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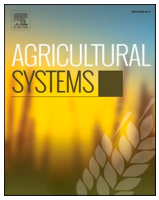

Research Paper

Natural capital enhances farm production, profitability and financial resilience: findings from a study on 230,000 ha of farmland in Australia

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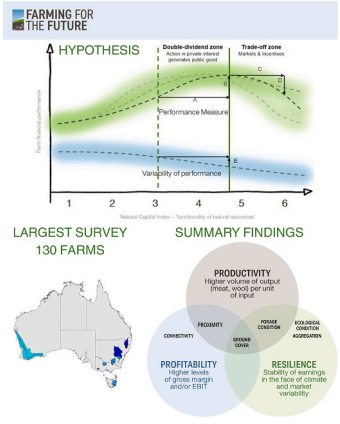
HIGHLIGHTS

- Largest data set linking natural capital to farm production, profits and resilience.
- Farm business performance was positively associated with natural capital.
- Higher natural capital farms had higher livestock productivity, by up to 3 %.
- Higher natural capital farms had higher gross margin and higher farm earnings.
- Farms with higher levels of natural capital were more resilient.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Ambitious targets under the Paris Climate Agreement and the Kunming-Montreal Global Biodiversity Framework bring increasing urgency for agriculture to play an active role as a nature-based solution to climate and biodiversity loss. But widespread uptake of nature-based solutions by the agriculture sector has proved elusive. This paper presents the results of the *Farming for the Future Livestock Program*, a large-scale program that sought to quantify the financial implications of natural capital for farm business performance in Australia's

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Environmental assets
Longitudina

broadacre livestock sector, which covers 350 million ha and contributes more than 50% of the country's gross value of agricultural production.

OBJECTIVE: We aim to build a better understanding of the financial implications of natural capital on farms - a critical knowledge gap that limits effective policy and landholder adoption of nature-based solutions in the agriculture sector. We aim to quantify the effect of on-farm natural capital on farm business performance.

METHODS: We collected natural capital data from 114 farms via satellite imagery analysis and on-ground vegetation surveys, alongside production and financial data collected via detailed producer surveys. We used five natural capital metrics (*Ecological Condition*, *Aggregation*, *Proximity*, *Ground Cover*, and *Forage Condition*) to understand the effect of natural capital on farm business performance (productivity efficiency, profitability and financial resilience) on farms with a combined land area of >230,000 ha, in the largest analysis of its kind to date.

RESULTS AND CONCLUSIONS: Our multi-region models tested a total of 20 natural capital – farm business performance relationships (4 business performance measures x 5 natural capital metrics). There was moderate or strong evidence for 6 of these (5 positive, one negative) and weak statistical evidence for a further 6 relationships (4 positive, 2 negative). Region-specific models yielded similar results to the multi-region model. This suggests that high-performing livestock businesses benefit from high levels of natural capital. High levels of specific types of natural capital were associated with increased production efficiency of up to 3%, improved livestock gross margin, higher farm earnings, and higher levels of climate resilience.

SIGNIFICANCE: We highlight the important role that integrating robust information about the financial implications of natural capital in production systems can play in shaping appropriate and adoptable nature-based climate solutions for the agriculture sector.

1. Introduction

Ambitious targets under the Paris Climate Agreement and the Kunming-Montreal Global Biodiversity Framework bring increasing urgency for agriculture to play an active role as a nature-based solution to climate and biodiversity loss (Kok et al., 2018; Norris, 2008; Pe'er et al., 2022). It is estimated that 'natural climate solutions' in the agriculture sector – i.e. solutions that seek to mitigate carbon sequestration through the management of agricultural landscapes - could contribute an additional ~4-5Gt of CO_2 sequestration per year, equivalent to 15% of the total required to keep global warming below 2 °C (Griscom et al., 2017; Nabuurs et al., 2023), whilst simultaneously addressing issues around ongoing biodiversity loss and landscape degradation (Folkard-Tapp et al., 2021; Griscom et al., 2017).

The agricultural sector contributes to export earnings of many countries, accounting for 4% of global GDP and for more than 30% of GDP in some countries (World Bank, 2022). Agricultural production also contributes to food security, poverty alleviation (Herrero et al., 2009; Loayza and Raddatz, 2010; Vågsholm et al., 2020) and climate resilience (Townsend, 2015). Global reliance on agriculture for food and fibre, along with its critical connections to economies (Çakmakçı et al., 2023), livelihoods (Ren et al., 2022), and community wellbeing (Martinez et al., 2022) highlight the importance of understanding the economic, environmental and social implications of any proposed nature-based climate solutions for the agriculture sector prior to widespread implementation.

To date, widespread uptake of nature-based solutions by the agriculture sector has proved elusive. We believe a current lack of understanding relating to the financial implications of natural capital on farms is the critical knowledge gap that limits effective policy and landholder adoption of nature-based solutions in the agriculture sector. Pathways for improving environmental management in farming systems have historically been viewed as an environment - production trade-off where gains in one are assumed to come at the expense of the other (Meyfroidt, 2018; Miralles-Wilhelm, 2021). This perspective has been seen as a limiting factor in the adoption of more sustainable practices. However, this is increasingly being challenged by a growing recognition of the need for an agricultural sector that supports today's population whilst also maintaining ecosystems and building land and soil quality. This shift is now evident in global initiatives such as the UN Sustainable Development Goals (SDG) and the IUCN Sustainable Agriculture and Land Health Initiative (Larbodière et al., 2020; United Nations, 2015). Specifically, SDG 2 explicitly targets the dual objective of achieving food security *and* sustainable agriculture.

Previous studies have explored the potential for environment-production synergies at the landscape scale, often through models based on major re-allocation of land-use patterns (Fischer et al., 2017; Kanojia et al., 2025; Phalan et al., 2011). However, such large-scale transformations ultimately depend on decisions made by individual landholders (Lambin et al., 2000). This means that the changes required to meet global climate and biodiversity targets must be implemented on a farm-by farm-basis. As such, synergies between environmental outcomes and agricultural productivity that are demonstrable at the individual farm scale are likely to be the most actionable and influential.

Most agricultural producers who undertake actions to improve their natural resource management are primarily motivated by the prospect of enhanced farm productivity and resilience (Aisbett and Kragt, 2010; Ecker et al., 2012; Mallawaarachchi and Szakiel, 2007; Pannell et al., 2006; Pannell and Roberts, 2015). Understanding the economic implications of on-farm natural capital practices, particularly those that enhance farm productivity, profitability and resilience, may be crucial to effectively engaging the worlds farmers. Given that farmers manage 38% of the earths land surface (World Bank, 2020), identifying natural capital strategies that align with their economic interests could also foster positive and productive outcomes at the landscape scale.

