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Research article

Delineating the spatial drivers of agri-environment scheme adoption at field and farm levels

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ABSTRACT

Agri-environment schemes (AES), introduced by the EU Common Agricultural Policy (CAP), aim to compensate land owners for implementing environmentally-friendly practices. Whilst literature has examined their effectiveness and how farmer characteristics govern AES adoption, there is a lack of knowledge about the spatial drivers of AES, particularly structural, biophysical and landscape factors in the UK. Using the Humber region as a case study, this paper explores how the uptake of Countryside Stewardship options has varied from 2016 to 2021. It also examines 2500 farms from the field- and farm-level data of 2019 to better understand what type of land British farmers are adopting AES on. Logistic regression analysis is used to identify the factors (including farm and landscape characteristics, designated sites and land quality) that best explain overall AES adoption, as well as specific scheme adoption, at the field- and farm-level. Our analysis reveals that 'buffer strips', 'hedgerow management', 'permanent grassland', and 'winter bird food' are the most commonly adopted schemes of 2019. AES are generally adopted on larger fields and farms that feature marginalised, unproductive and vulnerable land, except for 'buffer strips' which showed a larger tendency to appear on fields with more profitable, higher quality land. This study, therefore, supports the notion that AES are generally placed on lower quality land and that large proportions of agricultural land owners are not effectively targeted. With the expected loss of direct payments to farmers in the UK as a result of the Department for Environment, Food & Rural Affairs (DEFRA) post-Brexit re-evaluation of rural policy, these results call for the Sustainable Farming Incentive (SFI) to be made more accessible and inclusive to a broader diversity of farmers.

1. Introduction

The Common Agricultural Policy (CAP) – the overarching agricultural programme of the European Union – aims to improve the environmental sustainability of farming through various mechanisms defined under the two 'pillars' of CAP funding. Pillar I pays the majority of farmers for maintaining land in good agricultural conditions (through Basic or Direct Payments), and in the 2013 revision, stricter cross-compliance and 'green payments' were introduced, requiring farmers to have Ecological Focus Areas (EFAs). Pillar II features voluntary measures, including agri-environment schemes (AES, also called agri-environment-climate measures), which function to compensate farmers for adopting environmentally-friendly practices (Hasler et al., 2022; Kleijn and Sutherland, 2003). The introduction of AES can be read as a response to the market failure of intensified agricultural production, which produces negative externalities of environmental depletion and degradation (Hounsome et al., 2006; Clements et al., 2021). The array of schemes available to land owners is country-specific and, whilst each scheme targets a specific environmental issue, their combined effect aims to fulfil the overarching AES objectives to conserve biodiversity, restore landscapes and diminish nutrient and pesticide emissions (Kleijn et al., 2001; Kleijn and Sutherland, 2003). To attain this, CAP allotted 7% (20 billion EUR) of their overall funding for 2014–20 to AES (Pe'er et al., 2020).

Literature has long focussed on AES effectiveness, with early studies claiming that the ecological effectiveness of AES was at best highly questionable (Kleijn et al., 2001; Kleijn and Sutherland, 2003; Kleijn et al., 2006). However the number of studies on AES has increased dramatically in recent years, and it has generally become accepted that despite major inefficiencies in AES programmes (Scown et al., 2020), AES are capable of producing moderate ecological benefits (Whittingham, 2011) at both the farm (Crowther and Gilbert, 2020; Bullock et al., 2021) and regional (Batáry et al., 2011; Threadgill et al., 2020) scales. It has also emerged that the ecological benefits of AES are mediated by the

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composition of the landscape, oftentimes focussing on landscape complexity as a differentiating factor (Scheper et al., 2013; Hass et al., 2018; Batáry et al., 2011, 2020).

In terms of literature relating to the allocation of AES, studies exploring the role of farmer behaviour and characteristics have been a large focus (Hounsome et al., 2006; Emery and Franks, 2012; Lastra-Bravo et al., 2015; Greiner, 2016; Pavlis et al., 2016; Defrancesco et al., 2018; Cullen et al., 2020; Leonhardt et al., 2022; Teff-Seker et al., 2022). Outside of social predictors, spatial predictors - including farm and biophysical characteristics - of AES implementation have been explored relatively less frequently. Larger farm sizes have been consistently associated with higher rates of AES adoption (Hounsome et al., 2006; Lastra-Bravo et al., 2015; Pavlis et al., 2016; Zimmermann and Britz, 2016; Defrancesco et al., 2018; Leonhardt et al., 2022; Paulus et al., 2022). Farms with fields or landscapes constituting unproductive and/or marginal areas have been indicated to be greater adopters of AES in Europe (Lastra-Bravo et al., 2015; Zimmermann and Britz, 2016; Früh-Müller et al., 2019; Paulus et al., 2022), which Scheper et al. (2013) highlighted as being important in producing broader ecological diversity. More specifically in Germany, AES adoption has been correlated with landscape multifunctionality (Früh-Müller et al., 2018) and the presence of protected areas, water, forested areas, and lower soil fertility (Paulus et al., 2022). However, besides farm size, spatial drivers of AES allocation in the UK have not yet been examined.

