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

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This manuscript is a non-peer reviewed preprint submitted to EarthArXiv and will be submitted for a possible publication in a peer reviewed journal.

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 (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 PAs (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 & 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 PAs. Previous studies like Joppa & 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 private and public PAs 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 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.

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). 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.

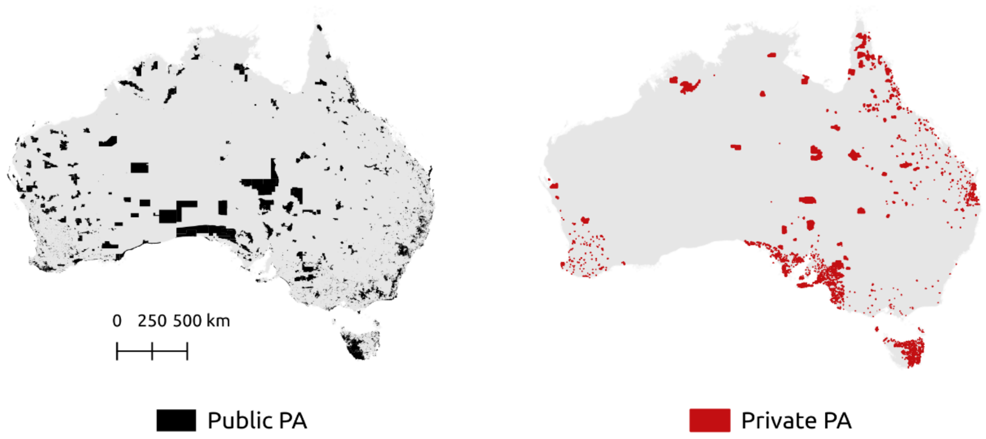

Figure 1 The distribution of public and private PAs in Australia from the CAPAD 2022 database.

This analysis fits logistic regression models to understand how the locations of public and private PAs 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 & 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 & 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. 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 model the probability that a random 100 m pixel is found within the PA network, as a function of LC categories (1-8 scale with decreasing land capability); slope; soil organic carbon; travel time to nearest cities; and the richness of threatened species. We develop two statistical models: one for PPAs and one for public PAs. For the PPA model we take random samples of points (n = 10,000) from across all areas designated as PPAs in Australia, and for background points we take the same number of random points across all private land (excluding the PPAs) in Australia. Likewise for public PAs, background samples are 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.

Then logistic regression models are used to predict the probability that a given point is located within a (P)PA based on all the covariates. We applied the Bayesian approach to regression, and log transformed and scaled all numeric variables to improve the model fit, a commonly recommended practice for logistic regression models (Gelman et al., 2020). We implemented the logistic regression model using a Bayesian approach using brms package in R, using default priors provided by the package (Bürkner, 2017). Model accuracy was assessed using spatial cross-validation (SCV) with five folds. This cross-validation approach accounts for the spatial structure of the data, thus separates the data into geographically distinct training and testing sets ensures that nearby locations are either included together in the training or testing sets. By considering spatial correlation, more reliable estimate of the model’s performance is made. We used the k-nearest neighbour spatial clustering method to generate five folds (Brenning, 2012). Further model tests were conducted using Rhat statistic and trace plots. The results of the SCV and trace plots are provided in Supplementary materials (Appendix S2).

3. Results

Figure 2 presents the probability of an area being designated as protected, as a function of the covariates. The probabilities associated with different land capability (LC) categories show that, in both public and private protected areas (PAs), there is inherent bias towards being in areas less suitable for agriculture. This bias is more pronounced for private PAs (PPAs) compared to public PAs. For instance, the probabilities of PPAs’ locations having between extremely high LC and moderate LC are well below 0.5, and they are much lower than the probabilities for public PAs. Furthermore, as the suitability for agriculture decreases (e.g., from moderate-low LC to extremely low LC), the probability of PPAs occurring increases much more sharply than for public PAs. At the extremely low LC, the probabilities for both public and private PAs occurring are higher than 0.75 and nearly identical. Similarly, the probability that an area will be protected increases with increase in travel time to the nearest cities: i.e., they are more likely to be placed in areas away from the cities.