Knowledge of the private benefits that accrue from management of on-farm natural capital is also an important input to efficient public policy (Clayton et al., 2024; Pannell et al., 2006; Pannell and Roberts, 2015). Cost effective policy is a primary concern for global climate and biodiversity targets, given the funding shortfall that has been projected (Seidl et al., 2024). In situations where environmental benefits are achieved through a trade-off with production, government and/or market incentives may be justified. However, in situations where good environmental performance improves farm profitability and delivers a net financial benefit to the farmer (once the costs of transitioning to improved natural capital management have been accounted for) incentives paid to landholders are potentially unjustified (Pannell and Roberts, 2015). In these cases, uptake should be encouraged through education and engagement (Mallawaarachchi and Szakiel, 2007; Pannell and Roberts, 2015; Rolfe et al., 2021).

Despite the central role that robust estimates of the private economic benefits can play in shaping policy and incentivising adoption, the relationship between natural capital and farm performance remains poorly understood outside of experimental settings and small studies (Barbi et al., 2015; Gosnell et al., 2019; Rolfe et al., 2021; Rolfe and Gregg, 2015; Star et al., 2013). Moreover, very few studies, if any, have

reported the benefits associated with on-farm natural capital in explicit financial terms. This represents a significant gap in the evidence base needed to support widespread adoption of natural capital solutions in agriculture, particularly among producers who require clear economic justifications for altering land management practices.

Here, we report on the *Farming for the Future Livestock Program*, implemented from 2021 to 2024, which collected detailed natural capital, production and financial data from 114 livestock businesses located in three agricultural regions of Australia. The program collated the largest data set of its type in the world, enabling a detailed investigation into the relationship between natural capital and farm performance across a substantial part of the Australian farming landscape. This paper presents the high-level insights from this unique data collection program. Specifically, we relate measures of farm business performance (production efficiency, profitability, financial resilience) to a suite of farm-scale natural capital metrics to: (i) elucidate the relationship between natural capital and farm business performance; (ii) investigate trade-offs between business performance and farm-scale natural capital; and (iii) identify opportunities for natural capital to support farm business performance.

2. Methods

2.1. Study region

This project focussed on livestock or mixed cropping-livestock operations in the broadacre agricultural zone across four Australian states (New South Wales, Victoria, Tasmania and Western Australia; Fig. 1). The Australian broadacre zone covers approximately 350 million hectares (Hughes et al., 2022) and is responsible for more than 50% of the country's gross value of agricultural production (Xie et al., 2024). It is also a focal point for land clearing and associated environmental issues like water management (Heagney et al., 2021; Thornton and Elledge, 2022).

Farms in the Australian broadacre zone have mean size of ~7000 ha, with 66% operating as livestock specialists, 20% as cropping specialists and 14% as mixed cropping-livestock businesses (Table 1). A summary of characteristics of broadacre farms in each of the Australian states included in our study is provided in Table 1. Prior to European colonisation, the broadacre zone in eastern Australia was typically covered in Eucalypt woodlands and forests, with occasional grasslands and heathlands. Many farms contain remnants of these ecosystems, as evidenced by the on-ground assessments undertaken by this project. The broadacre zone in Western Australia was originally covered in a mix of Mallee or Eucalypt woodlands, interspersed with Acacia and Chenopod shrublands. A smaller quantum of remnant vegetation exists in this region today.

We surveyed 114 farms broadacre farms across the study region, with a combined land area of >230,000 ha. Farms were: a) located within one of three climatic sub-regions based on the underlying climatic sub-regions (Peel et al., 2007) (Fig. 1), b) 500–6000 ha in size, and c) predominantly livestock (sheep and/or cattle) operations (i.e. >50% of the farms productive land area used for livestock operations). These spatial and enterprise constraints enabled like-for like- comparisons of

