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Private benefits of natural capital on farms across an endangered ecoregion

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ABSTRACT

The conservation of natural capital on farms is being increasingly recognised as essential for addressing global biodiversity decline. At the same time, there is growing interest in the potential for natural capital on farms that generates high public benefits, to also generate private benefits, potentially fostering greater adoption of conservation practices on farms. Despite this, empirical analysis of private benefits of natural capital on farms remains limited. Addressing this gap can help in identifying conservation opportunities and selecting cost-effective policy mechanisms to deliver public good biodiversity conservation outcomes on private farmland. We present results from a hedonic model on private benefits associated with native woodland and bird biodiversity on commercial farmland in a critically endangered temperate woodland ecosystem in southeast Australia. Using quantile regression, we found significant heterogeneity in private benefits associated with such natural capital across farmland value quantiles. These private benefits increased from lower to upper land value quantiles, conditional on a range of attributes of the farmland parcel. In some instances, private costs were associated with enhancement of native woodland and bird biodiversity on farms, above even a very low baseline. We discuss the implications of these findings for targeting of investment and selection of policy mechanisms.

1. Introduction

Clearing of native vegetation for agriculture across many parts of the world (Gibbs and Salmon, 2015) has resulted in severe habitat fragmentation (Rogan and Lacher, 2018). This is recognised as a key driver of ongoing biodiversity decline globally (Fischer and Lindenmayer, 2007; Haddad et al., 2015; Ramírez-Delgado et al., 2022). Habitat conservation on farmland is integral to addressing global biodiversity decline (Balmford et al., 2019; Baudron et al., 2021; Fischer et al., 2008; Green et al., 2005; Tiang et al., 2021) and tackling issues with land degradation (Chapman and Lindenmayer, 2019; Crouzeilles et al., 2020).

Given the scale of the challenge, there is growing interest in whether, where, and when ecosystem services from habitat on farms and the biodiversity it supports, can provide private benefits and thus foster greater adoption of conservation practices on farms (Bateman and Mace, 2020; Cohen-Shacham et al., 2019; Cunningham et al., 2013; England et al., 2020; Fischer et al., 2008; Fischer et al., 2006; Norton, 2020). Examples of private benefits include shade and shelter for livestock (Masters et al., 2023), nutrient cycling and soil stability (DEWHA, 2009; FAO, 2019), pest regulation (Thompson et al., 2011) and health and wellbeing outcomes for farmers from nature connection and recreation (Brown et al., 2022; Ulrich et al., 2023). Private benefits are by no means the only determinant of adoption of environmental conservation practices; private input costs of restoration activities, along with a range of socio-economic considerations, are also important determinants of farmer adoption decisions (Pannell et al., 2006). However, accounting for private benefits from conservation on farms is an important

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consideration for understanding adoption and planning for and targeting public investment to support adoption to maximise net social benefits (Pannell et al., 2006; Polyakov et al., 2015b).

Despite the growing recognition of the potential synergies between natural capital[1] and farm productivity (e.g England et al., 2020; FAO, 2019; Fischer et al., 2017; Fischer et al., 2009; Groot et al., 2018; King et al., 2021; Vardon et al., 2019; Zoeller and Cumming, 2023), there remain important knowledge gaps about the magnitude and nature of possible private benefits from ecosystem services associated with natural capital such as native vegetation, on farms (Ansell et al., 2016; Bezner Kerr et al., 2022; Sanderson-Bellamy and Ioris, 2017).

We make a contribution to addressing this gap through an investigation of the private benefits associated with native vegetation and related bird biodiversity on farms within the critically endangered Box-Gum Grassy Woodland Ecological Community in southeast Australia (Australian Government, 2006a). This ecological community (hereafter called box-gum woodland) occurs in some of Australia's most productive agricultural environments, explaining why it has been heavily cleared for agricultural production (Rawlings et al., 2010).

Approximately 95% of the box-gum woodland has been cleared since the late 18th Century following European colonisation of Australia. Due to the severity of its decline in geographic extent and condition, in 2006, box-gum woodland was listed as a critically endangered ecological community under Australia's Environmental Protection and Biodiversity Conservation Act (Australian Government, 2006b). Most of what remains of the ecological community exists on private farmland as fragmented small patches or isolated paddock trees (Rawlings et al., 2010; Vardon et al., 2023). An ecosystem account of the ecological community indicates that its geographic extent between 2001 and 2017 has considerable regional variation, with gains and losses. In New South Wales, where the case study for this investigation is located, the area of box-gum woodland was estimated to have fallen by 8%, or 0.178 million ha between 2001 and 2017 (Vardon et al., 2023). Despite the severity of fragmentation of box-gum woodland, the remaining areas support some of Australia's most significant biodiversity (Rawlings et al., 2010) including rare and critically endangered species (Australian Government, 2006b; Rawlings et al., 2010).

Private benefits generated by woodland habitat and bird biodiversity on farmland such as agricultural production gains from shelter and pest regulation and wellbeing benefits from nature-connection, can be estimated using hedonic modelling (Bastian et al., 2002; Hanley and Barbier, 2009; United Nations, 2021). This is a statistical approach that relates the observed sale-price of farmland parcels to a vector of objectively defined attributes (Rosen, 1974). The estimated coefficients are interpreted as implicit marginal prices (or values) for each attribute. Hedonic modelling has been widely used to estimate the relationship between environmental attributes and residential property value (e.g. see Doll et al., 2022; Kovacs et al., 2022; Mutlu et al., 2023; Tapsuwan et al., 2009; Waltert and Schläpfer, 2010) and it is one of the methods recommended by the United Nations for the valuation of ecosystem services from natural capital (United Nations, 2021). The implicit price estimates do not capture the full social benefits (i.e., public and private benefits) from natural capital on farmland. As such, hedonic modelling has limitations for informing optimal allocation of resources for the conservation of natural capital on farmland which depends upon the balance across public and private benefits and costs associated with the conservation of natural capital on farmland.

We are aware of only a small number of hedonic modelling studies that have estimated the effect of environmental attributes on the value of commercial agricultural land (Bastian et al., 2002; Borchers et al., 2014; Chancellor et al., 2019; Ma and Swinton, 2011; Polyakov et al., 2015b; Uematsu et al., 2013; Walpole et al., 1998), none of which investigated the effect of on-farm or off-farm biodiversity on land value.

Several studies in North America found farmland prices were positively impacted by native forest cover (Bastian et al., 2002; Ma and Swinton, 2011; Borchers et al., 2014). However, these studies included income from game-hunting in forests on private farmland which is uncommon in Australia. In central Victoria, Australia, Polyakov et al. (2015b) found that private benefits associated with woodland on rural properties were significantly associated with property size. They found small and medium-sized lifestyle-oriented properties were associated with higher marginal benefits for woodland habitat compared to larger commercially-oriented farms. Walpole et al. (1998) found marginal costs associated with woodland farms in southeast Australia when it covered >50% of the property; otherwise, there was no significant effect of woodland cover on the capital value of farmland. The results from these previous studies suggest a potential trade-off between native woodland on farmland and agricultural production.

The purpose of this study was to investigate private benefits from ecosystem service flows associated with the box-gum woodland and its bird biodiversity attributes on commercial farmland. These private benefits may be small relative to the potential public benefits which include regulation of water flow across landscapes, carbon sequestration, and cultural existence values (Marais et al., 2019). Nevertheless, information about private benefits from natural capital on farms can provide valuable information when planning and targeting both public and private investment and in the selection of cost-effective policy interventions to support practice change on farms (Cortes-Capano et al., 2021; Ma and Swinton, 2011; Pannell, 2008; Pannell et al., 2012; Polyakov et al., 2015b; Wentland et al., 2020). In the context of agricultural landscapes, these are important considerations given the scarcity of public resourcing for biodiversity conservation relative to the magnitude of the problem of biodiversity loss (Wintle et al., 2019).

Our study was guided by four main questions.

Q1. Are private benefits associated with box-gum woodland on commercial farmland? We hypothesised that a positive association between farmland value and box-gum woodland would diminish as the proportion of woodland cover increased. This reflected our expectation that ecosystem services associated with box-gum woodland can provide private benefits on commercial farms but can also be associated with foregone farm income as it competes with available area for farming.

Q2. How does farmland parcel area affect private benefits associated with box-gum woodland? Following prior research reviewed above, we expected marginal benefits associated with box-gum woodland on farmland to diminish with increasing parcel area.

Q3 Are private benefits associated with bird biodiversity on commercial farmland? Given the lack of prior research, we did not have a priori expectations about this relationship.

Q4 A fourth question emerged through our modelling process, which was: how do private values associated with box-gum woodland and bird biodiversity change across the distribution of farmland value?

2. Data and methodology

2.1. Conceptual framework

Hedonic modelling is a revealed preference, non-market valuation method that can be applied to estimate private values associated with environmental assets (Hanley and Barbier, 2009). It is underpinned by the Lancaster – Rosen Theory of Value (Lancaster, 1966; Rosen, 1974), which holds that the value of an asset or good is a function of its attributes. In hedonic modelling, the capital value (i.e., market price) of private property is assumed to reveal information about the utility held for property attributes that buyers and sellers can observe and

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[1] We refer to the definition of *Natural Capital* adopted by the Natural Capital Coalition: "Natural capital is another term for the stock of renewable and non-renewable resources (e.g. plants, animals, air, water, soils, minerals) that combine to yield a flow of benefits to people." United Nations, 2023 Natural Capital and Ecosystem Services FAQ, URL: <https://seea.un.org/content/natural-capital-and-ecosystem-services-faq>.

differentiate (Hanley and Barbier, 2009; Rosen, 1974).