Public PAs tended to occur in area of higher soil organic carbon and PPAs tended to occur in areas with lower soil organic carbon. There was no significant association between slope and the location of PAs. PPAs tended to occur in areas of higher species richness compared to public PAs. The Rhat statistic for both models was 1, signifying model convergence, with trace plot for model convergence presented Appendix S2 (Figure S.2.3).

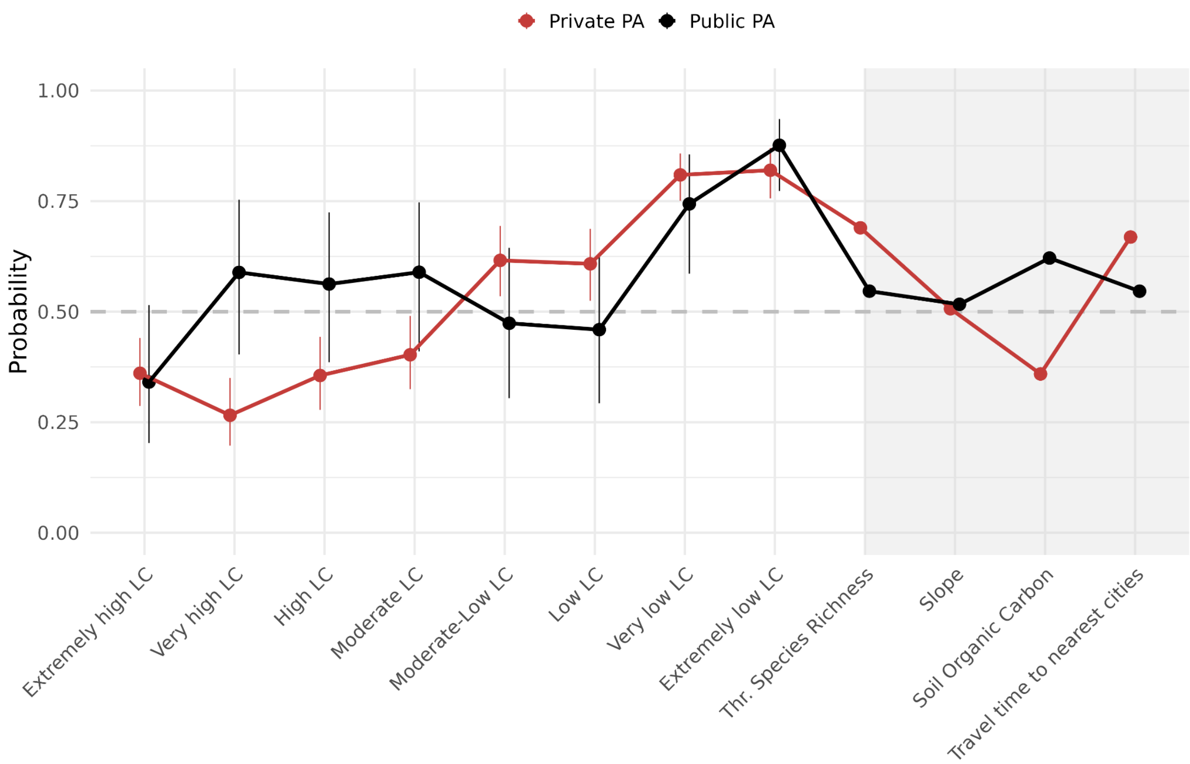

Figure 2. The mean estimate of the probability of a PA being designated as protected, as a function of the covariates and the 95% credible interval (error bars) of the estimate across the covariates. The grey shaded region depicts covariates used in addition to the land capability (LC) categories. The horizontal dotted grey line is plotted at a probability of 0.5; error bars that include 0.5 mean there is no significant effect of that predictor at 95% credible interval, meaning there is no statistical difference between the points sampled in the PAs and the background points.