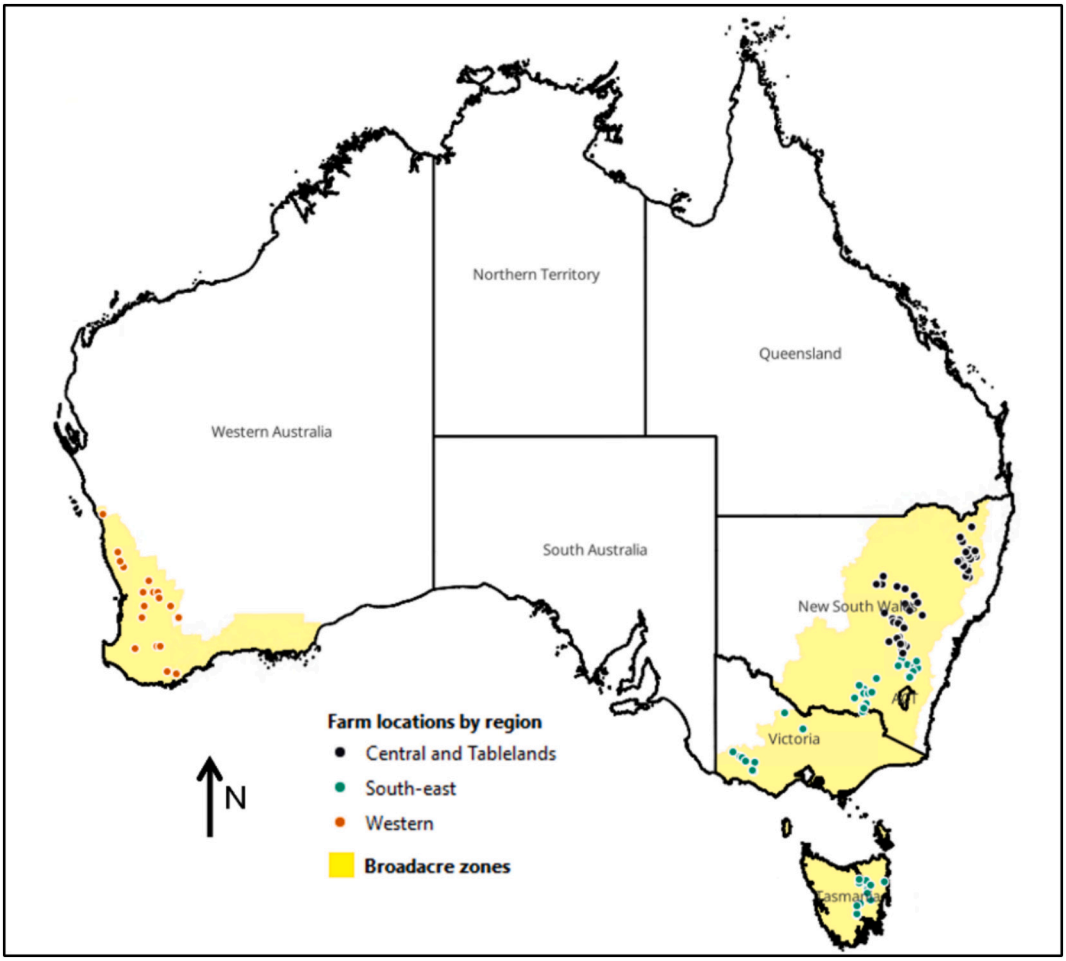

Fig. 1. Map showing the extent of the Australian broadacre zones in relevant states (NSW, Victoria, Western Australia and Tasmania). Dots show the location of sample farms and have been grouped into 'Regions' based on climatic subregion categories (Bureau of Meteorology, 2014; Peel et al., 2007).

Table 1
Characteristics of Australian broadacre farms – national and state level data as reported for 2024 (ABARES, 2025b). Percentages are calculated based on the total number of farms in each of the enterprise mix categories listed (not percentage by land area).

Characteristic	Australia	NSW	Victoria	Western Australia	Tasmania
Number of farms (no)	49,242	16,131	11,825	5,550	1,099
Mean farm size (ha)	7,165	3,415	776	13,578	854
Beef specialists (%)	39.7	36.4	39.2	19.6	34.1
Sheep specialists (%)	18.8	18.9	24.5	21.3	41.8
Mixed sheep-beef (%)	8.2	14.4	7.3	3.1	12.6
Cropping specialists (%)	19.6	12.7	18.9	33.8	0.2
Mixed cropping-livestock (%)	13.6	17.6	10.1	22.1	11.1

Table 2
Land and climate characteristics of surveyed farms in each focus region. Figures are mean for all farms included in the analysis (standard error in brackets). Temperature and rainfall averages are for the 5-year period 2017–2022).

	Central and Tablelands	South-east	Western
No. of farms in sample	56	42	16
Mean farm size (ha)	2050 (155)	1980 (195)	2700 (370)
Mean elevation (m)	715 (45)	365 (30)	255 (15)
Mean annual rainfall (mm)	704 (42)	612 (36)	396 (31)
Mean no. days 8–30 °C per year	309 (5)	319 (5)	278 (8)

farm performance and ensured that the sampled farms were broadly representative of farming enterprises within the study regions. Mean land climate characteristics for sample farms in each of the three climatic subregions included in our study are provided in Table 2.

2.2. Natural capital metrics

For the purposes of our study, natural capital is defined "the natural resources that producers manage for the benefit of their businesses" (Ogilvy et al., 2024). We use metrics that quantify the extent and condition of selected elements of natural capital on the farm, focussing specifically on *Ecological Condition*, *Aggregation*, *Proximity*, *Ground Cover*, and *Forage Condition*. The rationale for selection and calculation for these natural capital metrics is presented in Table 3, with additional detail provided in Rainsford et al. (2025a, 2025b).

Data to calculate the natural capital metrics in Table 3 were collected via on-ground vegetation surveys in conjunction with geo-spatial data layers. On-ground surveys were conducted at 130 farms between October 2021 and November 2023. Vegetation surveys included on-ground sampling of up to 30 points on each farm, with sampling

Table 3
Natural capital metrics: description, rationale, supporting literature and formula to calculate each at the farm-scale (from Rainsford et al., 2025a, 2025b).

Natural capital metric	Description	Rationale and associated ecosystem services	Supporting literature	Formula
Ecological Condition	An area-weighted measure of the degree of departure from a reference, or best-on-offer, ecological condition.	Ecological Condition will influence the extent to which a parcel of land contributes to most ecosystem services, especially supporting and cultural services, e.g., habitat for species, maintenance of genetic diversity.	Dudley and Alexander, 2017; Gardiner et al., 2018; Lunt and Spooner, 2005; McNellie et al., 2020; Reidsma et al., 2006.	$\sum_i^k Ai^* Wi$ / A_{farm} Ai = total area of Ecosystem Condition State i; Wi = weighting for Ecosystem Condition State i; A_{farm} = total farm area
Aggregation	The extent to which woody vegetation is arranged into contiguous patches or distributed across many discrete patches.	More aggregated habitats typically support more species than sparse or fragmented habitats of equivalent total area. Aggregated woody vegetation may also provide shelter services.	Bailey et al., 2010; Deslauriers et al., 2018	$[1/A_{total}(A_{G1}^2 + A_{G2}^2 + A_{G3}^2 + \ldots + + A_{Gn}^2)]/A_{farm}$ n = number of patches of wooded vegetation; A_1, A_2, A_3, … = area of each patch; A_{total} = total area of all wooded vegetation on the farm; A_{farm} = total farm area
Proximity	The average distance of production areas to woody vegetation.	Proximity of production areas to woody vegetation influences a range of ecosystem services, e.g., shade for livestock, wind-reduction, pollination and pest-suppression by beneficial invertebrates.	Baker et al., 2018; Kuyah et al., 2016; Weninger et al., 2021	Mean($10/d$) d = distance of production cell to nearest treed cell
Ground cover	The extent to which the land surface is covered by live and/or dead plant material (grasses, forbs, herbs, shrubs, mosses, lichens).	Ground cover contributes to soil fertility, soil erosion control, regulation of water flow, freshwater, forage. Ground cover slows surface water flows, increasing water infiltration and filtering sediments and particles from water and improving the quality of water flowing into dams, drainages and waterways, and increasing soil moisture.	Ellili-Bargaoui et al., 2021; Silver et al., 2021; Wang et al., 2023	$(\alpha + \beta + \gamma)/3$ α = mean of 50th percentile ground cover, β = mean of 10th percentile ground cover, γ = mean of variance of ground cover
Forage Condition	An area-weighted measure of palatability, productivity and perenniality for all pastures.	Forage Condition represents the quality of pastures for livestock.	Jaramillo et al., 2021; Meat and Livestock Australia, 2006	$\sum_i^k Ai^* Wi$ / A_{Grazed} A_i = total area of pasture condition score i; W_i = assigned weighting for pasture condition score i; A_{Grazed} = total area that is used for grazing.

stratified based on land characteristics. Farms were divided into areas of similar ecological type, as determined via remotely sensed data relating to land-use, canopy cover, ground cover, and state and condition (for grassy woodlands). Each distinct ecological type was surveyed at least 3 times (where this was possible) in at least three different paddocks on the farm. A sample farm map showing stratification and survey points is provided in the Supplementary Materials. Further details of survey stratification, on-ground sampling techniques and natural capital metric calculations are provided in technical documentation for the *Farming for the Future* program (Farming for the Future, 2024) and in (Rainsford et al., 2024).

