives. Another approach includes revolving funds, where NGOs or trusts acquire land, place it under conservation agreements, and resell it to private landowners committed to maintaining these protections. Additionally, philanthropic organisations or NGOs may directly purchase or lease land to manage it for biodiversity conservation. In some cases, agencies may designate land for conservation as part of offsets for development activities or to enhance public perception. The diversity of PPA types reflects their flexibility in addressing conservation needs across varying socio-economic and ecological contexts, while also enabling significant contributions to national and global biodiversity targets.'

In this study, we assess the distribution of PPAs and public PAs based on factors related to biodiversity and the likelihood of land being cleared for intensive activities such as agriculture and urban development. We aim to compare the locations of PPAs and public PAs examining the extent to which their biases differ with respect to a range of covariates thought to be correlated with biodiversity loss. To answer this question, we take random samples from within and outside of public PAs and PPAs (i.e. random samples from similar tenures) and run two separate logistic regression model (one for PPAs and other for public PAs) to predict the probability that a given point is a P(PA) based on a range of covariates.

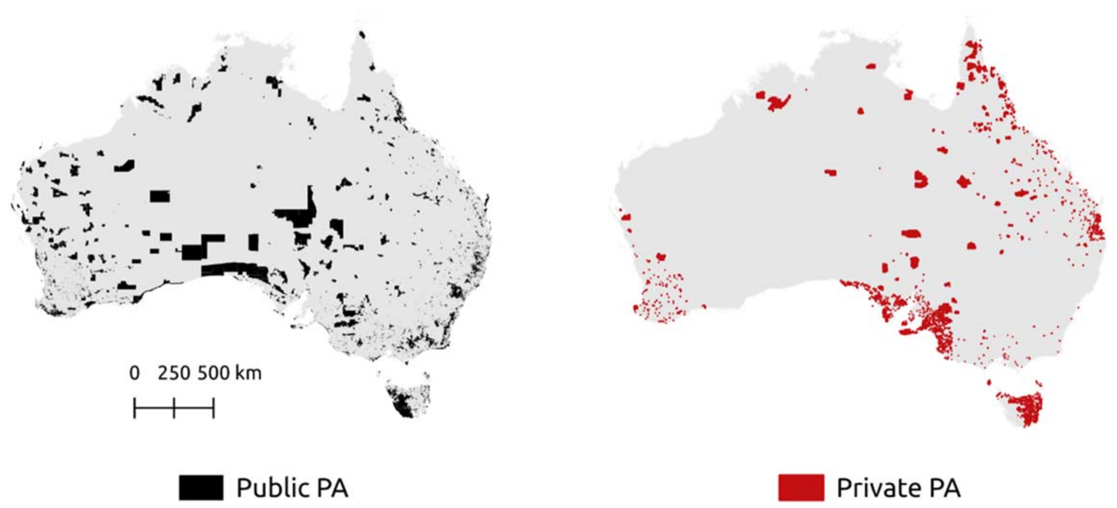

Figure 1. The distribution of PPAs and public PAs in Australia from the CAPAD (2022) database.

2. Methods

2.1. Data

Protected area (PA) data was extracted from the Collaborative Australian Protected Areas Database (CAPAD) which based on revision up to 30 June 2022 (CAPAD 2022). CAPAD is the national database on protected areas in Australia that also informs the World Database on Protected Areas (WDPA). The dataset was filtered to include all terrestrial PAs, and the governance type was selected to be 'government' for public PAs resulting in 9,570 public PAs, and 'private' for PPAs, resulting in 4,425 PPAs. The distribution of private and public PAs in Australia is shown in figure 1.