4. 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 private PAs. 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 conservation effectiveness. This study aimed to fill the knowledge gap regarding the location biases of both public and private PAs 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 and private PAs, 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 and private PAs tend to target locations with high richness of threatened species and with lower chances of being converted to intensive land use (Figure 2). 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 in Australian new PAs may have significant opportunity increase the conservation impact of the PA network (Pressey et al., 2021). Our results show this bias is larger in private PAs compared to public PAs (Figure 2). There may be several possible explanations for this trend. Prior to the mid-1990’s Australia’s public 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 (J. Fitzsimons & 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 of 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 public 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 (J. A. 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 note several limitations in this study. While Australia's national database (CAPAD) captures the details of public PAs relatively comprehensively, reporting on PPAs is comparatively less systematic and comprehensive (J. A. Fitzsimons, 2015). These datasets are usually held by conservation agencies that work in private land conservation in the different states of Australia and are not available publicly. When such data 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 predictors that could determine the suitability for agriculture or urban development, there is good prior information that the predictors we used are correlated with conversion probability, and therefore our results still give provide useful insights (Adams & Engert, 2023). However, it may be beneficial to explore incorporating additional predictors 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 private PAs 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 30x30 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.

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Supplementary materials

S1 Data sources and rationale for covariate selection

Table S1 Details of the dataset, rationale for selection, and their data sources. Sno = serial number.

Sno	Predictors	Description
1.	Land capability	Land capability refers to the inherent physical ability of the land to support various land uses and management methods over an extended period, without causing harm or deterioration to the soil, land, air, and water resources. The mapping is established using an eight-class system where values from 1 to 8 indicate a declining ability of the land to support various land uses. Class 1 signifies land that can sustain most land uses, even those that have a significant impact on the soil like regular cultivation. On the other hand, class 8 represents land that can only support very limited and low-impact land uses, such as nature conservation. When land suitability values are higher, there are more restrictions on how the land can be used, and it requires more resources, knowledge, and investment to sustainably manage the land. In extreme situations, these limitations may be so severe that they cannot be overcome with any level of input. Data resolution: ~ 30 m Data source: (Adams & Engert, 2023).
2.	Slope	The slope of the land is crucial for different land use including agriculture and urban development. Slope affects water flow, erosion, and water availability, making steep slopes challenging for agriculture, and resulting in an increase in agricultural costs. In urban development, slope determines infrastructure feasibility and affects costs and efficiency. The slope was calculated from the SRTM elevation in Google Earth Engine. Data resolution: ~ 30 m Data source: (Farr et al., 2007)
3.	Soil organic carbon	Soil organic carbon is an important variable in

		agriculture, as it contributes to soil fertility by improving soil structure, water holding capacity, and microbial activity. Increase in soil organic carbon increases agricultural productivity. Data resolution: ~ 90 m Data source: (Rossel et al., 2015)
4.	Travel time to nearest cities	The travel time to the nearest populated cities serves as a measure of agricultural costs, including transportation expenses, and cost of land that influences urban development like housing. Areas closer to cities tend to have higher suitability for conversion to agriculture due to easier access and potentially higher market demand. The dataset and the validation are described in a Nature Scientific Data Descriptor: https://www.nature.com/articles/s41597-019-0265-5 Data resolution: ~ 1 km Data source: (Nelson et al., 2019)
5.	Species of National Environmental Significance Database	The database contains data on the distribution of species related to the Environment Protection and Biodiversity Conservation Act 1999 (EPBC Act). The data description states that the majority of species distributions have been generalised to 0.01° (~1 km) grid cells, with some sensitive species generalised to 0.1° (~10 km). The data is provided as polygons for individual species. We converted them to rasters of 1 km pixels and calculated the number of overlapping pixels as the species richness of that pixel. Data resolution: ~1 km Data source: (Australian Government, 2023)