2.3. Business performance measures

Farm production and financial data were collected by experienced farm advisors and accountants who had extensive farming knowledge and experience relevant to each of the focus regions. Data collection included both farmer interviews and interrogation of formal business records (accounting records and other relevant documents). Data were collected for five financial years (2017–2022) and reported annually by financial year. Of the 130 farms where vegetation surveys were undertaken, 114 were able to provide high quality production and financial data for the full period of interest; the remaining 16 farms were excluded from further analysis.

Farm production and financial data were used to generate four measures of farm business performance: production efficiency, gross margin, earnings before interest and tax (EBIT) and financial resilience. These farm business performance measures were selected via a series of workshops with six professional farm advisors operating in our study regions, who identified them as being key decision-relevant metrics used by local farmers. The selected measures have been used in a range of published agricultural economic analyses (e.g. Godfrey et al., 2021; Kharel et al., 2025). Engagement with local farm advisors also informed our calculation approach to each of the selected farm performance measures to ensure that calculations were consistent with local industry standards. Further details relating to the calculation of farm business performance measures are provided in Table 4.

2.4. Model covariates

To account for the potential influence of temporal and spatial trends on natural capital-farm performance relationships, we included the terms *Year* and *Region* as covariates in the models. We included *Rainfall* to account for site specific annual rainfall totals, which are known to impact livestock productivity (Emediegwu and Ubabukoh, 2023; Henry et al., 2018); this covariate was calculated using daily precipitation grids produced by the Bureau of Meteorology (2025) from approximately 6500 rain gauge stations and interpolated to a 0.05 degree (approximately 5 × 5 km) national grid (Jones et al., 2009). The estimates are subject to approximations associated with interpolating observation point data to a national grid detailed in Jones et al. (2009). Our *Rainfall* covariate is the area weighted mean annual rainfall based on farm boundaries.

There are often very close associations between vegetation types, condition and configuration and soils and landform in addition to their influence of farm and environmental performance. Accordingly, we included a term *Land Capability Class* to account for underlying differences in soil and landscape quality, and to separate out the effect of

Table 4
Farm business performance measures.

Measure	Definition and calculation
Production efficiency Index (0–1)	Production efficiency is a comparative measure of how efficiently an enterprise produces output, using its inputs, compared to other similar enterprises. It can be thought of as the ratio of output produced to inputs used. Production efficiency was calculated using an established benchmarking technique known as Data Envelopment Analysis (DEA). We have compared outputs (cattle liveweight gain, sheep liveweight gain, wool) produced from physical quantities of inputs (labour, fodder, energy, chemicals, animal health costs, contractors, irrigation, land). We used an output-oriented DEA with variable returns to scale to calculate production efficiency. DEAs were estimated using the 'Benchmarking' package in R (Bogetoft and Otto, 2022). We have accounted for environmental factors (rainfall, number of days >30 °C, days 8–30 °C, elevation) that can impact production. This ensures that production efficiency scores account for the environmental constraints present on an individual farm and that production efficiency is comparable across farms. Production efficiency was calculated on an annual basis. The most efficient farm(s) in the data set have a production efficiency score of 1. Other scores are expressed as a proportion of the maximum: if a farm has an efficiency score of 0.95, it would produce 95% of the outputs of the most efficient farm from the same set of inputs.
Gross margin ($/ha)	Gross margin is a measure of variable profit for a particular activity, enterprise, or business – in this current study we calculate gross margin for the livestock enterprise. Gross margin is calculated as the sum of value of farm production, including: • production of cattle liveweight • production of sheep liveweight • production of wool minus variable costs: • cost of labour, fodder, energy, chemicals, animal health costs, contractors. Gross margin was calculated on a per hectare basis (per hectare of livestock area) and reported annually (based on financial year).
EBIT ($/ha)	Earnings Before Interest and Tax (EBIT) is a measure of whole farm profit, including profit from livestock, cropping and other enterprises). EBIT is calculated including the value of production and variable costs as described for Gross margin above, plus: • off-farm income (including farm-related contracts, agistment payments) minus costs: • depreciation / amortisation (estimated at 10% of fair market value for farm machinery and 2% of fair market value for infrastructure). As a whole farm measure, EBIT includes the value and costs associated with all enterprises (livestock plus cropping or horticulture that may be present as a 'mixed farming business'). EBIT was calculated on a per hectare basis (per hectare of livestock area) and reported annually (based on financial year).
Financial resilience Index	Financial resilience measures the stability of earnings (EBIT) relative to variation in rainfall. We calculated EBIT for all years for which data was supplied and estimated the variability (standard deviation) of EBIT over the length of the time series provided (up to 5 years). We developed a financial resilience metric that linked variability in EBIT to underlying variability in rainfall using the equation: *Financial resilience = 1/standard deviation (EBIT) / standard deviation (rainfall) * EBIT rank* The final term in the financial resilience equation (EBIT rank) accounts for a farm's relative performance each year. To score highly on this metric, farms need to perform consistently and perform well compared to their peers in any given year.

vegetation (extent condition and configuration) from these underlying factors. *Land Capability Class* was calculated as the area weighted mean based on data published by Adams and Engert (2023).

The state of a farm's natural capital can be linked to farm management decisions. Our focus was on the financial contribution made by natural capital itself (i.e. the contribution made by the extent and condition of physical natural resources on the farm) rather than any particular farm management mode or activity. Accordingly, we sought to separate out the effects of farm management (actions) from effects associated with the underlying natural capital (states) by including a covariate '*Farming mode*', based on clustering of 6 farm management variables relating to pasture, livestock and environmental management. Clustering analysis identified three farming modes with varying levels of input intensity (Table 5; see Supplementary Materials for full details).