Prior literature fully describes the conceptual hedonic model (for example see Bastian et al., 2002; Ma and Swinton, 2011; Polyakov et al., 2015b); hence we provide only a brief description here. Following Bastian et al. (2002), the general hedonic model is specified as follows: let P be the price of farmland and $Z = z_{1,}z_2, \ldots\ldots z_n$ represents the vector of its attributes the hedonic price function is represented as

$$P(Z) = P(z_{1,}z_2, \ldots\ldots z_n). \tag{1}$$

The marginal effect on farmland parcel price, $P(Z)$ of any element of the vector Z can be estimated from Function (1). In this study, P is the sale price per hectare obtained from commercially available farmland sales transaction data[2] and Z is a vector of attributes that contribute to the capital value of the land. We assumed that the value of commercial farmland is determined by attributes relating to agricultural and non-agricultural benefits, across categories: natural capital; biophysical and land use; infrastructure; and proximity to markets and services access. Natural capital attributes were the focus in this study, and while hedonic modelling provides a framework for estimating the value of ecosystem services or disservices, the nature of the benefits or costs are speculative – they may reflect provisioning (e.g., food and fibre), supporting (e.g., nutrient cycling), regulating (e.g., climate regulation) or cultural (e.g., recreational and aesthetic) ecosystem services (Millennium Ecosystem Assessment, 2005).

The hedonic model used in this paper is based on an adaptation of the national-scale model of Chancellor et al. (2019) which was developed to account for all factors expected to affect the value of commercial farmland.

2.2. Study area

Our study area was the 189,000 km^2 intersection of the distribution of possible box-gum woodland (Department of Agriculture and the, 2020) and the wheat-sheep zones of New South Wales (NSW), Australia (Fig. 1). The area broadly matches the locations of the survey sites used to construct a bird occupancy model (Hingee et al., 2022) that we drew upon in this study (see Data section). The study area covers 38% of all possible box-gum woodland locations in Australia.

The study area falls within three NSW wheat-sheep regions: The Riverina to the south, Central West in the middle, and North West Slopes and Plains to the north (Fig. 1). Annual rainfall varies from approximately 400 mm to 1600 mm, declining from east to west and north to south (AdaptNSW, 2023). According to a 2021 census, the human population across the NSW wheat-sheep zone (the area within the solid borders in Fig. 1) was 562,087 (ABARES, 2021). Primary industry (agriculture, forestry and fisheries) was the third largest employer in the Riverina (9.9% of employment) and Central West (12.5% of employment) and the largest employer in the North West Slopes and Plains (accounting for 19.3% of employment) (ABARES, 2021). There was an estimated 10,862 farm businesses operating in the three regions combined, and of these businesses, the majority (86%) operated dryland agricultural systems as either grazing only (50%), mixed cropping-grazing (20%), or specialised grain cropping (16%) (ABARES, 2021). The Gross Value of Agricultural Production in the NSW regions within our study area was around $AU 9.28 billion in 2021 (ABARES, 2021).

2.3. Data

The data used consisted of farmland parcel sales from 1990 to 2018 and a variety of characteristics for each parcel, across categories of: natural capital; biophysical and land use; infrastructure; and proximity to markets and services access. The starting year of 1990 coincided with the first introduction of native vegetation clearing legislation in NSW (Bombell and Montoya, 2014). A total of 28,460 sale events was used in the analysis.

2.3.1. Sales

The farmland parcel sales data were derived from CoreLogic property sales data which included information on sale price, sale date, land area, land use, geographic location, number of bedrooms and bathrooms in a dwelling, and land parcel identifiers. The geographic boundary of each transacted parcel was obtained by linking the parcel identifiers with NSW state government cadastral datasets (SEED, 2023).

These data were filtered to include only commercial broadacre dryland farm parcel sales within our study area. This involved removal of non-farm sales (e.g., mine sites and residential properties), irrigated farmland (e.g., dairy and horticulture), and properties listed as ‘hobby farms’. Sales for a contract price lower than $1000 or no land area were also removed. For full details on the filtering, see Chancellor et al. (2019).

The sales data included bundled parcel sales, where several land parcels (usually of different sizes) were grouped, and a single contract price was supplied. For parcels that were part of a bundled sale transaction, the price per hectare was the total multi-sale contract price divided by the total land area of all parcels involved. A limitation of this approach is that all parcels within a multi-sale transaction are treated as having equal value, which may not be the case.

2.3.2. Natural capital

For the purposes of this study, natural capital was defined by two key natural assets of interest: box-gum woodland and bird biodiversity. We created estimates of these natural assets for each farmland parcel.

Due to high inter-annual fluctuations in the estimated box-gum woodland locations, we used the average box-gum woodland canopy cover for the years 2001 to 2017. The increased accuracy gained from using averages supported more robust comparisons between spatially-distinct parcels. We did not investigate temporal changes in box-gum woodland cover or biodiversity due to the difficulty of detecting changes in the highly fluctuating time-series. The proportion of box-gum woodland cover on each farmland parcel per year was the percentage of the parcel that was estimated by Vardon et al. (2023) from Landsat imagery and other sources, to be possible or likely locations of box-gum woodland. Additional detail on the mapping process and method is outlined in Van Dijk (2019). The box-gum woodland location mapping did not distinguish between native and non-native understorey (DEE, 2017; Van Dijk, 2019).

We computed a woodland bird expected species richness biodiversity metric for each parcel and year. This metric was selected because of its links to ecosystem function (Ikin et al., 2019; Tilman et al., 2014) and because of the value people may place on the presence of diverse bird species (Lindenmayer et al., 2022; Methorst et al., 2021). For each year, we estimated the probability that a species occupies a possible/likely box-gum woodland pixel using a large statistical model for the spring occupancy probability of 60 woodland bird species. Pixels that intersected parcels by $<10\%$ (i.e., 62.5m^2) were ignored and parcels without any box-gum woodland pixels were omitted. Our statistical model, trained on 5,189 expert bird surveys across 518 different locations (Hingee et al., 2022), required tree canopy cover within 500 m and 3 km (Liao et al., 2020), and climatological information from WORLDCLIM 1.4 at 0.5 min spatial resolution (Hijmans et al., 2005; data obtained using the *raster* (Hijmans, 2017) package for R (R Core Team, 2020). The model also required certain summaries of recent weather (within 12 months), for which we used the long-term climatological averages for precipitation and average temperature and the mean of the model's training data for the remaining weather variables. There were 855 parcels omitted due to errors associated with resampling the WORLDCLIM data for unusually thin parcels. Every pixel of likely or possible box-gum woodland was treated as remnant woodland (rather than a

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[2] www.corelogic.com.au

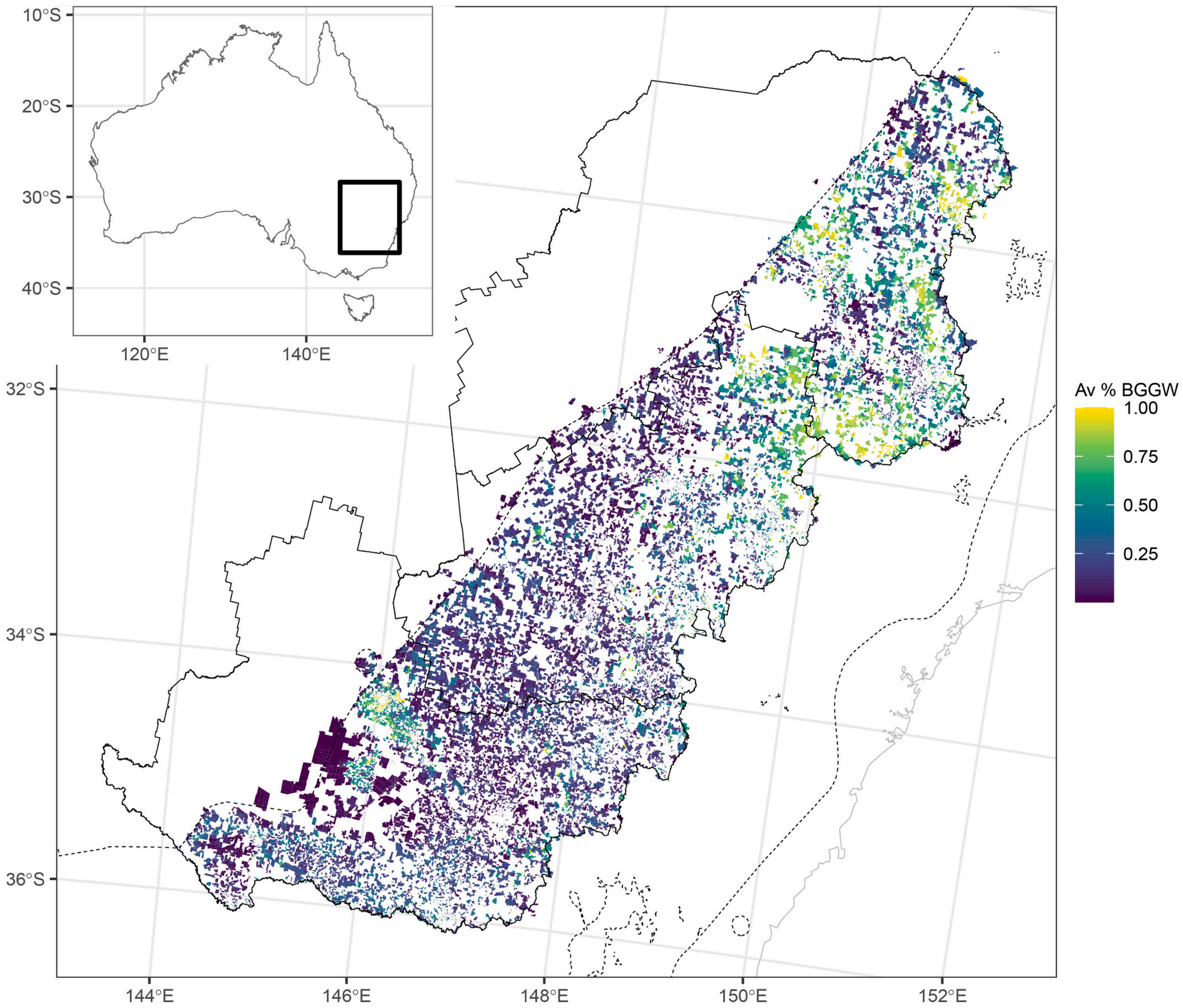

Fig. 1. Study region, showing average box-gum woodland cover on farm parcels in the NSW wheat-sheep zone of Australia. Dashed region: possible box-gum woodland locations from ECNES mapping (DAWE, 2020). Solid border: NSW wheat-sheep regions.