S2 Model diagnostics

S.2.1Correlation between the variables

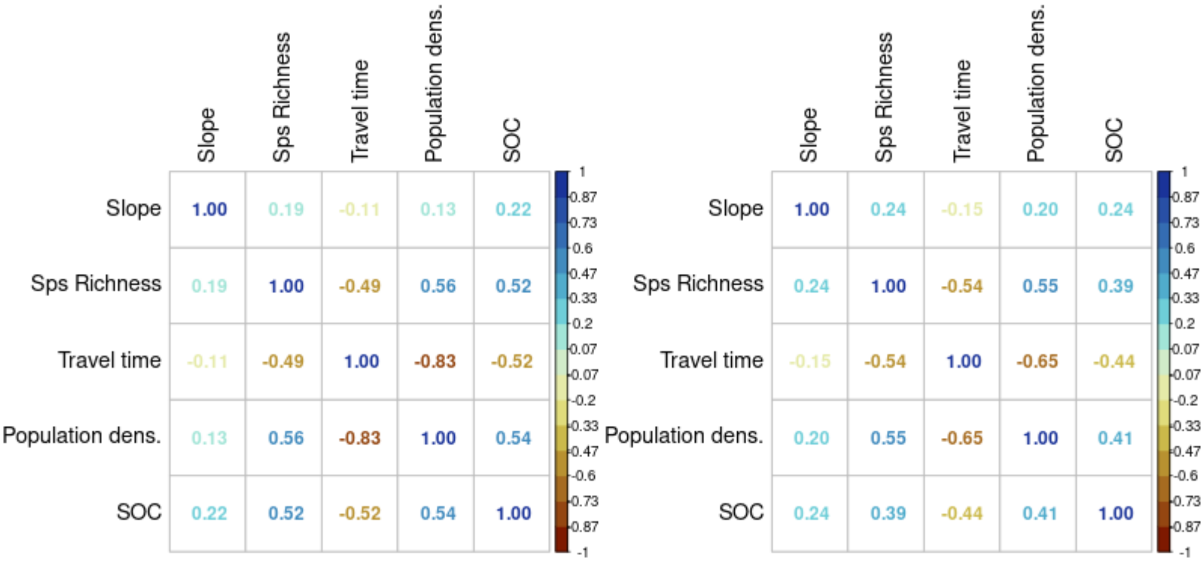
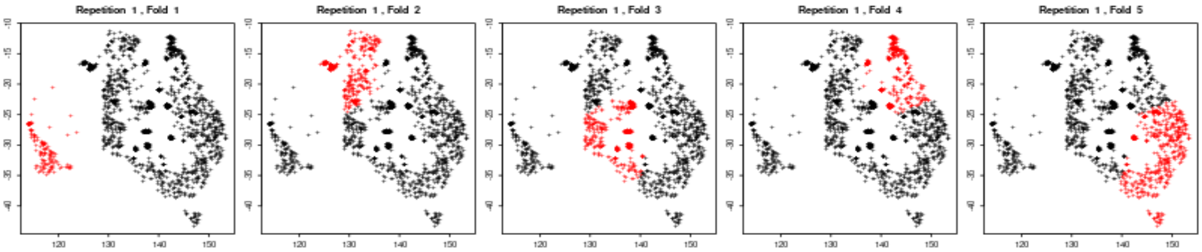


Figure S.2.1 Correlation between the continuous predictors. The left plot shows correlation of variables across private land and the right plot shows for public land. Population density was removed from the regression model as it was highly correlated with the travel time to nearest cities.

S.2.2 Spatial nested cross-validation results

The spatial nested cross-validation shows median accuracy of 0.74 (for private protected areas) and 0.65 (for public protected areas), indicating that the models have a reasonably good ability to discriminate between the protected and non-protected areas.

Spatial folds for the model for private PAs



Spatial folds for model for public PAs

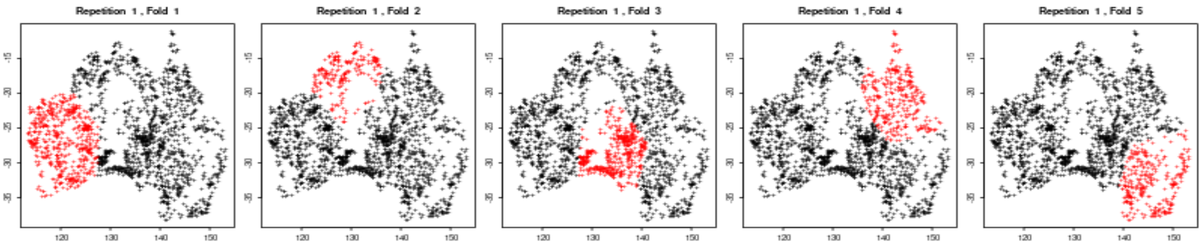


Figure S.2.2 Spatial blocks for private and public protected area (PA) models. There are five spatial folds, for each fold, the black colour shows training samples and the red colour shows testing samples.