We added an additional covariate to account for repeated measures effects arising from annual re-sampling of financial and production data from the same farms, whereby business performance may be influenced by a farmer's management abilities or other unobserved factors. We used the term *Diff,* which was calculated by quasi-differencing, with the reference term (rho) estimated from the correlation coefficient between lagged and non-lagged residuals. This approach is appropriate where repeated measures models also include a time invariant explanatory variable (like our natural capital metrics) (Girma, 2000). The *Diff* term was excluded from modelling of our financial resilience index, which consolidated multi-year observations into a single performance measure.

2.5. Data analysis

Original reporting for the *Farming for the Future Livestock Pilot Program* in Ogilvy et al. (2024) modelled relationships between farm business performance and each natural capital metric individually, using a separate model for each natural capital metric, in order to establish whether high quality natural capital and strong farm business performance were co-occurring (positively associated) or coming as a trade-off (negatively associated). The analysis identified several positive associations, for example, between production efficiency and *Ecological Condition*, *Proximity* and *Ground Cover*. But a moderate-to-high degree of correlation among some natural capital metrics (Pearson's coefficient range 0.28–0.79; see Supplementary Materials) limits the interpretation of single natural capital metrics models: they are descriptive rather than explanatory (Gregorich et al., 2021).

In contrast, this current study takes an explanatory approach. It seeks to isolate the effects of specific natural capital metrics on farm business performance, whilst accounting for the observed correlation among metrics, as well as the potential influence of covariates, like *Rainfall* and '*Farming mode*'. Accordingly, we have implemented an information theoretic approach, following Anderson (2008), to select the 'best' model from a set of candidate models containing all possible combinations of natural capital metrics.

Candidate models of the relationship between farm performance measures and natural capital metrics were constructed using Generalised Additive Models (GAMs). This approach was selected because it enables identification of non-linear relationships between variables and effects like thresholds, maxima and minima (Beck and Jackman, 1998; Zuur et al., 2009). Models with production efficiency, gross margin or EBIT as the dependent variable included covariates *Year*, *Region*, *Farming mode*, *Rainfall*, *Land capability class* and *Diff*; models with financial resilience as the dependent variable included a reduced set of covariates (*Region*, *Farming mode*, *Rainfall*, *Land capability class*), excluding *Year* and *Diff* as these were only relevant for multi-year models. We ran a model dredge using the MuMIn package in R (Barton, 2022) to select the subset of natural capital metrics to include in each model, using corrected Akaike's Information Criterion (AICc) as the model selection criterion.

GAMs were used to implement a global model that included all farms in the *Farming for the Future Livestock Program* data set ($n = 114$ farms), as well as region-specific models that included subsets of farms in each of the 3 study focus regions (see Fig. 1). GAM parameterisation is shown in Eq. 1. Smoothed terms are denoted s(term).

$$\begin{aligned}\text{Performance indictor} = {} & \text{Year} + \text{Region} + \text{Farming Mode} + s(\text{Rainfall}) \\ & + s(\text{Land Capability Class}) + s(\text{Diff}) \\ & + s(\text{Natural Capital Metrics (optional)})\end{aligned} \tag{1}$$

GAMs were implemented using *mgcv* package in R (Wood, 2011). We removed all outliers (any point more than 4 absolute median deviations from the median) prior to analysis. This removed only a small number of data points ($n = 3$–4, depending on the farm business indicator). Each GAM was limited to a maximum of three knots (inflection points) to prevent overfitting and enable interpretation of key non-linear trends like threshold or parabolic (maxima or minima) effects. Production efficiency models were fit using a beta error distribution as this metric is bounded at 0 and 1. Gross margin, EBIT and financial resilience models were fit using a Gaussian error distribution. We interpret GAMs following Muff et al. (2022); we considered $p < 0.001$ to be 'very strong evidence' of a relationship between natural capital and farm performance, $0.001 < p < 0.01$ to be 'strong evidence', $0.01 < p < 0.05$ to be 'moderate evidence', $0.05 < p < 0.1$ to be 'weak evidence' and $p > 0.1$ to be 'no evidence'.

Table 5
Key characteristics of sample farms, by Farming Mode.

	1			2			3		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
	Farming Mode 1			Farming Mode 2			Farming Mode 3		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Farm area (ha)	1,640	1,740	878	2,060	1,720	1,250	2,130	1,840	1,230
Livestock area (ha)	1,140	1,160	416	1,650	1,190	1,070	1,960	1,680	1,150
Cropping area (ha)	522	237	717	459	376	436	310	115	456
Aggregate stock (DSE)	13,300	12,600	4,960	10,400	6,950	7,610	7,470	6,300	4,810
Aggregate stock (DSE/ha)	12.0	12.1	2.7	6.6	6.1	2.7	4.1	4.2	1.8
Sheep stock (DSE)	10,700	11,700	5,250	6,480	5,170	4,970	5,110	4,280	4,250
Sheep stock (DSE/ha)	10.0	10.4	3.8	4.6	4.6	2.8	2.7	2.6	1.7
Cattle stock (DSE)	3,930	926	5,620	5,910	3,150	7,030	4,140	3,520	3,630
Cattle stock (DSE/ha)	3.19	0.95	4.11	3.34	1.96	2.99	2.30	1.77	1.87
Sown pasture - perennial (proportion)	0.65	0.70	0.20	0.40	0.42	0.17	0.13	0.10	0.07
Sown pasture - annual (proportion)	0.19	0.15	0.18	0.09	0.06	0.07	0.06	0.06	0.04
Pasture - naturalised (proportion)	0.20	0.18	0.15	0.57	0.53	0.19	0.92	0.94	0.10
Chemical use intensity	0.05	0.04	0.04	0.02	0.01	0.03	0.01	0.00	0.01

3. Results

Our global models tested a total of 20 natural capital – farm business performance relationships (4 business performance measures x 5 natural capital metrics). There was moderate or strong evidence for 6 of these (5 positive, one negative) and weak statistical evidence for a further 6 relationships (4 positive, 2 negative; Table 6, Fig. 2). There was evidence of positive associations between natural capital and livestock business performance across one or more financial performance metrics for all of the natural capital metrics investigated, pointing to substantial potential for natural capital to contribute positively to the financial performance of livestock enterprises.

Farms with higher *Proximity* and/or *Forage condition* scores displayed higher levels of production efficiency, with a gain of approximately 3% efficiency moving from the lowest to the highest natural capital scores (Fig. 2a). There was evidence of a trade-off in Production efficiency once *Proximity* exceeded 0.4, and also weak evidence that Production efficiency may decline with increasing *Ground cover* (Fig. 2a).