revegetated location) and we assumed the despotic bird species Noisy Miner (*Manorina melanocephala*) was always present. The native Noisy Miner is common over much of eastern Australia and aggressively excludes smaller-bodied birds (Lindenmayer et al., 2023; Maron et al., 2013; Westgate et al., 2021). An estimate of occupancy probability of a species for a whole parcel was computed as the maximum of estimated occupancy probability over all box-gum woodland pixels within the parcel. This operation conveniently does not require identifying individual woodland patches from satellite imagery, which is difficult to automate and is mathematically equivalent to two consecutive maximising steps: maximums of occupancy probability over pixels within each patch of box-gum woodland in a parcel (the statistical model was trained on box-gum woodland patches that span multiple pixels, of approximately 2 ha to 10 ha in area (Hingee et al., 2022)), which are good approximations of the occupancy probability of whole patches as neighbouring pixels lead to very similar estimates; and a maximum over all patches in the parcel, which follows use in (Hingee et al., 2022) for multiple patches. The expected species richness in a parcel was the sum of the maximum bird occupancy probabilities for the parcel. This expected species richness was then averaged over the years 2001–2017 (Fig. 2).

Biodiversity metrics based on the ecological function of species, such as functional evenness, can have closer associations with ecosystem productivity, ecosystem resilience to perturbations and other ecosystem functions than species richness (Villéger et al., 2008). There is also a nascent body of social science research identifying positive relationships between the ecological function of species traits and cultural ecosystem services or disservices (Zoeller and Cumming, 2023). Hence, we also calculated functional evenness as a measure to capture the ecological function of bird species present (Fig. 3) using the dbFD package with the Gower dissimilarity distance (Laliberté and Legendre, 2010) and weighting each species by its maximum occupancy probability in the parcel. Values for functional evenness are unitless, and given the weights we assigned, this measure described the evenness of occupancy probabilities in functional trait space (Villéger et al., 2008). Following Ikin et al. (2015), we used traits of primary food (5 categories), foraging method (5 categories), seasonal movements (3 categories), social aggregation (3 categories), nesting aggregation (3 categories) and the logarithm of body mass (numerical) to calculate functional evenness.

A vegetation clearing variable was included as a proxy for land

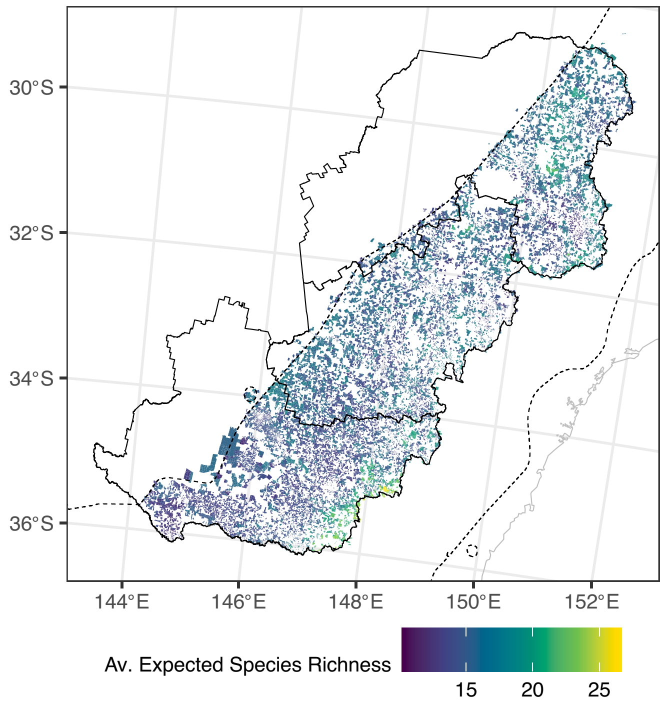

Fig. 2. Average of annual model-based estimates of expected bird species richness on farm parcels across the study region.

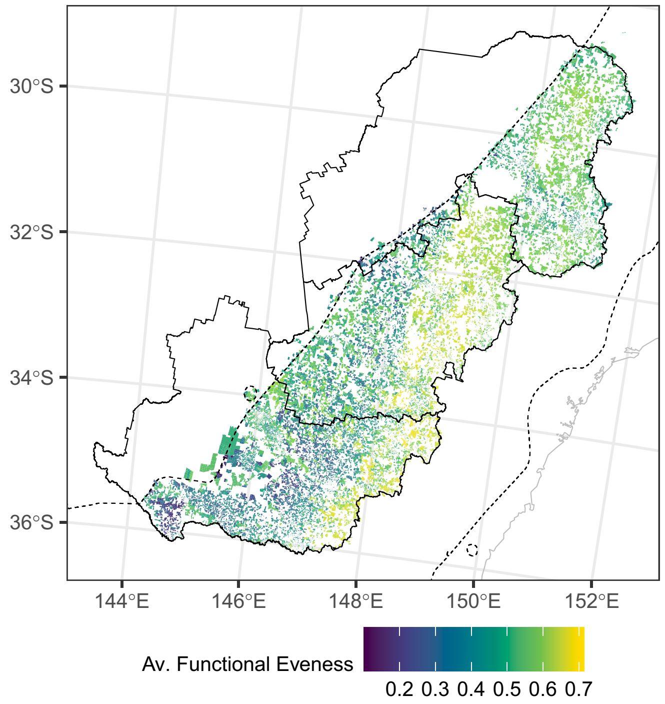

Fig. 3. Average of annual model-based estimates of bird functional evenness on farm parcels across the study region.

clearing at the parcel scale. This variable was based on the National Forest and Sparse Woody Vegetation Data (Version 3, 2018 Release) (DOEE, 2018). A linear trend of woody vegetation cover at a parcel level was derived from the available time period of 1988 to 2018. The corresponding gradient of the linear clearing trend was our vegetation clearing variable and provides an indication of either vegetation clearing or growth.

2.3.3. *Biophysical and land use*

Given the importance of water as a resource or impediment to agricultural production, we included annual rainfall estimates for the sale year and previous three years (BOM, 2019) and also a set of variables capturing surface water availability. This latter set of variables was based on Digital Earth Australia Water Observations (previously titled Water Observations from Space) (Geosciences Australia, 2023; Mueller et al., 2016). Pixels were labelled according to three (overlapping) categories for the percentage of time water was detected: 1) 0–1.5%, 2) 0–5% and 3) 0–20%. The average frequency of water detection across the pixels within each category was used in our hedonic model. The lower category (1.5%) was most likely to capture flooding events, and the higher categories (i.e., 20% and 5% to a lesser degree) were more likely to capture ephemeral water storages (Mueller et al., 2016).

To account for topography within farmland parcels, a measure of the slope of the parcel was calculated based on the Shuttle Radar Topographical Mission digital elevation model, which has approximately 90 m resolution (Geosciences Australia, 2011). Land topography is defined according to the percentage of a given parcel that was either: flat; undulating; hilly; or steep. Our variable selected was the proportion of the parcel classed as steep. It is expected that a high percentage of steep land on a parcel limits its suitability for farming and reduces sale price.

Soil condition variables were included due to their important role in pasture and crop production, and through this, their expected relationship with farmland parcel price. Land degradation processes such as soil erosion may also be observed in soil condition variables and negatively impact price. We included acidification risk, carbon loss risk, erosion by water risk, and erosion by wind risk, all constructed using spatial overlays to parcel shapes based on Leys et al. (2017). While it is necessary to control for soil condition using these variables, interpretation of their coefficients is more difficult. Acidification, for example, has increased in many areas due to intensive fertiliser use (Leys et al., 2017), but this may not have an immediate impact on market price unless there is explicit knowledge of the intensive land use and soil condition risk.

Given that the suitability of land for cropping and grazing influences land value, we used a 50 m-resolution land use map to compute cropping and grazing land use variables (ABARES, 2018). Two dummy variables were established to capture whether at least 50 ha of cropping or grazing occurred on a parcel to indicate if these land use practices were a significant land use (i.e., a value of one indicates that cropping or grazing was an important land use on the parcel). The area of cropping and grazing used all 50 m-resolution pixels that intersected the parcel, and consequently, parcels smaller than 50 ha that were unusually shaped (e.g., long and thin) were occasionally marked as Cropping or Grazing.

2.3.4. *Infrastructure*

It is expected that the presence of a residential homestead and other built infrastructure (e.g., storage and machinery sheds) will have a positive effect on farm price. Bedroom and bathroom data from CoreLogic were used to develop a variable for the presence or absence of a residential homestead. A second variable was generated to capture the presence or absence of farm buildings using spatial State Government building data overlayed on land parcel polygons.

2.3.5. *Proximity to markets and services access*

To account for access to markets and urban-based services and amenity, we included estimates of transport costs from each farm parcel to townships with populations of at least 1000 people and 100,000 people, respectively. We expected an inverse relationship between transport costs and land value. The travel distance was calculated from the road network node closest to the property boundary. Road class was incorporated into the calculation of travel cost where the cost rate was one unit per km for sealed roads and two units for unsealed minor roads. The travel route minimised a transport cost index based on road class and distance using a C++ implementation of the Djikstra algorithm (Dijkstra, 1959). The road network was based on Geoscience Australia Topo250k Series 3 data (Geosciences Australia, 2016) and populations were from the 2016 Australian census (ABS, 2017).