This analysis fits logistic regression models to understand how the locations of public PAs and PPAs are correlated with covariates that describe biodiversity value and threatening processes. To get a bias-free estimate of the model parameters, it is important to get corresponding background samples from public and private land to compare to the samples from public and private PAs. For this, we used the land tenure data from the ABARES land use data (ABARES 2021) which provide boundaries for 'freehold' (land with private ownership) and 'crown land' (land with public ownership). We used a national scale land capability (LC) map as the main dataset for assessing the suitability of land for agricultural conversion (Adams and Engert 2023). The LC layer represents the natural physical capacity of the land to support different land uses and is categorical data with eight classes, ranging from extremely low capability to extremely high capability (see SI table S1 for more details). The LC layer was extended from the land and soil capability layer originally developed for the state of New South Wales (NSW) to the whole of Australia by harmonising data across other states and territories using statistical models (Adams and Engert 2023). Additionally, to account for a broader range of variables alongside the LC layer, we also included slope (Farr *et al* 2007); soil organic carbon (Rossel *et al* 2015); and travel time to the nearest cities (Nelson *et al* 2019). These covariates were chosen based on their known significance in influencing land productivity in Australia. For the purposes of this study, 'unproductive land' refers to areas with low land capability, characterised by limited suitability for agricultural or other intensive land uses due to factors such as poor soil quality, steep slopes, or remote locations.

To account for threatened species, we used the distribution of the threatened species listed under the federal Environment Protection and Biodiversity Conservation Act (EPBC Act) (Australian Government 2023). At the time the data was extracted (March, 2022), distribution maps were available for 2,194 species. A species richness map was constructed by overlaying the distributions of these species. The stacked aggregate number of species indicator allows for an indicative assessment of threatened species richness in each location, which aligns with the aim of evaluating placement bias. By considering the total number of species present, we can gain an initial understanding of the threatened species within the designated region. Further details of the data and the preprocessing steps undertaken are provided in the supplementary information (S1).

2.2. Modelling

We employed a Bayesian logistic regression approach to model the relationship between the covariates and PA designation. All numeric variables were log-transformed and scaled to improve model fit, a commonly recommended practice for logistic regression models (Gelman *et al* 2020). Since, the land capability is an ordinal variable, we used it as a monotonic effect predictor in the model. Modelling was implemented in R using the brms package (Bürkner 2017) using default priors.

The logistic regression equation is:

$$\mathrm{logit}(p) = \quad \beta_0 + S_{\mathrm{mo}}(x, \zeta_x) + X_i^T \beta$$

Where:

- logit(p): Log-odds of a pixel being part of a Protected Area (PA)
- β_0: Intercept term
- S_{mo}: Global monotonic coefficient for the ordinal predictor, land capability
- x: Levels of ordinal variable
- ζ_x: Monotonic simplex, a weighted representation of x levels, ensuring monotonicity
- X_i^T: vectors of continuous covariates with their corresponding coefficients β

The default priors in brms are:

$$b_0 \sim \mathrm{Normal}(0,\ 10)$$

$$S,\ \beta \sim \mathrm{Normal}(0,\ 1)$$

The log-odds were converted to odds ratios for interpretation using:

$$\mathrm{Odds\ \ Ratio} = e^{Estimate},\ \mathrm{Lower\ \ CI} = e^{Lower\ \ Log-Odds},\ \mathrm{Upper\ \ CI} = e^{Upper\ \ Log-Odds}$$

We report fixed effects (as odds ratios) and conditional effects (in probabilities) to provide a comprehensive understanding of predictor effects. Conditional effects illustrate the predicted probabilities of PA designation across predictor levels, offering an intuitive interpretation of variables such as land capability (an ordinal predictor).

Separate models were developed for Private Protected Areas (PPAs) and public PAs. For the PPAs we randomly sampled 10,000 points from PPA pixels across Australia and an equivalent number of background points from private land (excluding PPAs). Likewise for public PAs, background samples were taken from crown land. Since more than 90% of the PPAs in the data are located in areas with 'freehold' tenure, we restrict the sampling of control pixels for PPAs to this tenure type.

2.3. Model evaluation

To evaluate the models, we followed a rigorous three-step process:

1. Model selection: We used Leave-One-Out Cross-Validation (LOO-CV) for model selection, implemented via the loo() function in brms. LOO-CV evaluates models based on the Expected Log Pointwise Predictive Density (ELPD). LOO-CV penalises overly complex models to avoid overfitting, ensuring generalisability to unseen data. Using loo_compare(), we assessed 32 candidate models, an intercept-only model, and all possible combinations of the five covariates (one ordinal and four continuous variables). loo_compare( ) makes a pairwise comparisons between each model and the model with the largest ELPD (the preferred model). These results are provided in the supplementary materials.