Farms with high *Proximity* and *Ground cover* had significantly higher gross margins from the livestock enterprises in their farm business (Fig. 2b). Again, there was evidence of a trade-off when *Ground cover* was greater than 0.75 and weak evidence for a trade-off with *Ecological condition* (Fig. 2b). Farms with higher *Ground Cover* scores also reported higher EBIT per ha (Fig. 2c).

Higher *Ecological condition*, *Aggregation*, *Ground cover* and *Forage condition* scores were associated with higher levels of financial resilience (Fig. 2d). Farms that scored highly for these natural capital metrics experienced more stable earnings in the face of rainfall variability over the study period (2017–2022) – a period which included at least one period of drought declaration across our study region (Bureau of Meteorology, 2024).

Region-specific models yielded similar results to the global model. Of all 80 natural capital–farm business performance relationships tested (global model plus 3 regions × 4 business performance measures x 5 natural capital metrics) 91% were positive or neutral (30% positive, 14% curvilinear with both positive and negative segments, 46% neutral; Table 7). Natural capital – farm performance relationships were observed to be variable across regions and between farm types (Table 7), and a small number of negative natural capital – farm business performance relationships were observed (Table 7). For example, there was a negative association between '*Ecological Condition*' and gross margin in Western Australian farms. Full summaries of outputs for our region-specific GAMs are provided in the Supplementary Materials.

4. Discussion

4.1. Relationship between natural capital and financial performance on Australian livestock farms

Positive relationships between natural capital metrics *Proximity* and *Forage condition* and production efficiency imply that both distance of the woody vegetation to production areas and the quality of the pasture for livestock can increase the amount of output (meat, wool) from a given set of inputs. For example, shelter from trees close to livestock areas may increase lamb survival, especially in the case of multiple births (Keenan et al., 2023); use of perennial pasture species with high palatability might promote higher livestock growth rates. The quantum of productivity gain observed in low versus high natural capital farms (3%) is noteworthy, given that productivity growth in the Australian broadacre agriculture sector has averaged only 0.2% per annum over the past decade (ABARES, 2025a).

Positive relationships between natural capital metrics *Proximity* and *Ground cover* and gross margin suggests that, where vegetation is close to the productive part of a farming property, it is better able to deliver key ecosystem services, like shelter for livestock, directly to production activities. In some cases, ecosystem services from vegetation in close proximity to production areas may replace purchased inputs – like synthetic pesticides - and further improve gross margin.

Natural capital metrics *Ecological condition* and *Aggregation* showed the strongest positive association with financial resilience. These metrics reflect key aspects of ecosystem and habitat quality, which are likely to influence the quality of associated biodiversity and the provision of ecosystem services. This finding suggests that consolidated patches of high-quality vegetation, along with the biodiversity and ecosystem services they support, may act as an important stabilising factor that could buffer livestock enterprises in the Australian broadacre zone against future climate variability. In addition to *Ecological condition* and *Aggregation*, *Ground cover* and *Forage condition* were also highly correlated with financial resilience. Our observation that higher financial resilience is associated with higher levels of natural capital aligns with findings from experimental investigations, case studies and applied demonstrations. These studies indicate that natural capital practices, including the use of persistent, perennial, palatable forages, adaptive grazing management, cover-cropping and tree establishment, can increase drought resilience for production (Cong et al., 2014; England et al., 2020; Maseyk et al., 2022).

The positive relationships between financial and natural capital metrics reported in our study suggest that high-performing livestock businesses can exist, operate in, and maintain high levels of natural capital. They also suggest that farm businesses may be able to improve their natural capital to improve the productivity, profitability and financial resilience of their farm business. But the type of natural capital

Table 6
Natural capital – farm performance relationships based on GAMs. Edf is estimated degrees of freedom; Ref.df is reference degrees of freedom; Statistic is F-value; Relationship describes the overall direction of the natural capital-business performance relationship (positive or negative). Only natural capital metrics that were included in the 'best' model from our model dredge process are shown. Full model outputs including summaries for non-natural capital model terms are provided in the Supplementary Materials.

Business performance measure	Natural capital metric	Edf	Ref.df	Statistic	*p*-value	Strength of evidence	Relationship
PRODUCTION EFFICIENCY	PROXIMITY	1.73	1.92	4.30	0.036	Moderate	positive
	GROUND_COVER	1.65	1.88	3.66	0.055	Weak	negative
	FORAGE_CONDITION	1.62	1.85	2.10	0.078	Weak	positive
LIVESTOCK GROSS MARGIN ($ per ha)	ECOLOGICAL_CONDITION	1.00	1.00	2.90	0.089	Weak	negative
	PROXIMITY	1.00	1.00	4.06	0.045	Moderate	positive
	GROUND_COVER	1.87	1.98	3.21	0.046	Moderate	positive
EBIT ($ per ha)	GROUND_COVER	1.77	1.95	2.69	0.055	Weak	positive
FINANCIAL RESILIENCE	ECOLOGICAL_CONDITION	1.12	1.22	6.86	0.004	Strong	positive
	AGGREGATION	1.92	1.99	7.25	0.001	Strong	positive
	PROXIMITY	1.82	1.96	5.55	0.010	Moderate	negative
	GROUND_COVER	1.00	1.00	8.19	0.004	Strong	positive
	FORAGE_CONDITION	1.00	1.00	6.50	0.011	Moderate	positive