2.4. *Empirical model and variables*

Hedonic modelling involves the application of statistical regression to estimate the relationship between the observed capital value (market sale price) of a property to its attributes. The challenge is to specify the empirical hedonic price function to capture the true relationship between land price and land attributes. Our process of model specification was guided by economic theory, such as an expectation of diminishing returns as the proportion of box-gum woodland cover increased. However, as is common in hedonic modelling, the form of our empirical model was also guided by an iterative modelling approach (Bastian et al., 2002), which involved testing and evaluation of several functional forms. The descriptive statistics for the key model variables are presented in Table 1 and the full set of covariates used in the final quantile regression models are listed in Appendix Table A.1.

It is common for hedonic models to use the standard ordinary least squares (OLS) method (Uematsu et al., 2013) to estimate a relationship between the dependent variable and a set of explanatory variables (Cameron and Trivedi, 2010). However, we discarded the OLS model due to heteroskedasticity and heavy-tailed residual price distribution. The lower tail included sales that appeared to be gifted land, such as sales to family members, rather than a true market sale: very low contract prices that were a simple number (e.g., $10) and did not reflect the economic value of the parcel. Quantile-quantile plots of an OLS model residual suggested that the upper tail was also heavy.

Quantile regression, introduced by Koenker and Bassett (1978), is an extension of the OLS model and estimation. Instead of estimating average relationships, quantile regression estimates the relationship between the dependent variable (y) and explanatory variables (x) at different points in the conditional distribution of y. This method offered a more complete view on the relationships between farmland price and our explanatory variables, including estimation of heterogeneous impacts of attributes on farmland prices across the distribution of farmland parcel value (Cameron and Trivedi, 2010; Davino et al., 2014). For a detailed summary of the theoretical foundation of quantile regression and discussion of its relative advantages over OLS, refer to Cameron and Trivedi (2010) and Uematsu et al. (2013).

Although quantile regression has shown promise in hedonic modelling applications, it remains relatively under-utilised in the context of agricultural land values (Uematsu et al., 2013). To date, the only documented applications we are aware of include those of Kostov (2009), Chancellor et al. (2019), and Uematsu et al. (2013).

We removed 29 parcel sales containing mines and one parcel with an unusually high rate of surface water (average 4% surface water in the 0–5% category). Scatter plots suggested a different relationship between parcel size and price for Cropping or Grazing parcels (see Supplementary Material, Fig. S.1). To account for this, we included interactions between (log) parcel size and Cropping and Grazing. We removed Cropping and Grazing parcels smaller than 50 ha due to inaccuracies in computing the area of cropping and grazing. We also removed parcels smaller than 100 ha because preliminary model diagnostics showed large residuals for the smallest 10% of remaining cropping parcels.

Our quantile regression models incorporated the effect of time non-parametrically by using a dummy variable for each calendar year. Regional effects were partially accounted for via a categorically-valued indicator of three broadacre agricultural regions that constitute the NSW Wheat-Sheep zone (DAFF, 2022). Inclusion of the regional effect variable also serves to reduce omitted variable bias which is a common issue in hedonic models (Polyakov et al., 2015b; Ritter et al., 2020).

An interaction term between box-gum woodland proportion and parcel area made it possible to examine the effect of box-gum woodland for different parcel sizes. The square of box-gum woodland percentage of the parcel allowed the potential for diminishing returns within the model.

Variance inflation factors (Zuur et al., 2010) confirmed that collinearity was not an issue for the main effect variables. Our final model was a set of quantile regressions for the 10–90% percentiles (in 10% intervals) of the conditional log price per hectare. Here, the quantile land value range will be discussed as: low or cheaply priced farmland quantiles (10–40%), median farmland quantile (50%), and upper (60%) or premium-priced farmland quantiles (70–90%). Standard errors and p-values of statistical significance were estimated using 100 bootstrap repetitions. Experimentation with preliminary models showed that p-value results were very similar with higher (i.e., 200 and 300) bootstrap repetitions.

We evaluated model fit using estimated percentiles of residuals, binned according to covariate value (Supplementary Material, Fig. S.2 – S.5). This diagnostic is similar to the *cqcheck* function from the *qgam* package (Fasiolo et al., 2021). For a given estimated percentile, the corresponding percentile of the residuals should equal zero. The diagnostic plots indicated that the effect of log parcel area decreased with parcel area (i.e., the effect of parcel area was not log-linear) (Supplementary Material, Fig. S.5). However, for simplicity, we did not incorporate additional terms in the final model. Similarly, a quadratic relation between functional evenness and log farmland price was indicated by the diagnostic plots model (Supplementary Material, Fig. S.7) and omitted for simplicity. All analyses were performed using Stata 15.0 (StataCorp, 2017).

3. Results

Our quantile regressions were fitted to 28,460 commercial farmland parcel sale contracts. We present estimated coefficients of variables of most interest in Table 2, across regression models for the 10%, 30%, 50%, 70% and 90% quantiles. The full suite of estimated coefficients is provided in the Appendix Table A.2. The variables of most interest to us were: (1) the proportion of box-gum woodland on farm parcels and its interaction with parcel area, and (2) bird biodiversity at a parcel scale captured with species richness and functional evenness bird biodiversity metrics.

The estimated coefficients for many of our key variables differed substantially between quantiles, confirming that a heteroskedastic modelling method such as quantile regression was justified. For

Table 1
Descriptive statistics of the selected key variables.

Variable	Unit	Mean	Std.dev	Min	Median	Max
Price/ha	$AU/ha	9879	41,098	1.0[#]	2000[#]	2,800,000[#]
Parcel size	Hectares	356	584	1.0[#]	200[#]	9000[#]
Proportion of box-gum	Proportion	0.31	0.27	0.0001	0.21	1
Bird Biodiversity - Species Richness	No. species	14.54	1.80	10.19	14.20	26.64
Bird biodiversity - Functional Evenness	Index (0–1)	0.49	0.12	0.12	0.51	0.71

[#] Approximate figures are provided to maintain confidentiality of unit record data.

Table 2
Regression results for selected variables and quantiles.

	OLS	Selected quantiles (Bootstrap Std. Errors, 100 reps, in parentheses), $n = 28{,}460$														
Variable		0.1			0.3			0.5			0.7			0.9		
Log(area)	−0.601	−0.456	***	(0.024)	−0.510	***	(0.012)	−0.590	***	(0.010)	−0.654	***	(0.009)	−0.717	***	(0.010)
Proportion box-gum	1.015	1.726	***	(0.318)	1.706	***	(0.163)	1.182	***	(0.130)	0.756	***	(0.139)	0.230		(0.150)
Proportion box-gum squared	−0.191	−0.442	**	(0.229)	−0.517	***	(0.116)	−0.288	***	(0.096)	−0.094		(0.102)	0.210		(0.117)
Proportion box-gum*log(area)	−0.138	−0.285	***	(0.040)	−0.235	***	(0.019)	−0.158	***	(0.015)	−0.093		(0.016)	−0.039	**	(0.016)
Bird biodiversity - Species Richness	−0.011	−0.049	***	(0.013)	−0.022	***	(0.007)	−0.013	**	(0.005)	0.003		(0.006)	0.028	***	(0.008)
Bird biodiversity - Functional Evenness	0.231	0.040		(0.176)	0.045		(0.101)	0.193	***	(0.073)	0.331	***	(0.080)	0.626	***	(0.116)

example, the difference between parcel area coefficients for the 30% and 70% quantile models was >10 standard errors away from zero corresponding to a statistically significant Wald test p-value of $6 \bullet 10^{-32}$. We include the OLS estimation results in Table 2 only for comparison.

3.1. *Farmland value and the proportion of box-gum woodland, across parcel area*

For the 10% to 70% quantiles, we found that the marginal benefit associated with box-gum woodland on farmland diminished as the proportion of box-gum woodland on a parcel increased (i.e., coefficients for the proportion of box-gum woodland squared, were negative, Table 2). We also found that marginal benefits associated with box-gum woodland diminished with parcel area (i.e., proportion of *box-gum*log (area)* coefficients were negative, Table 2).

The overall effect of the proportion of box-gum woodland cover on the farmland value distribution at the 30% (low price/ha), 50% (median price/ha) and 70% (high price/ha) quantiles and for hypothetical parcels of 50, 500 and 3000 ha area is presented in Fig. 4. Pointwise estimates of 95% confidence intervals (coloured ribbons, Fig. 4) were