Understanding the nature of AES allocation based on land(scape) characteristics in the UK is important not only because the unique suite of schemes offered in the UK could provide novel insights into AES placement, but also due to the UK's agricultural transition period occurring post-Brexit. The new UK initiatives led by the Sustainable Farming Incentive (SFI) are provisioned under a collective framework known as the Environmental Land Management schemes (ELMs) - which, according to a statement of principles released by DEFRA (2022), are akin to AES. As a result, learning lessons from the adoption of past (pre-Brexit) AES has been highlighted as a priority area by DEFRA, with one of their objectives (from an official inquiry from 2020 to 21) being to investigate "What lessons should be learned from the successes and failures of previous schemes paying for environmental outcomes?" (House of Commons, 2021). By reflecting on the spatial drivers of AES implementation under the CAP system in 2019, this analysis aims to provide insights into its successes and failures. Namely, how successful AES was at targeting a variety of farm and land types, which is paramount to enabling a larger uptake of AES to ultimately increase connectivity and improve ecological effectiveness. This study therefore explores the role of spatial determinants of AES in the Humber catchment area, UK, by focussing on the role of landscape factors (land quality, topography and designated sites) and farm characteristics (farm and field size, and productivity) in determining AES adoption at the farm- and field-level. The following research questions will be addressed:

(1) To what extent do spatial characteristics drive the adoption of AES at field- and farm-level?
(2) Do these relationships with spatial predictors vary between different AES?

2. Materials and methods

2.1. Study area

The Humber catchment study region is located in the northeast of England, featuring several counties and National Character Areas (NCAs) (Fig. 1). The shape of the study area is based on five NCAs, which are each a distinct natural area defined by a unique combination of ecological, cultural and economic activities. It covers an area of 4664 km^2 consisting of flat peatlands to hilly terrain, ranging from −13 to 265 m in elevation (Ziv et al., 2020). The climate is described as temperate and maritime (Peel et al., 2007), with a mean annual temperature range of 4.35–14.78 °C and a total annual precipitation of 535.41–1108.48 mm (Met Office, 2018). Hydrologically, the Southern section of the catchment area drains via the River Ancholme into the