2. Goodness-of-fit assessment: Once the best model was selected, we evaluated its goodness-of-fit using posterior predictive checks, a key diagnostic tool in Bayesian modelling. These checks compare the observed data to data simulated from the posterior distribution of the fitted model to evaluate how well the model captures the underlying data structure. The function produces a diagnostic plot (in our case we use a histogram) to visually assess the discrepancies between the observed data and the simulated predictions. Lesser discrepancies indicate good model fit. Posterior predictive checks provide an intuitive, in-sample evaluation of model adequacy.

3. Spatial Cross-Validation (SCV): We also evaluate the predictive robustness of the selected model in a spatially realistic context, we implemented spatial cross-validation (SCV) using the Area Under the Receiver Operating Characteristic Curve (AUC) metric. SCV splits the data into geographically distinct training and testing folds. This approach ensures that predictions are made for unseen spatial areas, reducing the risk of information leakage and providing a more realistic assessment of model performance. We employed the k-nearest neighbor spatial clustering method to generate 10 spatially distinct folds (Brenning 2012). This method helps

account for spatial heterogeneity and ensures that geographically proximate locations are included in the same fold.

3. Model diagnostics

We assessed model convergence using Rhat statistics and trace plots to ensure the reliability of parameter estimates. The results of LOO-CV comparisons, posterior predictive checks, SCV, and convergence diagnostics are provided in the Supplementary Materials (Appendix S2).

4. Results

4.1. Model selection and fitting

The model which included all covariates had the highest Expected Log Pointwise Predictive Density (ELPD) for both the public PAs and the PPAs, indicating that all variables contribute meaningfully to predicting PA designation. The selected models for public PAs and PPAs also perform reasonably well in terms of posterior predictive checks and prediction accuracy (AUC), making them suitable for analysing the location bias. The posterior predictive check plots (figure 2) show that the models for public PAs and PPAs produce posterior predictions consistent with the observed data, suggesting both models are well-calibrated and capture the observed mean responses effectively. Further, the spatial cross-validation AUC values for both models indicate reasonable predictive performance, with slightly better discrimination (AUC) for the model for PPAs. The median AUC values (0.7 for public PAs and 0.73 for PPAs) suggest moderate ability to distinguish between classes. The Rhat statistic for both models was 1, signifying model convergence, with trace plot for model convergence presented in the supplementary materials.

4.2. Model parameters

The regression coefficients (log-odds) were estimated for each covariate included in the model and converted to odds-ratio (OR) (table 1). All covariates except slope were significantly associated with PA location. PPAs are 1.45 times more likely (OR = 1.45, 95% CI: [1.38, 1.52]) to be established in areas with lower land capability compared to random sites. Whereas public PAs are 1.30 times more likely (OR = 1.30, 95% CI: [1.25, 1.35]) to be placed in lower land capability. The effect of soil organic carbon (SOC) further underscores these differences: PPAs show a significant negative association with SOC (OR = 0.54, 95% CI: [0.51, 0.58]), indicating avoidance of agriculturally productive areas. Conversely, public PAs are 1.70 times more likely to be located in areas with higher SOC (OR = 1.70, 95% CI: [1.62, 1.79]). Further, PPAs are twice as likely to be in remote places (OR = 2.06, 95% CI: [1.95, 2.18]). Public PAs, on the other hand are 1.18 times likely to be in remote places (OR = 1.18, 95% CI: [1.13, 1.23]). The effect of slope on PA placement is minimal for both types. PPAs have an OR of 1.03 (95% CI: [0.99, 1.06]), and public PAs have an OR of 1.06 (95% CI: [1.03, 1.09]). This indicates that slope is not a major factor in determining PA placement. Finally, species richness exhibits the strongest association for PPAs, with an OR of 2.34 (95% CI: [2.22, 2.47]), compared to 1.21 (95% CI: [1.16, 1.26]) for public PAs. This indicates that PPAs are over twice as likely to be in areas with high threatened species richness.