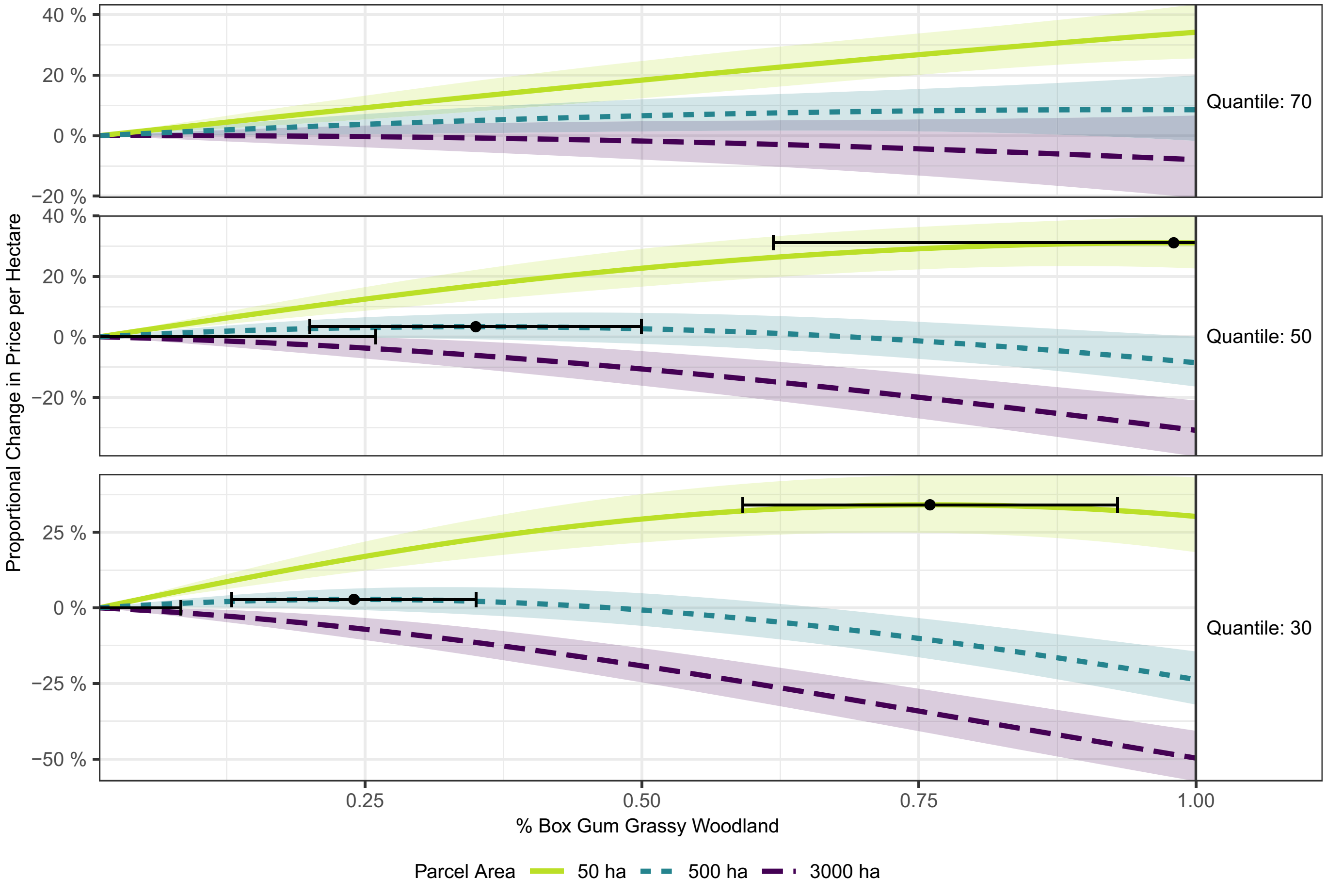

Fig. 4. The estimated proportional change in price-per-hectare from increasing box-gum woodland area *for* the 30th, 50th and 70th quantile of farmland value, relative to 1% box-gum woodland. Ribbons show pointwise estimated 95% confidence intervals. Horizontal error bars show estimated 95% confidence intervals for the optimum box-gum woodland proportion; optimums were not estimated for the 70th percentile as returns may not diminish for this quantile.

generated using Stata's *lincom* routine.

For small parcels (50 ha), the models indicate that box-gum woodland supports private benefits for all points of the farmland value distribution. This is shown by the marginal effect of box-gum woodland on farmland price which was positive and diminishing for the 30% through to 70% quantiles (top line in each panel, Fig. 4). This was also true for moderately sized parcels (500 ha; middle line in each panel, Fig. 4). For large parcels (3000 ha), the model indicates neutral or private costs associated with box-gum woodland. The model estimates for large parcels indicate the marginal effect of increasing box-gum woodland on land value is approximately neutral for the high-priced quantile (70% quantile) in the range of up to 50% of existing box-gum woodland (left of top panel, Fig. 4). Otherwise, the models indicate the marginal effect of increasing box-gum woodland on the value of large farmland parcels was negative (i.e., was associated with private costs) (bottom line in middle and lower panels, Fig. 4).

The estimated proportions of box-gum woodland on a parcel that optimised the 30% and 50% conditional quantiles of farmland value are shown as black dots in Fig. 4 along with horizontal error bars showing estimated 95% confidence intervals based on +/− 2 standard errors. This is the point at which the proportion of box-gum woodland on a parcel maximises private benefits, and the effect of additional woodland would be reduced land value. These estimates were computed using Stata's *nlcom* routine (Hirschberg and Lye, 2010). The covariance between estimated model coefficients suggested that the standard errors may be less reliable for the 3000 ha parcel. The optimum box-gum woodland cover was not estimated for the 70th quantile because of the high uncertainty in estimated coefficients for the proportion of box-gum squared.

Our model suggested that private benefits associated with box-gum woodland on farmland increases from the lower to upper farmland value quantiles. The optimal proportion of box-gum woodland estimated for lower and median quantiles was very high at around 80% and 95% for small parcels, respectively, and 25% and 35% for moderately sized parcels, respectively. For parcels valued at the median quantile, compared to a baseline (1% box-gum woodland cover), the optimal proportion would change the value of a parcel by 30% for small parcels and 3% for moderately sized parcels.

In comparison to smaller parcels, model estimates for the 3000 ha parcel for the 30% and 50% quantiles (bottom line in each panel of Fig. 4) indicated the optimal proportion of box-gum woodland may be at the baseline 1% or lower. However, the error bars showing estimated 95% confidence intervals for the optimal proportion, suggest that the optimum may also be >1%. At the higher quantile (70%), increments in box-gum woodland was estimated to have a largely neutral effect on marginal farmland price for proportions of box-gum woodland less than about 50% (left of top panel, Fig. 4).

3.2. *Farmland value and bird biodiversity*

The estimated coefficients for the biodiversity metrics had opposing signs for quantiles 10% to 60%: they were negative for species richness and positive for functional evenness. However, for many of the lower quantiles (10% to 40%) the effect of functional evenness was statistically consistent with zero effect ($P > .05$). The coefficients for both bird biodiversity metrics were positive for high-end, premium land value quantiles (90% quantile) with high statistical significance ($P < .01$).

The effect size of species richness and functional evenness on farmland value also differed between quantiles. A one-unit increase in species richness (i.e., the expected presence of one additional bird species) shifted the lower end of the land value distribution (10% and 30% quantiles) downward by 3%. This dropped to only 1.2% for the median quantile for farmland value. A one-unit change in species richness shifted the land value premium (90%) quantile upward by 2.9%.

The association between functional evenness and farmland value exhibited a similar pattern to the effect of species richness on land value, i.e., there was increasing marginal benefit for biodiversity from the lower to upper quantiles. The effect of functional evenness was insignificant at the lower quantiles (10% and 30%) and was significant and positive, with an increasing effect size, from the median to upper quantiles. The positive effect on farmland value for an incremental change (0.2-point increase) in functional evenness tripled from +4% to +13% for the 50% and 90% quantiles, respectively.

4. Discussion

We applied quantile regression to estimate private benefits associated with native woodland and bird biodiversity on commercial farmland across a critically endangered ecological community in New South Wales, southeast Australia (Fig. 1). We posed the following key questions at the outset of this study: 1) Are private benefits associated with box-gum woodland on commercial farmland? 2) How does farmland parcel area affect private benefits associated with box-gum woodland? 3) Are private benefits associated with bird biodiversity on farmland? And the fourth question, identified through the modelling process, was: how do private values associated with box-gum woodland and bird biodiversity change across the distribution of farmland value?

Our modelling suggested that in some contexts, box-gum woodland on commercial farmland can provide private benefits and that these diminish as the proportion of woodland of a farmland parcel increases (Question 1). This was an expected result, and consistent with Polyakov et al. (2015b) and our understanding of the tension between the conservation of woodland on commercial farmland and the area available for agricultural production (Pannell et al., 2006; Smith and Sullivan, 2014).

The results also supported the expected finding of diminishing marginal private benefits from increments in box-gum woodland as the size of the farmland parcel increased (Question 2). Our results indicated private benefits are very sensitive to farmland parcel area (as shown by Fig. 4). For large parcels in the lower quantiles for farmland value, we found marginal costs from additional box-gum woodland beyond a very low (1%) proportion.

Our estimates for the proportion of box-gum woodland that maximised capital value of farmland per hectare, followed a similar pattern to Polyakov et al. (2015b), where higher optimal proportions are associated with smaller farmland parcels. However, their dataset included small lifestyle properties whereas ours was restricted to commercial agricultural landholdings. Therefore, an explanation offered in Polyakov et al. (2015b) that the diminishing returns reflect a reduced preference for amenity values from woodland among larger agricultural production-focused landholders compared to smaller lifestyle landholders, may not be applicable in our case. However, it is possible that lifestyle priorities are also relevant for those with commercial farming interests who purchase smaller parcels potentially for conservation purposes. Additional investigation would be required to confirm how preferences relating to box-gum woodland vary by parcel area for commercial farmers as it may also be that these associations reflect missing explanatory variables or interactions in our model.

The quantile regression estimation of our hedonic model made it possible to evaluate how the relationships discussed above varied across the distribution of farmland price per hectare. Our results showed that not only is the private benefit associated with box-gum woodland on farmland sensitive to its proportion of a parcel and parcel area, as others have found (e.g. Polyakov et al., 2015b), but also to the price per hectare of the land relative to other similar parcels (Question 4).

The marginal private benefits associated with additions in box-gum woodland, across farmland area, was estimated in our models to increase across the lower to upper farmland value quantiles. This finding aligns with Uematsu et al. (2013) who speculated that natural amenities are perceived as a luxury rather than a necessity, on farmland in the upper and premium land value quantiles. Our natural amenity attributes differ substantially from those of Uematsu et al. (2013), who defined natural amenity as an index of biophysical factors such as rainfall and terrain. Nonetheless, our findings reinforce the notion that private benefits associated with natural amenity (i.e., natural capital) tends to be discounted for lower farmland quantiles relative to upper and premium land value quantiles.

Our findings included very high model-based estimates for optimal box-gum woodland as a proportion of the parcel – 95% for small (50 ha) and 37% for medium (500 ha) parcels (shown in Fig. 4). As a farmland parcel area increased, our models suggested large decreases in the optimum box-gum woodland cover of the lower and median quantiles of farmland value. For these quantiles and for parcels as large as 3000 ha, we estimated marginal costs were associated with additions in box-gum woodland cover, potentially even at very low (1%) cover percentages. For upper priced farmland (70th percentile) sold in 3000 ha parcels, estimated marginal costs associated with additions in box-gum woodland area were not statistically significant.