S.2.3 Trace plots

Trace plots help assess whether the MCMC chains have converged to the target distribution. Convergence indicates that the chains have reached a stable equilibrium and are sampling from the desired posterior distribution. Figure A3 shows that models for both the private and the public PAs do not show any trend or pattern, thus the models have converged.

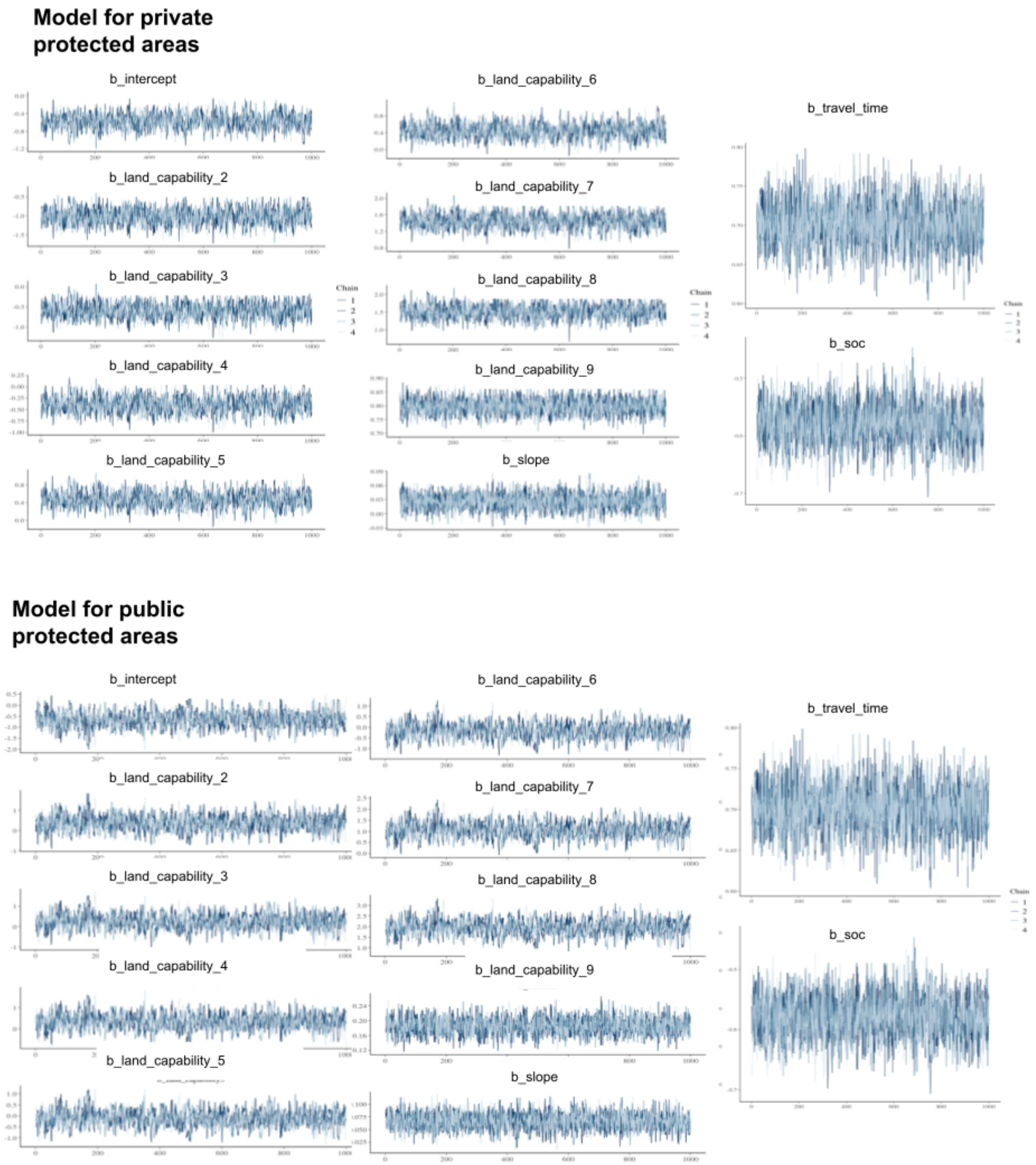


Figure S.2.3 Trace plots or MCMC diagnostic plots for the model on private PAs.