4.3. Relationship of the covariates with PA location

The conditional effects plots (figure 3) provide further insight into how these variables influence the probability of PA placement. An interesting pattern emerges when comparing the probabilities of PA placement on public and private lands as land capability changes. As shown in figure 3, the probabilities of PA placement are higher for public PAs on lands with extremely high land capability (productive areas). However, this trend reverses as land capability decreases, with PPAs having higher probabilities of placement on less productive lands. For both public PAs and PPAs, the probability of establishment increases steeply with species richness and decreases markedly in areas with higher SOC.

5. Discussion

Protected areas have emerged as a core strategy to reduce biodiversity losses. While public PAs have been criticised for being targeted towards marginal 'residual areas' (Venter *et al* 2018) that have lower potential for intensive land use, rather than for important biodiversity, this location bias is insufficiently studied in PPAs. Therefore, this study aimed to investigate whether PPAs exhibit similar biases towards residual areas and how they compare to biases in the locations of public PAs. By studying location bias, policy makers and managers can make informed decisions about where to establish new PAs or manage existing ones to enhance overall

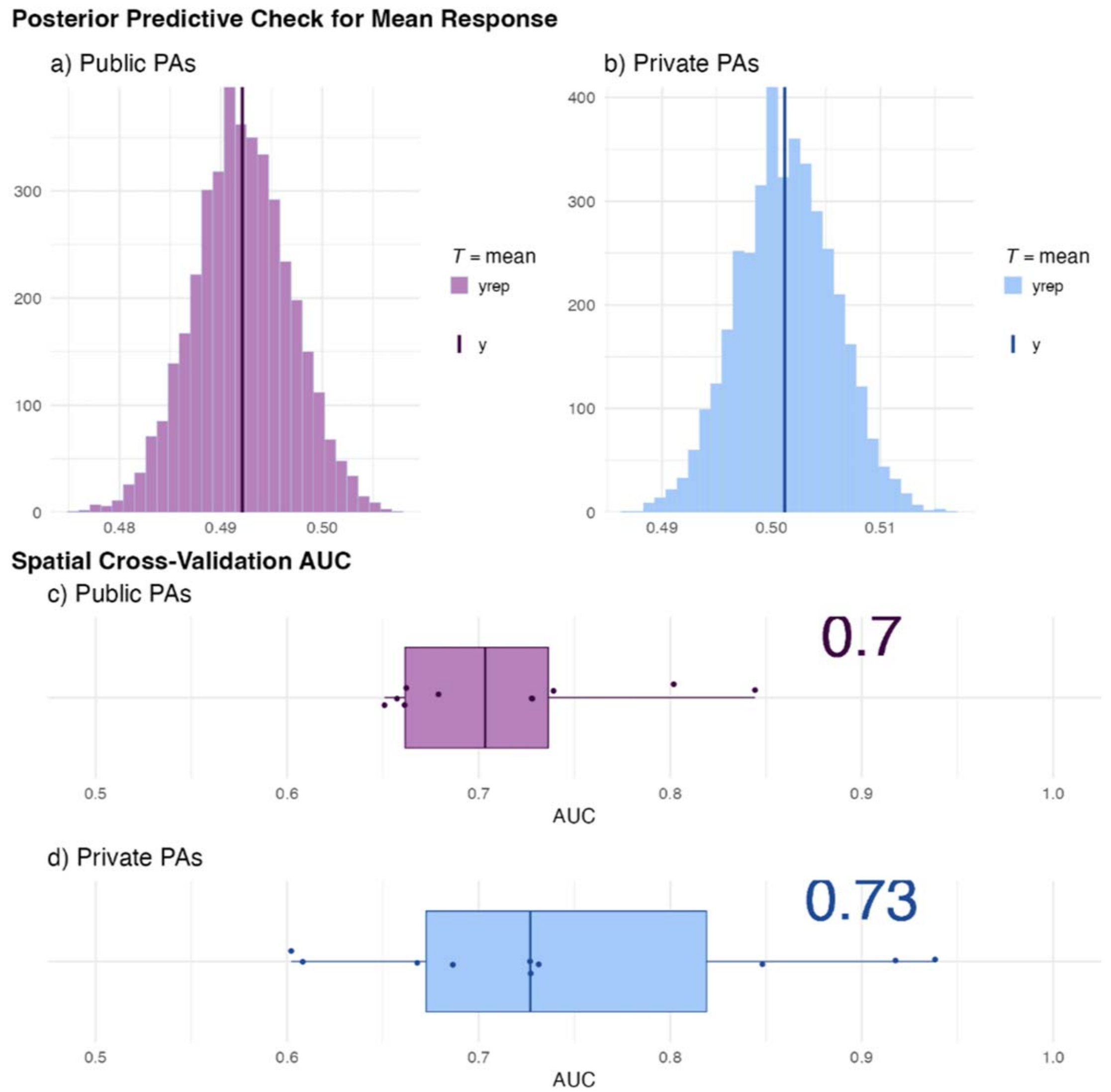