It is reasonable to have some scepticism over the results for the small and medium parcels due to significant tradeoffs that high proportions of woodland can pose for commercial agriculture. We suggest these high optimal proportions may be explained by the fact that the box-gum woodland attribute in our models did not distinguish between native and non-native grassy understorey. Maintaining the native understorey is important for retaining the integrity of the box-gum ecological community (Vardon et al., 2023) and requires complete removal of cropping and significantly reduced grazing pressure (Rawlings et al., 2010).

Fig. 5 and Fig. 6 illustrate some examples of commercial grazing (Fig. 5) and cropping (Fig. 6) land uses occurring within patches of sparse mature trees which would be captured as box-gum woodland in our models, and where the native understory is heavily modified. Thus, the estimates for optimal box-gum woodland in our models are unlikely to reflect the opportunity costs of maintaining native understorey, for commercial farming.

It is common practice for cropping or grazing, or both, to occur in and around box-gum woodland on farms. This has not only significantly modified the native grassy understorey (Vardon et al., 2023), as shown in Fig. 5 and Fig. 6, it has also resulted in suppressed natural regeneration of canopy trees (Fischer et al., 2009). The result has been upwardly skewed age profile of trees (Sherren et al., 2011) where the full impact of ongoing farming activities for tree cover on farms across our study area has yet to be realised (Fischer et al., 2009).

Our model estimates suggest a disparity between private benefits of box-gum woodland on commercial farmland and the trajectory of declining tree cover over time, which is a result found elsewhere (Sherren et al., 2011). In rural areas where the retention or increase in box-gum woodland and bird biodiversity is likely to generate private benefits, our results suggest social welfare losses will occur over the long-term if natural regeneration failure of box-gum woodland is not addressed.

Fig. 5. Image of box-gum trees in our study area, illustrating integration with a commercial grazing (photo: Dan Florance, ANU). Given the native understorey is heavily modified, this example would not meet the definition of box-gum woodland ecological community as specified in Australian Government's environmental protection legislation.

Fig. 6. Images of box-gum trees in our study area, illustrating integration with a commercial canola cropping (photo by: Tabitha Boyer, ANU). Given the native understorey is heavily modified, this example would not meet the definition of box-gum woodland ecological community as specified in Australian Government's environmental protection legislation.

Decisions of farmers to invest in practices that support natural regeneration will depend not only on the likely private benefits. They will also depend on when the benefits occur over time, and the costs involved in conservation activities, including the opportunity costs (Pannell et al., 2006). Public subsidies may be justified to compensate farmers for private costs involved in supporting natural regeneration of box-gum woodland. Our findings suggest that when such subsidies are justified, they should be targeted towards owners of small to medium farmland parcels in the upper or premium land value quantiles.

Given the lack of prior research on the relationship between bird biodiversity and farmland value, we did not propose specific hypotheses (Question 3). However, our findings provided important insights. We found marginal private costs were associated with additions in bird species richness, as a measure of bird biodiversity, for parcels in the lower to median land value quantiles (10 to 50% quantiles), relative to parcels with similar attributes. The reverse was true for parcels in the upper land value quantiles (50 to 90% quantiles), where increases in functional evenness as a measure of bird biodiversity, were associated with marginal private benefits. Although the underlying mechanism for these results is difficult to identify, we offer two possible explanations. One is that our results reflect conservation-based preferences of owners of farmland within premium quantiles, who may consider bird biodiversity as a luxury amenity. This explanation follows Uematsu et al. (2013) for natural amenities on farms more generally. Another possibility is that our bird biodiversity metrics capture patch condition and related production-focused ecosystem services that are valued more highly by owners of farmland in the upper quantiles.

Our study has some limitations for informing the socially optimal balance across the restoration of the box-gum woodland ecological community on farmland and agricultural production. This would require information about both public and private benefits associated the retention or restoration of natural assets, and the costs involved in restoration activities. However, our findings can be used in several ways to improve the management of box-gum woodland across our case study region.

First, our findings can be used to guide owners of farmland about opportunities for improving the capital value of their land via conservation actions. Owners of small farmland parcels across the full range of land value quantiles could retain or improve their capital value (all else being equal) through retaining or increasing box-gum woodland, even if the baseline proportion is already reasonably high. Owners of medium-sized parcels with woodland proportions below around a third of the parcel, would also have opportunities to retain or improve their capital value by implementing box-gum woodland conservation actions. However, it is possible that public subsidies may still be required to engage these owners in conservation actions in consideration of the private costs involved in undertaking conservation activities, and given that the private benefits may accrue well into the future (Norton, 2020; Read and Wainger, 2023; Smith and Sullivan, 2014).

Second, our findings also provide an evidence-base to guide agricultural land valuation practices that have traditionally penalised the valuation of farms that have retained native vegetation and are subject to land clearing restrictions (Byron et al., 2004). Our results suggest the land valuation and finance sector more generally, should re-evaluate protocols or accepted heuristics that devalue farms with box-gum woodland, even where the coverage of a parcel is high, and especially for small to medium parcels in the upper quantile value range.

Third, our findings can be used to prioritise investment via public or philanthropic conservation programs that aim to increase uptake of conservation actions on farms. Our findings suggest the value-for-money from such programs would be highest when they are targeted towards owners of farmland who are most likely to experience private benefits from undertaking box-gum woodland and bird biodiversity conservation. This is because these owners would be more likely to undertake conservation activities at lower cost. This is an important consideration given the scarcity of public resourcing relative to the magnitude of the problem of biodiversity loss in Australia (Wintle et al., 2019).

Fourth, our findings have practical implications for guiding the optimal selection of policy mechanisms aimed at encouraging or inhibiting land management changes on farms. The optimal selection has been shown to be very sensitive to private benefits of the activities being promoted (Pannell, 2008). Consider application of our findings to extension-focused policy mechanisms in Australia, for example. There is a history of applying these mechanisms in Australia to encourage the uptake of environmental conservation practices on farms, but not without criticism (see Marsh and Pannell, 2000). Our findings suggest that extension-focused policy mechanisms may not be cost-effective if targeted towards owners with large, relatively low-value parcels. This is because, for this cohort, increases in box-gum woodland beyond a very low base (1%) may be associated with marginal private net costs. This is due to costs associated with losses in capital land value and the input expenses associated with conservation activities themselves. Therefore, delivering extension alone, would be highly unlikely to lead to increased conservation practices.

Finally, findings from our study also provide several insights into the evaluation of private benefits associated with bird biodiversity on farmland. First, biodiversity metrics can have opposing value relationships, and therefore we suggest it is important to incorporate and compare different metrics when assessing the private value of biodiversity on farmland. Second, increases in bird biodiversity can be both positively and negatively associated with farmland value as the relationships vary significantly across a diverse agricultural land market. This finding has implications for modelling applications that aim to optimise the spatial allocation of biodiversity conservation efforts across agricultural landscapes (see Polyakov et al., 2023; Polyakov et al., 2015a).

5. Conclusions

We estimated private values associated with native vegetation and related bird biodiversity on farms across an area of southeast Australia that coincides with the critically endangered box-gum grassy woodland ecological community. In a study area of 189,000 km^2 we developed a hedonic model that leveraged 30 years of historical land sales, bird biodiversity summaries from estimates of occupancy probability for 60 native bird species (Hingee et al., 2022), and box-gum woodland maps based on satellite measurements. We applied quantile regression to address issues identified with heteroskedasticity and heavy-tailed residual price distribution.

The contribution of this study to the existing literature is two-fold. First, we offer a hedonic modelling study of farmland value which, for the first time, explicitly includes critically endangered box-gum grassy woodland and estimates of bird occupancy probabilities as attributes of individual farmland parcels. Second, the application of quantile regression provided a novel approach to the estimation of heterogeneity in the relationship between natural capital attributes across the distribution of farmland value.

Most of what remains of the severely fragmented box-gum woodland, is on private farmland. This makes conservation efforts by farmers integral to preventing the collapse of this critically endangered ecological community. Despite the importance of the public benefits associated with box-gum woodland, our study focused on the estimation of private benefits associated with its conservation, for two main reasons. First, there are significant gaps in knowledge about the potential for private benefits to be generated from box-gum woodland and bird biodiversity on private farmland. Second, accounting for private benefits can provide important insights into the likelihood of farmer adoption of conservation actions, and the implications this has for prioritising public investment and policy mechanism selection.

Our study reveals significant variation in private values associated with box-gum woodland and bird biodiversity on farmland. We identified that both private benefits and costs can be linked to these environmental assets, contingent on parcel area, the proportion of woodland, and the land value quantile of farmland. Recognising and considering this heterogeneity is important for effectively targeting investment and selecting cost-effective policy mechanisms. This is critical if the limited resources available to support conservation on farms is to have a chance of influencing the critically endangered status of the box-gum woodland ecological community. Finally, our results offer new evidence for Australia's finance sector as it repositions its finance products, considering natural capital. Past penalties applied for finance-contingent valuations of farmland that is uncleared or subject to clearing restrictions can be refined, especially for farmland in the upper quantile ranges. Improved land valuation practices will help provide accurate market signals to farm managers, finance providers and future investors across our study area.

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CRediT authorship contribution statement

Helena Clayton: Conceptualization, Formal analysis, Methodology, Project administration, Writing – original draft, Writing – review & editing. **Kassel L. Hingee:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Will Chancellor:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **David Lindenmayer:** Conceptualization, Formal analysis, Funding acquisition, Supervision, Writing – original draft, Writing – review & editing. **Albert van Dijk:** Formal analysis, Investigation, Writing – original draft. **Michael Vardon:** Conceptualization, Methodology, Writing – original draft. **Chris Boult:** Conceptualization, Data curation, Formal analysis, Methodology, Software.