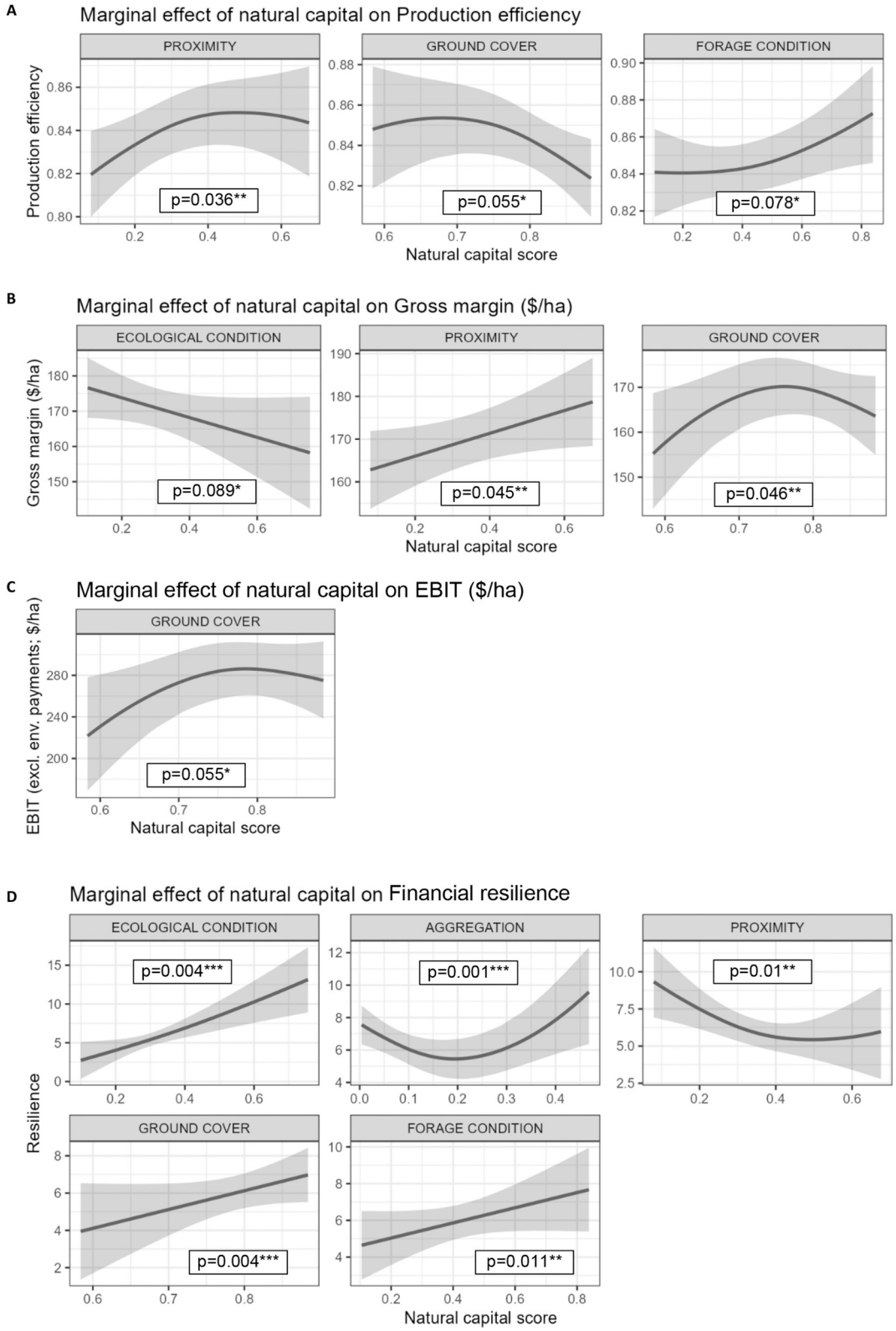

Fig. 2. Natural capital – farm business performance relationships from GAMs for A) production efficiency, b) Livestock gross margin, c) EBIT and d) financial resilience. Shading shows 95% confidence interval of the mean. *p* value shows statistical significance level for natural capital term in global GAM model.**** = very strong evidence ($p < 0.001$); *** = strong evidence ($0.001 < p \leq 0.01$); ** = moderate evidence ($0.01 < p \leq 0.05$), * = weak evidence ($0.05 < p \leq 0.1$).

Table 7
Summary of natural capital – farm business performance relationships from global model ($n = 114$ farms) and region-specific models. Figures are p values showing statistical significance level for natural capital term in global and region-specific GAM models. Blank squares are cases where natural capital metrics were not selected for inclusion in models during the model dredge process. Full statistics for region-specific models are provided in the Supplementary Materials.

Model	Region	PROXIMITY	GROUND COVER	FORAGE CONDITION	ECOLOGICAL CONDITION	AGGREGATION
PRODUCTION_EFFICIENCY						
GLOBAL	All regions	0.036	0.055	0.078		
REGIONAL	Central and Tablelands		0.001	0.003		
REGIONAL	South East				0.017	
REGIONAL	Western Australia	<0.001		<0.001	<0.001	
LIVESTOCK_GROSS_MARGIN_HA						
GLOBAL	All regions	0.045	0.046		0.089	
REGIONAL	Central and Tablelands			0.094		
REGIONAL	South East	0.010	0.005		0.067	
REGIONAL	Western Australia	0.001	0.001	<0.001	<0.001	<0.001
EBIT_HA						
GLOBAL	All regions		0.055			
REGIONAL	Central and Tablelands			0.041		
REGIONAL	South East					
REGIONAL	Western Australia	<0.001	<0.001			<0.001
FINANCIAL RESILIENCE						
GLOBAL	All regions	0.030	0.093	0.100	0.004	0.007
REGIONAL	Central and Tablelands	0.039		0.001	<0.001	
REGIONAL	South East	0.043	0.044		0.01	<0.001
REGIONAL	Western Australia	<0.001	<0.001	<0.001	0.002	<0.001

Moderate or strong statistical evidence for a positive relationship at p<0.05
Weak statistical evidence for a positive relationship at p<0.1
Statistical evidence of a non-linear relationship with optimal natural capital at a) intermediate or b) high AND low levels
Weak statistical evidence for a negative relationship at p<0.1
Moderate or strong statistical evidence for a negative relationship at p<0.05

matters, and some trade-offs were observed. For example, high levels of *Ecological condition* were associated with higher financial resilience but lower livestock gross margin. Conversely, *Proximity* was associated with higher gross margin but lower levels of financial resilience. This suggests that, in the context of natural capital, it may be more appropriate to consider production-resilience (rather than production-environment) trade-offs.

We also note some negative associations between natural capital and farm business performance in specific regions. For example, there was evidence of a trade-off in production efficiency once *Proximity* exceeded 0.4, and weak evidence that Production efficiency may decline with increasing *Ground cover* beyond a score of ~0.75. This indicates that the quantity of inputs required to achieve improved natural capital states may exceed the associated production benefit for some natural capital types beyond some threshold point. The weakly positive, then negative, relationship between production efficiency and ground cover (and EBIT), with a turning point at a *Ground cover* score of ~0.75, is consistent with industry views of an ideal grazing pressure to balance animal and plant performance (Meat and Livestock Australia, 2006). There was also a negative association between *Ecological Condition* and gross margin in Western Australia and some other farming regions. This suggests that robust context specific insights will be necessary to avoid unintended adverse outcomes for farm businesses, and that, in some specific cases, financial support (for example from government payments or other market incentives) may be required to make natural capital investment a financially viable option for farmers.