Figure 2. Posterior predictive checks to evaluate the models for public PAs and PPAs. The observed means ($T(y)$ for both public PAs and PPAs closely aligned with the posterior predictive distributions ($T(y$rep) indicating good model fit in terms of the central tendency of the response variable. Panel c and d show the box plot for the distribution of AUC across the 10-fold spatial cross-validation with the median AUC score of 0.7 for public PAs and 0.73 for PPAs.

Table 1. Odds ratio calculated from logistic regression coefficients.

Predictor	Odds ratio (PPAs)	95% CI (PPAs)	Odds ratio (Public PAs)	95% CI (Public PAs)
Species richness	2.34	[2.22, 2.47]	1.21	[1.16, 1.26]
Slope	1.03	[0.99, 1.06]	1.06	[1.03, 1.09]
Travel time	2.06	[1.95, 2.18]	1.18	[1.13, 1.23]
Soil organic carbon (SOC)	0.54	[0.51, 0.58]	1.70	[1.62, 1.79]
Land capability (LC)	1.45	[1.38, 1.52]	1.30	[1.25, 1.35]

conservation effectiveness. This study aimed to fill the knowledge gap regarding the location biases of both public PAs and PPAs over the continent of Australia by evaluating the probability of PA placement on public and private land. The study focussed on Australia because of its substantial number and widespread spatial distribution of both public PAs and PPAs, which were evaluated using threatened species richness data, land conversion suitability layers, and other covariates that predict the risk of loss.

Our findings indicate that both public PAs and PPAs tend to target locations with high richness of threatened species and with lower chances of being converted to intensive land use (figure 3). As a result, PAs in Australia tend to be focused on protecting biodiversity that may remain intact without protection rather than biodiversity at risk of decline, thus limiting conservation impact (Pressey *et al* 2021). Our results show this bias is larger in