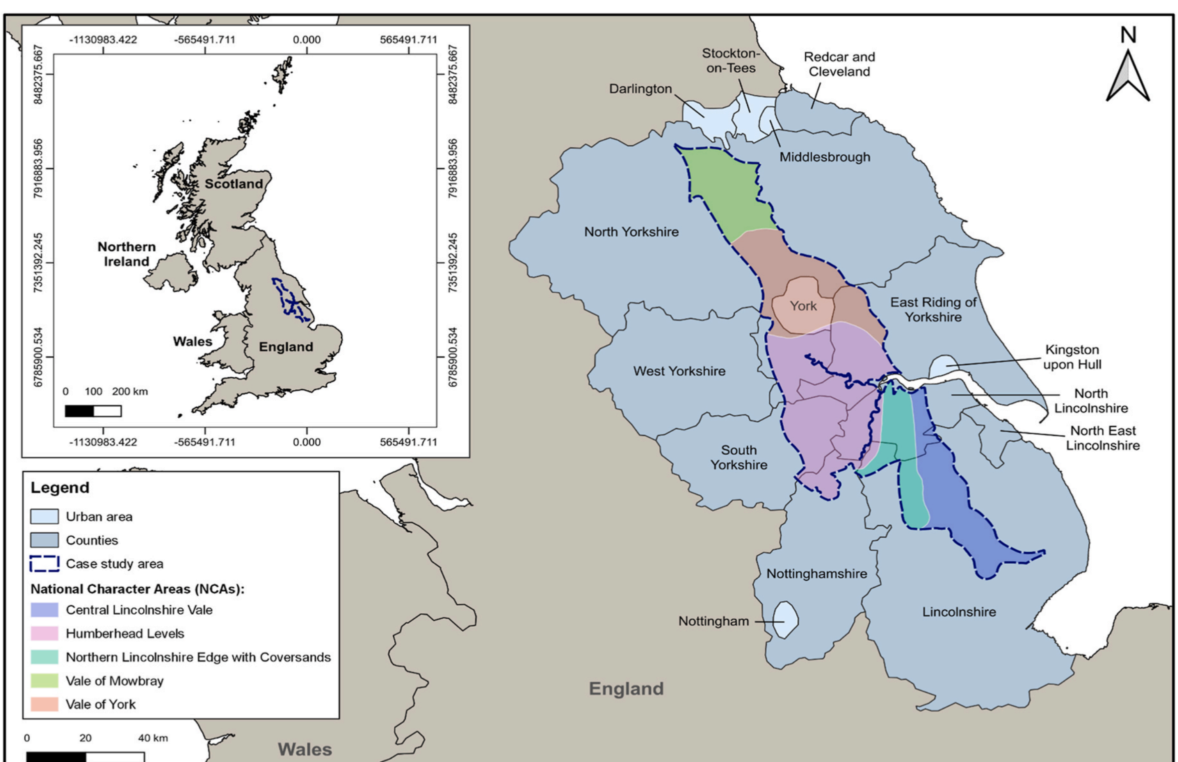

Fig. 1. Geographic location of the case study region, within the UK. The case study area encompasses multiple counties.

Humber estuary, and further south drains through the River Eau towards the Wash (Ziv et al., 2020). As well as featuring urban areas and semi-natural habitats, the Humber catchment region is also a major agricultural area, with fields covering ~80% of the case study area (Rural Payments Agency, 2020a). The most common crop is wheat, which covers 225,000 ha and represents 14% of England's wheat (DEFRA, 2023a). Livestock, including pigs, sheep and cattle, also constitute a substantial proportion of agricultural land in the area, with pigs constituting 38% of England's stock (Ziv et al., 2020; DEFRA, 2023a).

2.2. Data description and pre-processing

2.2.1. Field and farm information

Field- and farm-level information was obtained from the Rural Payments Agency (RPA), an agency of the UK Department for Environment, Food and Rural Affairs (DEFRA), for 2016 to 2021. RPA supplied separate datasets on field polygons, the Basic Payment Scheme (BPS) and Ecological Focus Areas (EFA) present in the study area for 2016 to 2019 (Rural Payments Agency, 2020a,b,c). There were a total of 3512 farms and 56,511 fields, with an average field size of 5.2 ha and farm size of 99.5 ha (with a single farm comprising a mean of 15.529 fields). The BPS data provided information on fields and farms that participated in the scheme, which is an EU-wide strategy to financially support eligible farmers. Any fields that were affiliated with several farms were removed from the dataset prior to analysis.

The EFA data consisted of information regarding fields that were required to integrate an EFA (i.e. arable land over 15 ha); an area of land upon which certain agricultural practices that are beneficial for the environment are carried out. EFA options include one or more of fallow land, margins/buffer strip, catch crops, nitrogen-fixing crops, and hedgerows in this case study region. Owing to disparities in area readings associated with the EFA data, this data was kept as binary (i.e. presence/absence of EFA on farm) and numerical total (i.e. number of different EFAs present on the field).

AES data also provided by RPA was organised by the start date and end date of contracts (Rural Payments Agency, 2021). Consequently, this was classified into datasets of individual years that a field featured an AES, even if a contract began or ended part way through the year. Any schemes not considered 'hedgerows and boundaries', 'mid-tier' or 'higher-tier' were removed from the dataset, including 'woodland management plan', 'tree health restoration' and 'feasibility study and historic building restoration', as they represented <1% of the data and they would have required different analysis owing to the nature of these schemes. 'Mid-tier' schemes are designed for the majority of farmers, whilst 'higher-tier' schemes involve more complex, site-specific environmental management schemes and often involve high-priority areas (DEFRA, 2019).

2.2.2. Ecological data

A total of 9 variables were selected on the basis of characteristics that were expected to influence AES uptake (Table 1). Of the farm characteristics, field and farm size were measured in Quantum Geographic Information System (QGIS) software. Economic size represented crop production of the farm. It was calculated using crop-specific EU standard output coefficients (Eurostat, 2022), which represent the average monetary value of the agricultural output at farm-gate price. The economic size of each farm was then calculated by multiplying the area of each crop by the corresponding standard output coefficient. The river network and small woody features presence and percentage cover were examined for the field area plus a 20 m buffer, to ensure a landscape-scale approach was considered. To explore designated sites, Nitrate Vulnerable Zones (NVZ) represented vulnerable areas as a result of agricultural activity, and in this case from agricultural nitrate pollution. Sites of Special Scientific Interest (SSSI) represented protected areas in this analysis. SSSIs are considered to represent ecologically important areas, supporting many vulnerable species, habitats and natural features. SSSIs are part of some AES options - for example 'permanent grassland' (GS1) can optionally be used to help the sustainable management and buffering of SSSIs or priority habitats. Lastly, Agricultural Land Classification (ALC) is a system used to grade the quality of agricultural land. There are five grades, ranging from excellent to very poor quality, which is classified according to climate, gradient, soil depth, wetness, droughtiness and stoniness. All variables were re-projected to EPSG 27700, clipped to the case study region and the vector variables were rasterised (unless already at field-level). Extractions were done using QGIS and R software, as well as the *plyr* package (QGIS Development Team, 2009; R Core Team, 2022; Wickham, 2011).