Declaration of competing interest

The authors declare they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data are spatially defined and identifiable to a specific farm location. Therefore, for privacy reasons data from this study cannot be made available.

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We pay our respects to the past and present elders of the Ngunnawal and Ngambri indigenous nations that we work from, and the nations within our study region: the Wiradjuri, Kamilaroi, Wailwan, Ngunnawal and more. We extend our gratitude to the trees, grasses, soils and wildlife that comprise the Box-Gum Grassy Woodland ecological community.

Appendix A. Extended data and results

A.1. Descriptive statistics

Table A.1
Full set of descriptive statistics ($n = 28,460$).

	Unit	Mean	Std.dev	Min	Median	Max
Dependent variable						
Parcel price/ha	$AU/ha	9879	41,098	1.00[#]	2000[#]	2,800,000[#]
Structural attributes						
House	0/1, =1 if yes	0.16	0.37	0.00	0.00	1.00
Buildings	0/1, =1 if yes	0.08	0.27	0.00	0.00	1.00
Farmland parcel area	Hectares	356.08	584.31	1.00[#]	200[#]	9000[#]
Sales attributes						
Part of bundled sale	0/1, =1 if yes	0.012	0.32	0.00	0	1.00
Spatial attributes						
Travel cost Town	$AU	37.83	24.49	0.20	33.38	168.42
Travel cost City	$AU	313.02	72.95	104.68	313.88	570.80
Region - Central West (baseline)						
Region - North West	0/1, =1 if yes	0.21	0.40	0.00	0.00	1.00
Region – Riverina	0/1, =1 if yes	0.44	0.50	0.00	0.00	1.00
Climatic attributes						
Annual rainfall current	Millimetres	546	192	136	528	1584
Annual rainfall 1 year prior	Millimetres	562	193	135	545	1654
Annual rainfall 2 years prior	Millimetres	569	191	133	556	1521
Annual rainfall 3 years prior	Millimetres	565	187	139	553	1555
Biophysical attributes						
Steepness of parcel	Proportion	0.04	0.13	0.00	0.00	1.00
Soil acidity risk	Index (0–100)	12.98	30.89	0.00	0.00	100.00
Soil carbon depletion risk	Index (0–100)	15.37	26.81	0.00	0.00	100.00
Soil water erosion risk	Index (0–100)	29.17	41.56	0.00	0.00	100.00
Water coverage 20%	Proportion	0.19	0.55	0.00	0.01	13.60
Water coverage 5%	Proportion	0.15	0.41	0.00	0.01	3.70
Water coverage 1.5%	Proportion	0.06	0.12	0.00	0.00	1.05
Land use attributes						
Land use - cropping (>50 ha)	0,1, = 1 if yes	0.4861911	0.4998181	0.00	0.00	1.00
Land use – grazing (>50 ha)	0,1, = 1 if yes	0.0778988	0.268017	0.00	0.00	1.00
Natural capital attributes						
Proportion box-gum	Proportion of parcel	0.31	0.27	0.00	0.21	1.00
Biodiversity_Species Richness	No. species	14.54	1.80	10.19	14.20	26.64
Biodiversity_Functional evenness	Index (0–1)	0.49	0.12	0.12	0.51	0.71
Clearing trend over time	Gradient	0.21	0.60	−5.41	0.06	5.61

[#] Approximate figures are provided to maintain confidentiality of unit record data.

A.2. Estimated coefficients for all variables in the model

Table A.2
Full model estimation coefficients (n = 28,460).

		Quantiles (Bootstrap Std. errors, 100 reps, in parentheses), n = 28,460														
Variables	OLS	0.1			0.3			0.5			0.7			0.9		
Structural attributes																
House (=1 if yes)	0.111	0.158	***	(0.034)	0.192	***	(0.015)	0.183	***	(0.015)	0.117	***	(0.015)	0.044	***	(0.017)
Buildings	0.197	0.207	***	(0.051)	0.21	***	(0.023)	0.214	***	(0.019)	0.220	***	(0.021)	0.244	***	(0.033)
Farmland parcel area (log)	−0.601	−0.456	***	(0.024)	−0.51	***	(0.012)	−0.59	***	(0.010)	−0.654	***	(0.009)	−0.717	***	(0.010)
Sale attributes																
Multisale (=1 if yes)	−0.113	−0.451	***	(0.047)	−0.217	***	(0.023)	−0.109	***	(0.02)	0.003		(0.019)	0.117	***	(0.031)
Spatial																
Travel cost – Town	−0.212	−0.223	***	(0.016)	−0.227	***	(0.010)	−0.219	***	(0.009)	−0.212	***	(0.009)	−0.176	***	(0.014)
Travel cost – City	−0.091	0.000		(0.078)	−0.084	**	(0.040)	−0.13	***	(0.033)	−0.167	***	(0.033)	−0.186	***	(0.043)
Regional effects (base = Central West)																
Region - North West	0.210	0.144	***	(0.040)	0.167	***	(0.023)	0.187	***	(0.020)	0.223	***	(0.022)	0.272	***	(0.027)
Region – Riverina	0.182	0.183	***	(0.039)	0.180	***	(0.022)	0.180	***	(0.016)	0.190	***	(0.019)	0.233	***	(0.022)
Climatic																
Annual rainfall current	0.000	0.000	***	(0.000)	0.000	**	(0.000)	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)
Annual rainfall 1 year prior	0.000	0.000		(0.000)	0.000	***	(0.000)	0.000	**	(0.000)	0.000	**	(0.000)	0.000		(0.000)
Annual rainfall 2 years prior	0.000	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)	0.000		(0.000)
Annual rainfall 3 years prior	0.000	0.000		(0.000)	0.000	**	(0.000)	0.000	***	(0.000)	0.000	**	(0.000)	0.000		(0.000)
Biophysical																
Steepness	−0.845	−0.672	***	(0.132)	−0.785	***	(0.067)	−0.857	***	(0.049)	−0.922	***	(0.058)	−1.065	***	(0.07
Soils_acid	0.001	0.000		(0.001)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)	0.000		(0.000)
Soils_carbon	0.001	0.002	***	(0.001)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)	0.001	***	(0.000)
Soils_water	0.002	0.003	***	(0.000)	0.003	***	(0.000)	0.002	***	(0.000)	0.002	***	(0.000)	0.001	***	(0.000)
Water coverage 20%	−0.022	−0.13	**	(0.060)	−0.03		(0.028)	−0.025		(0.034)	0.099	**	(0.051)	0.182	***	(0.064
Water coverage 5%	0.175	0.384	***	(0.076)	0.175	***	(0.047)	0.157	***	(0.044)	0.035		(0.069)	−0.166	**	(0.080)
Water coverage 1.5%	0.234	−0.135		(0.143)	0.226	**	(0.101)	0.256	***	(0.071)	0.253	***	(0.094)	0.524	***	(0.110)
Land use																
Land use - cropping	−0.516	0.574	***	(0.212)	−0.568	***	(0.105)	−1.101	***	(0.087)	−1.356	***	(0.094)	−1.230	***	(0.135)
Land use - cropping*log(area)	0.120	−0.060		(0.040)	0.146	***	(0.019)	0.229	***	(0.015)	0.261	***	(0.017)	0.228	***	(0.023)
Land use – grazing	−0.446	0.370		(0.216)	−0.084		(0.106)	−0.500	***	(0.088)	−0.870	***	(0.097)	−0.904	***	(0.131)
Land use - grazing*log(area)	0.065	−0.081	**	(0.040)	−0.005		(0.019)	0.068	***	(0.015)	0.135	***	(0.017)	0.161	***	(0.022)
Natural capital																
Vegetation clearing trend	−0.029	−0.007		(0.026)	−0.046	***	(0.015)	−0.043	***	(0.012)	−0.034	**	(0.015)	−0.016		(0.013)
Proportion box gum cover	1.015	1.726	***	(0.318)	1.706	***	(0.163)	1.182	***	(0.130)	0.756	***	(0.139)	0.230		(0.150)
Proportion box gum cover Squared	−0.191	−0.442	**	(0.229)	−0.517	***	(0.116)	−0.288	***	(0.096)	−0.094		(0.102)	0.210		(0.117)
Box gum cover*log(area)	−0.138	−0.285	***	(0.040)	−0.235	***	(0.019)	−0.158	***	(0.015)	−0.093		(0.016)	−0.039	**	(0.016)
Biodiversity_species richness	−0.011	−0.049	***	(0.013)	−0.022	***	(0.007)	−0.013	**	(0.005)	0.003		(0.006)	0.028	***	(0.008)
Biodiversity_functional evenness	0.231	0.040		(0.176)	0.045		(0.101)	0.193	***	(0.073)	0.331	***	(0.080)	0.626	***	(0.116)
Temporal dummy variables (base year = 2018)																
Y1990	−1.440	−1.602	***	(0.132)	−1.555	***	(0.094)	−1.497	***	(0.108)	−1.438	***	(0.113)	−1.436	***	(0.128)
Y1991	−1.451	−1.517	***	(0.15)	−1.486	***	(0.073)	−1.500	***	(0.058)	−1.485	***	(0.060)	−1.417	***	(0.084)
Y1992	−1.488	−1.561	***	(0.108)	−1.537	***	(0.069)	−1.509	***	(0.054)	−1.551	***	(0.059)	−1.482	***	(0.089)
Y1993	−1.536	−1.718	***	(0.100)	−1.610	***	(0.075)	−1.541	***	(0.062)	−1.534	***	(0.050)	−1.427	***	(0.078)
Y1994	−1.518	−1.594	***	(0.112)	−1.568	***	(0.059)	−1.493	***	(0.047)	−1.512	***	(0.045)	−1.498	***	(0.059)
Y1995	−1.336	−1.451	***	(0.123)	−1.370	***	(0.055)	−1.365	***	(0.048)	−1.352	***	(0.050)	−1.312	***	(0.057)
Y1996	−1.345	−1.568	***	(0.124)	−1.410	***	(0.071)	−1.334	***	(0.063)	−1.323	***	(0.062)	−1.249	***	(0.079)
Y1997	−1.256	−1.455	***	(0.089)	−1.280	***	(0.056)	−1.233	***	(0.049)	−1.241	***	(0.051)	−1.104	***	(0.074)
Y1998	−1.159	−1.255	***	(0.100)	−1.239	***	(0.059)	−1.219	***	(0.045)	−1.182	***	(0.044)	−1.152	***	(0.064)
Y1999	−1.203	−1.462	***	(0.136)	−1.288	***	(0.069)	−1.194	***	(0.056)	−1.189	***	(0.058)	−1.081	***	(0.074)
Y2000	−1.144	−1.335	***	(0.110)	−1.201	***	(0.055)	−1.148	***	(0.048)	−1.156	***	(0.043)	−1.060	***	(0.075)
Y2001	−1.035	−1.112	***	(0.096)	−1.113	***	(0.042)	−1.107	***	(0.040)	−1.082	***	(0.046)	−0.996	***	(0.049)
Y2002	−0.826	−0.842	***	(0.087)	−0.919	***	(0.04)	−0.898	***	(0.039)	−0.905	***	(0.036)	−0.853	***	(0.049)
Y2003	−0.669	−0.811	***	(0.102)	−0.722	***	(0.054)	−0.724	***	(0.044)	−0.740	***	(0.054)	−0.693	***	(0.064)
Y2004	−0.592	−0.825	***	(0.125)	−0.658	***	(0.065)	−0.569	***	(0.050)	−0.557	***	(0.049)	−0.493	***	(0.069)
Y2005	−0.505	−0.737	***	(0.115)	−0.478	***	(0.059)	−0.456	***	(0.052)	−0.490	***	(0.049)	−0.417	***	(0.063)