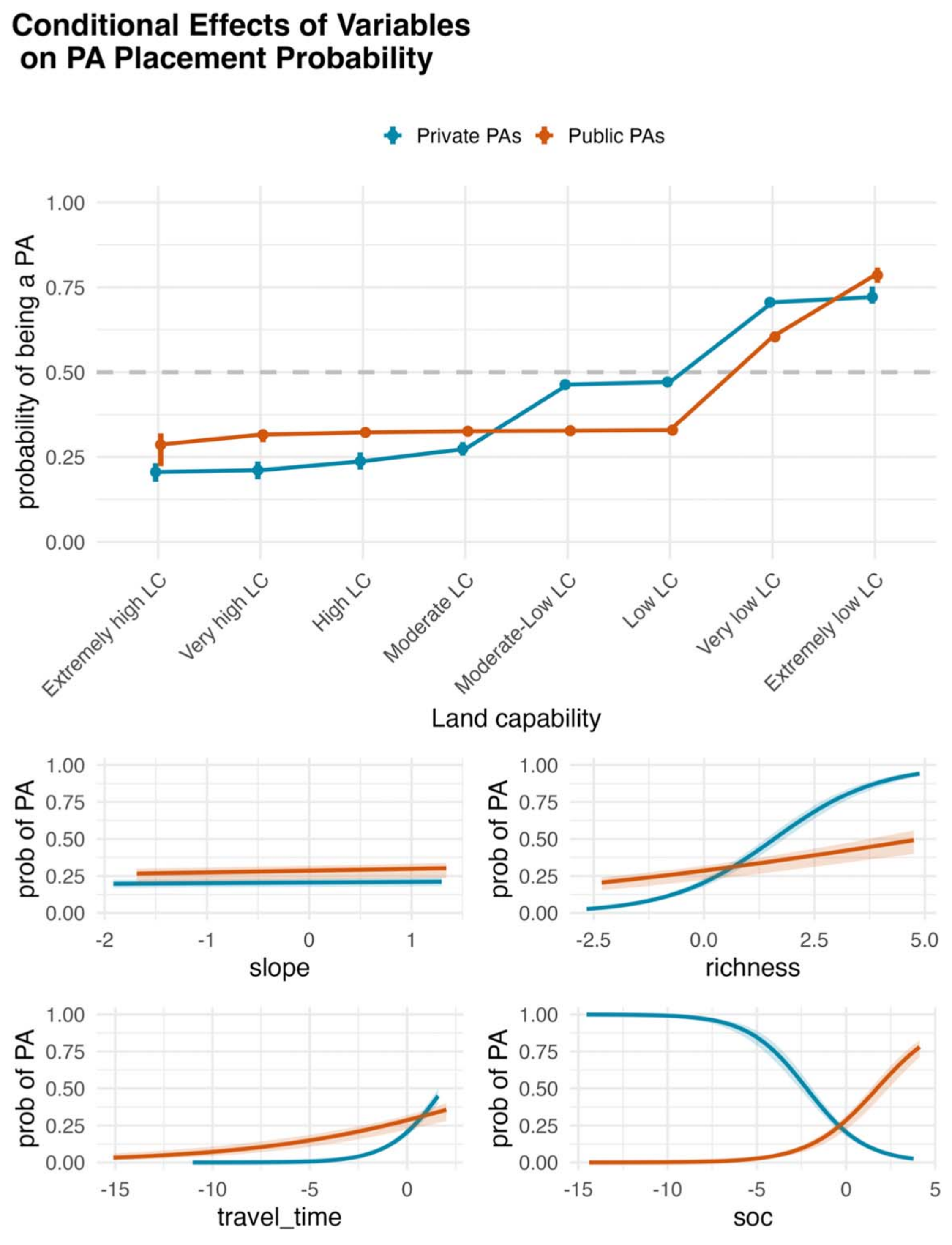

Figure 3. Predicted probabilities of protected area placement across variables. The x-axis represents the predicted probabilities, while the y-axis for continuous variables is presented on a logged and scaled scale. The plots illustrate the influence of each predictor on the likelihood of PA placement.

PPAs compared to public PAs (figure 3). There may be several possible explanations for this trend. Prior to the mid-1990′s Australia's PA system relied primarily on protecting 'residual' land not suitable for agriculture (Pressey *et al* 1996). The development of the National Reserve System and application of scientific principles in reserve creation codified in systematic conservation planning led to more targeted approaches to address gaps in conservation coverage (Fitzsimons and Wescott 2001). While there is technical capacity to identify areas at risk of being lost, this characteristic has received less focus in planning new protected areas than other conservation metrics like representation and complementarity that focus on biodiversity (Pressey *et al* 2021). In addition, areas with higher agricultural potential and thus higher risks of conversion, also tend to have higher opportunity costs, and are often more expensive to acquire. Indeed, the representation of ecosystem and species types was the most prevalent theme in PA-related policies in Australia (Hernandez *et al* 2021). These factors may apply similarly to PPAs.

Similar biases in the location of PAs have previously been reported. For example, Joppa *et al* (2009) and Venter *et al* (2018) conducted studies at a global level and found that PAs tend to occur in areas of lower agricultural value and did not target locations with high concentrations of threatened species. Venter noted a comparable trend in Australia, with prime agricultural land and major human settlements concentrated along the coastlines. PAs in these coastal regions were strategically positioned to avoid fertile areas and tended to be small. Although our findings indicate a similar pattern of targeting public PAs towards unproductive land, they differ from these global studies regarding the targeting of threatened biodiversity. This inconsistency may stem from the utilisation of different biodiversity metrics or variations in data resolution. In our study, we employed a considerably higher-resolution biodiversity data using 1 km pixel size while Venter *et al* used a coarser resolution of 30 km pixel. Our results align more with other studies at similar scales: for example, public PAs in Spain and Italy are placed in areas with high biodiversity levels but are also placed on land less suitable for other land use (Nobel *et al* 2023). Likewise, landholders in Brazil also tend to place protected areas with lower agricultural suitability and higher transportation costs (d'Albertas *et al* 2021).