It is important to note that the relationships we report are trends that were observed *within* farming modes, and so they do not represent the effects of moving from one farming mode (like intensive farming) to another farming mode (like regenerative agriculture). Rather, they indicate that irrespective of the current farming mode, targeted management of natural capital could be used to help manage and improve business performance. This is important, as it suggests that most, if not all, farms could both improve their business performance and contribute positively to climate and nature targets by making relatively small changes towards more effective management of their natural capital base. Additional gains may be possible from changing between farming modes, but we have not explored this question in the current study.

4.2. Natural capital benefit pathways

Our results suggest that natural capital and its associated ecosystem services can provide private production benefits to producers via three potential pathways, outlined below:

Pathway 1: Natural capital can increase farm output. Evidence of this pathway comes from the finding that high *Proximity* and *Forage condition* scores are associated with increased production efficiency. This is supported by previous studies demonstrating that improved forage condition can achieve higher levels of livestock weight gain (Burnett et al., 2012; Tracy et al., 2010) and that provision of shade and shelter from shelterbelts can lead to improved livestock health and survival rates (Stewart et al., 2024).

Pathway 2: Natural capital can reduce farm inputs. Evidence of this pathway comes from the finding that the proximity of woody vegetation to productive areas can increase gross margin in livestock enterprises. In addition to the increased levels of production from the provision of shade and shelter (Stewart et al., 2024), woody vegetation in close proximity to production areas is also likely to provide additional ecosystems services that can reduce the volume of purchased inputs required. For example, it can increase populations of bats (Lumsden and Bennett, 2005) and birds (Rainsford et al., 2025a), which prey on pest insects and may reduce the need for pesticide inputs.

Pathway 3: Natural capital can increase farm financial resilience. Evidence of this pathway comes from the finding that higher *Ecological*

condition, *Aggregation, Forage condition* and *Ground cover* scores all contribute to improve income stability over time for livestock enterprises in the Australian broadacre zone. Support for this pathway also comes from experimental investigations, case studies and applied demonstrations, which indicate that natural capital practices, including the use of persistent, perennial, palatable forages, adaptive grazing management, cover-cropping and tree establishment, can increase drought resilience for production (Cong et al., 2014; England et al., 2020; Maseyk et al., 2022). Although we have only tested for resilience to climate effects, natural capital may also confer resilience by reducing input costs and buffering farmers from volatile input markets (like those for chemical fertilisers).

4.3. Towards improved natural capital management on farms

Family-run farms are responsible for managing ~75% of the world's agricultural land (Lowder et al., 2021). It follows that implementing agricultural practice change as a large-scale natural climate solution will require good integration with farm-scale decision-making processes (Lambin et al., 2000). Providing information about how natural capital contributes to farm business performance can help overcome barriers to implementation in three ways, outlined below.

First, programs that demonstrate and report the outcome of effective natural capital management in financial terms help to bring natural capital into the financial decision-making realm. Social research shows that only a subset of farmers will implement natural capital management because of the environmental benefits it might provide (Davies and Hodge, 2006; Pröbstl-Haider et al., 2016). A larger proportion of farmers will implement management where it can be demonstrated to deliver a positive financial return (Liu et al., 2018; Piñeiro et al., 2020). Post-program survey of producers who participated in this research program found that "74% of farmers agreed or strongly agreed that the combination of NC and economic reports for farmers has the potential to change how natural capital is managed on Australian farms" (Orange Compass, 2025).

Second, programs that demonstrate the outcome of effective natural capital management across a large number of comparative farms provide farmers with an opportunity for accelerated peer-to-peer learning in an urgent policy space (Jack, 2012). Producers currently rely mainly on direct observations of specific aspects of their own business to make decisions about investment in on-farm natural capital (Paxton, 2019). Access to insights from a larger number of farms allows producers to access robust information about farm performance outcomes from a broader range of natural capital investment and management strategies than they would otherwise have access to. This can improve their understanding of potential synergies between ecosystem health and farm financial performance, reduce decision-making uncertainty, and support an evidence-based transition towards improved environmental and financial outcomes. In this context we note that there are a number of pitfalls in the development and communication of effective comparative frameworks, including difficulties in dealing with resource optimisation, causality and risk (Fleming et al., 2006) and we highlight the need for robust research methodologies and effective communication. Post-program survey of producers who participated in this research program found that 78% of farmers reported that they were able to identify specific farm management actions they could take to improve their economic performance as a result of the comparative analysis presented to them as an output of this research (Orange Compass, 2025).

Third, programs that quantify the types of natural capital interventions that are likely to deliver private financial benefits, and those that are not, deliver important insights required for the design of effective and efficient public policy. According to Pannell's public-private policy framework, landholder engagement and extension programs may be effective where private benefits of adoption can be demonstrated, but more expensive interventions, like payments of ecosystem services may be required where the net private benefits returned to the landholder, once costs of transitioning to improved natural capital management have been accounted for, would otherwise be minimal (Pannell, 2008; Pannell et al., 2012). Designing effective policy at the minimum cost is an important consideration if we are to activate agriculture as a low-cost natural climate solution pathway (Griscom et al., 2017).

4.4. Concluding remarks

Our approach recognises the importance of farm-scale decision-making for achieving landscape-scale change. We identify three general pathways through which natural capital could contribute positively to the financial performance of livestock farms. We use business metrics that can be easily integrated into current on-farm decision-making processes to help enable farm-scale change.

When we consider the outcomes of changed on-farm decision-making at the landscape scale, it is clear that agriculture could contribute positively to climate and nature targets whilst also supporting continued productivity and profitability in the agriculture sector. But we note that the specific natural capital elements and associated ecosystems services that are of the most value to farmers are likely to vary widely depending on farm type, location, climate and other factors. Local assessments across the world's farming regions will be required to optimise environmental and economic outcomes, and to avoid unintended adverse outcomes (Nabuurs et al., 2023).

CRediT authorship contribution statement

Elizabeth Heagney: Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Daniel Gregg:** Conceptualization, Methodology. **Dan Hill:** Data curation, Methodology. **James Radford:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Grace Sutton:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Fred Rainsford:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Daniel O'Brien:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Angela Hawdon:** Conceptualization, Data curation, Methodology. **Imogen Semmler:** Conceptualization, Data curation, Methodology. **Mark Gardner:** Conceptualization, Data curation, Methodology. **Milly Taylor:** Data curation, Methodology. **Sue Ogilvy:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

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Data availability

The authors do not have permission to share data.

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