(*continued on next page*)

Table A.2 (*continued*)

Variables	OLS	Quantiles (Bootstrap Std. errors, 100 reps, in parentheses), n = 28,460														
		0.1			0.3			0.5			0.7			0.9		
Y2006	−0.329	−0.409	***	(0.091)	−0.321	***	(0.051)	−0.332	***	(0.040)	−0.387	***	(0.039)	−0.399	***	(0.049)
Y2007	−0.324	−0.356	***	(0.098)	−0.295	***	(0.054)	−0.310	***	(0.043)	−0.341	***	(0.043)	−0.376	***	(0.063)
Y2008	−0.433	−0.732	***	(0.148)	−0.402	***	(0.062)	−0.361	***	(0.052)	−0.369	***	(0.046)	−0.380	***	(0.068)
Y2009	−0.412	−0.549	***	(0.105)	−0.340	***	(0.052)	−0.292	***	(0.044)	−0.349	***	(0.042)	−0.364	***	(0.063)
Y2010	−0.526	−0.754	***	(0.129)	−0.445	***	(0.078)	−0.413	***	(0.065)	−0.445	***	(0.060)	−0.481	***	(0.077)
Y2011	−0.507	−0.672	***	(0.142)	−0.481	***	(0.069)	−0.445	***	(0.056)	−0.493	***	(0.054)	−0.462	***	(0.078)
Y2012	−0.685	−0.979	***	(0.177)	−0.558	***	(0.049)	−0.465	***	(0.043)	−0.505	***	(0.042)	−0.491	***	(0.049)
Y2013	−0.520	−0.537	***	(0.138)	−0.463	***	(0.050)	−0.476	***	(0.043)	−0.488	***	(0.046)	−0.443	***	(0.061)
Y2014	−0.519	−0.564	***	(0.106)	−0.399	***	(0.052)	−0.392	***	(0.041)	−0.426	***	(0.038)	−0.463	***	(0.055)
Y2015	−0.293	−0.413	***	(0.113)	−0.229	***	(0.054)	−0.236	***	(0.047)	−0.270	***	(0.047)	−0.351	***	(0.060)
Y2016	−0.171	−0.299	**	(0.13)	−0.186	***	(0.059)	−0.179	***	(0.057)	−0.185	***	(0.056)	−0.162	**	(0.076)
Y2017	−0.126	−0.263	**	(0.108)	−0.174	***	(0.049)	−0.120	***	(0.048)	−0.133	***	(0.041)	−0.071		(0.056)
Intercept	12.128	10.817	***	(0.455)	11.444	***	(0.230)	12.304	***	(0.212)	12.968	***	(0.214)	13.324	***	(0.266)
Pseudo R2 (R-squared for OLS)	0.5810	0.260			0.353			0.411			0.469			0.531		

** Significance at 5%

*** Significance at 1%

A.3. Results and discussion for other variables

Parcel area

The estimated coefficient for the log of parcel area was significant and negative across all quantiles, indicating the value of farmland per hectare decreased as parcel area increased. The magnitude of this negative effect increased substantially with increasing quantile, indicating that the discount for larger parcel areas increased with per hectare land value. These results are likely a reflection of economies of size and are consistent with findings from several other hedonic studies of rural land value (e.g Ma and Swinton, 2011; Polyakov et al., 2015b), though not all (Ritter et al., 2020).

Vegetation clearing

The trend in vegetation clearing variable was negative across all quantiles, and significant other than for the upper and lower quantiles. The size of the effect on land value is small. This is consistent with findings of Chancellor et al. (2019) who found a small but significant overall negative relationship between this variable and farmland prices.

Multi-parcel sales

The effect of parcels sold as part of a bundle was significant across most of the quantiles and attracted a discount, except for the premium price-per-hectare at the upper end of the distribution (90%) where aggregated parcels attracted a price premium. The size of the discount was largest at the lower end of the quantile. The results suggest aggregation is important to include in hedonic models for agricultural land, but the direction of the effect on land price is ambiguous, which has been found elsewhere (Ritter et al., 2020).

Infrastructure

The estimated coefficients for the infrastructure attributes in the model – presence of a house and farm buildings – are all significant and positive. In the study region, landownership is dominated by family-run farms (Binks et al., 2018) and therefore it is expected that the presence of a dwelling would add to the value of farmland. We found a large (+20%) positive effect of a house on land price for low quantiles, which dampens in the upper quantiles (down to −4% for 90% quantile). It is also expected that farm building infrastructure, such as storage and machinery sheds, delivers a significant, positive price premium. The size of this positive effect was fairly consistent across the quantiles (around +25%) and was highest for the parcels in the upper quantiles of the farmland value distribution.

The estimated effect of cropping and grazing land use on farmland price varied substantially across the quantiles in terms of the significance and size of the effect. The effects were sensitive to the size of the property, as shown by the significance of the interaction terms between land use and farm area across most quantiles.

Proximity to services

The costs associated with travel from a farm parcel to a small or large population centre was estimated to have a significant negative effect on farmland value. The estimated coefficients for the cost of travel of a population centre of 1000 people indicates farmland values are very sensitive to increments in this travel cost. A one unit increase in the cost of travel to a small population centre was estimated to reduce the median land value price as much as 20%. The sensitivity is not as high for travel to a larger population centre. A one unit increase in the cost of travel to a large population centre (100,000 people) was estimated to reduce the median price of farmland by 12%.

We found region had a significant effect ($P < .01$) on farmland value over and above other spatially defined variables in the model such as rainfall and travel cost. The three geographic regions defined by the Australian Bureau of Statistics within our study area (Riverina; Central West, and North West Slopes and Plains (DAFF, 2022) were included as dummy variables. The baseline region was defined as the Central West. Relative to this region, farmland in the other two regions attracted a price premium of around +20% at the median for parcels in the Riverina and Northwest relative to the Central West. The estimated coefficients were consistent across all quantiles.

Biophysical characteristics

We included a range of biophysical attributes in the model, representing key agricultural productivity factors. These included slope of the parcel, annual rainfall, soil condition, and water coverage. The price for farmland with steep slope was substantially lower compared to flatter terrain, and this effect increased with quantile. This is indicated by the significant ($P < .01$) negative coefficients across all quantiles. At the median, the price of farmland per hectare that is rated 'steep' attracts a large penalty. This is an expected result, reflecting the difficulties for agricultural production posed by steep terrain. Given the importance of sufficient and reliable rainfall for agricultural production, we expected the four annual rainfall variables to have a significant positive effect on farmland prices, with increasing effect from lower to upper quantiles. However, many of the estimated coefficients were insignificant across all four rainfall variables (current and 3 years of prior annual rainfall). This may be due to similar rainfall conditions experienced across the case study area of southeast New South Wales. The soil condition variables indicate a degree of risk for nutrient loss and erosion. Given higher values of the soil condition variables represent negative outcomes for agricultural productivity, we expected estimation of significant negative coefficients. However, significant positive (albeit low value) coefficients were estimated. The value of coefficients largely remained the same across all variables and quantiles. Three water coverage variables were included in the final model. These include indicators of ephemeral water bodies (water coverage, 20%), intermittent water bodies (water coverage, 5%) and flooding risk (water coverage, 1.5%), which have important implications for agricultural production capability.

We expected a positive correlation between water coverage of 20% and water coverage of 5% and farmland value and negative correlation with water coverage of 1.5%, however, the results are mixed and vary substantially across the quantiles. The positive and significant coefficients (at $P < .05$) for water coverage of 20% for the upper quantiles are consistent with what we expected. The positive and significant effect of water coverage of 5% for the lower quantiles is also expected, however, the negative effect for the upper quantile is difficult to explain. The results for water coverage of 1.5% are positive and significant (at $P < .05$) is unexpected in so far as higher values of water coverage of 1.5% indicated flood risk.

Temporal effect

Finally, a temporal effect (from 1990 to 2018) was included in the model as a set of dummy variables for each year, with 2018 as the base year. As expected, all estimated coefficients are negative and almost all are significant (at $P < .01$).

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108116.

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