Conservation on private land plays a vital role in Australia's efforts to conserve biodiversity (Fitzsimons 2015). Thus, the placement of PPAs in areas with low risk of clearing carries significant implications for biodiversity conservation efforts in Australia. While PAs contribute to protecting threatened biodiversity (as demonstrated here by their species coverage), they may be less effective in terms of avoiding biodiversity declines. Approximately 15% of Australia is cleared for agriculture or productive purposes, while less than half a percent is converted to other land use like urban and rural residential areas, and mining activities (ABARES 2016). Habitat loss and degradation, due to land conversion for agriculture and urban development, are among the most important drivers of biodiversity loss in Australia (Evans 2016)—by targeting conservation efforts in regions that are already unproductive or deemed low risk of clearing, the potential impact of PPAs in reducing biodiversity loss may be diminished. To increase their effectiveness, it is crucial to consider implementing future PPAs in locations where there is a high risk of habitat loss. This strategic placement would enhance the overall conservation outcomes and ensure that PPAs play an important role in safeguarding Australia's unique ecosystem and species.

We acknowledge several limitations in this study. While Australia's national database, CAPAD, provides relatively comprehensive coverage of public PAs, the reporting of PPAs is less systematic and complete (Fitzsimons 2015). PPA datasets are typically managed by conservation agencies operating across different states and are not uniformly available for public access. Nevertheless, CAPAD includes the majority of large PPAs, representing a significant proportion of the total private land under conservation (Fitzsimons 2015). For example, CAPAD reports a total PPA area of 10.6 million ha, accounting for approximately 4% of private land. In contrast, Ivanova and Cook (2020) who supplemented CAPAD data with additional information from local agencies, estimated the total PPA area at around 11.5 million ha—representing 5% of private land. This 1% discrepancy suggests that the potential error from inadvertently sampling background points from PPAs (Williamson *et al* 2021) is likely minimal, as the unreported PPAs account for a relatively small fraction of the total area under conservation on private land. When new data on PPA extent is available, the results of our study can be updated. Further, there may be multiple threatening processes driving biodiversity loss in Australia. Here we only focus on conversion of land due agriculture and urban development: these being some of the most important threats to biodiversity but are only a subset of a potentially large number of threats, including threats from climate change and invasive species (IPBES 2019). Although there are additional variables that could determine the suitability for agriculture or urban development, there is good prior information that the variables we used are correlated with conversion probability, and therefore our results still give provide useful insights (Adams and Engert 2023). However, it may be beneficial to explore incorporating additional variables representing other threatening processes in future research.

Increasing the extent of PAs, whether private or public, will have a limited impact on avoiding biodiversity loss if they are not placed in areas that are likely to avoid biodiversity losses. Having examined the placement of Australian private and public PAs using publicly available datasets, we found that PPAs, like public PAs, contribute to protecting threatened species but tend to occur in areas of lower land capability and away from cities. This means there may be considerable scope to improve the impact of public and PPAs through being more strategic in the locations of new PAs. Aichi Target 11 achieved some success in terms of quantity, but fell short in terms of quality (e.g., the most important areas for biodiversity) (CBD 2020). As we move into the post-2020 era of conservation, it is important that PAs not only increase in extent but also cover important under-represented biodiversity that would tend to be lost otherwise. If a PA is placed in areas with no threat of biodiversity loss, then there is no conservation impact in terms of avoided biodiversity loss, no matter how well-resourced or well-managed it is. If we want to achieve conservation success, we need to achieve conservation impact (Pressey *et al* 2021). Strategically siting PAs can help ensure that important areas for biodiversity conservation are covered, and that the conservation measures taken will be effective in promoting the long-term resilience of these areas. The new 30 × 30 protection goal could greatly expand PAs worldwide (CBD, 2022), but adding more land alone will not matter much unless we protect areas at risk of being lost.

Data availability statement

The data will also be utilised for another study; therefore, we will provide access upon request. The data that support the findings of this study are available upon reasonable request from the authors. https://github.com/wildeco/ppa_bias. Data will be available from 15 December 2024.

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