2.3. Data analysis

Methodologically, much of the literature regarding agri-environment schemes are either fully or partially qualitative, dealing primarily with interviews (Hounsome et al., 2006; Emery and Franks, 2012; Teff-Seker et al., 2022), questionnaires (Pavlis et al., 2016; Leonhardt et al., 2022; Teff-Seker et al., 2022) and focus groups (Teff-Seker et al., 2022; Panyasing et al., 2022) with landowners. These studies have analysed qualitative data through a combination of sociocultural interpretations (Emery and Franks, 2012), norm-based evaluations (Hounsome et al., 2006), Q methodology (Leonhardt et al., 2022) and thematic analysis (Teff-Seker et al., 2022). In the broader scope of agricultural literature, more recent qualitative papers have applied smart-Partial Least Squares (PLS) statistics to analyse complex interrelationships between variables

Table 1
Overview of the spatial variables and the extraction method used for the general linear models.

Group	Variable	Temporal extent	Format	Resolution (m^2)	Extraction type	Source
Farm characteristics	Field size	2019	Vector	Field-level	(Mean) field size of (farm's) fields (m^2)	Agency (2020a)
	Farm size	2019	Vector	Field-level	Farm size (m^2)	
	Economic size	2013	Vector	Farm-level	Economic size of farm (€/ha)	
Landscape characteristics	River network	2017	Raster	25	River within field (binary) and cover within farm's fields plus a 20 m buffer (%)	Ecology and Hydrology (2017)
	Small woody features	2015	Raster	25	Small woody features within field (binary) and cover within farm's fields plus a 20 m buffer (%)	Copernicus (2015)
Designated sites	Nitrate Vulnerable Zone (NVZ)	2017	Raster	25	NVZ area within field (binary) and cover within farm's fields (%)	Environment Agency (2021)
	Sites of Special Scientific Interest (SSSI)	2022	Raster	25	SSSI area within field (binary) and cover within farm's fields (%)	Natural England (2022e)
	Ecological-Focus Area (EFA)	2019	Vector	Field-level	Total number of EFAs on field (integer) and EFA presence on farm's fields (binary)	Agency (2020c)
Agricultural land quality	Agricultural Land Classification (ALC)	2019	Raster	25	Majority ALC of (farm's) fields	Natural England, 2020

in Vietnam and Peru (Van Hoa et al., 2022; Mamani et al., 2022 respectively) and meta-frontier data envelopment analysis in Indonesia (Nuhfil Hanani et al., 2023). However, as aforementioned, these papers focus primarily on the social aspects of agriculture. In this study, a quantitative method is used in order to best explore physical and geographical determinants. Approaches to analysing agricultural quantitative data include factor analysis (Pavlis et al., 2016; Cullen et al., 2020; Teff-Seker et al., 2022), correlations (Früh-Müller et al., 2019; Abidin et al., 2022) and regressions (Hounsome et al., 2006; Cullen et al., 2020; Leonhardt et al., 2022; Teff-Seker et al., 2022; Paulus et al., 2022).

As our data on AES uptake at the field- and farm-levels comprise binary data type values, a logistic regression was implemented using the *stats* package in R (R Core Team, 2022). Six models were run: (1) presence/absence of any AES at field-level; (2–5) presence/absence of the top four most common AES at field-level (see Table 2 for more detail), and; (6) presence/absence of any AES at farm-level. The variables listed in Table 1 functioned as the independent variables.

AES adoption comprised only 12.81% of the dataset, presenting a large class imbalance between the two outcomes (adoption vs. non-adoption). As such, a single random sample of the majority class (non-adoption) was taken, which was the same size as the minority class (adoption). For field-level models, the datasets used ranged in size from 1144 to 15,218 fields depending on the model, with 774 farms used for the farm-level model.

Continuous variables were z-standardised, categorical variables (i.e. ALC) were manually encoded for the most common three values across all records in the data (before resolving class imbalance). Multicollinearity was investigated using Variance Inflation Factor (VIF) scores using the *car* package in R (Fox and Weisberg, 2019), and all variables with a score≥10 were excluded. Furthermore, remaining variables were feature-selected through a backward stepwise algorithm using the *MASS* package in R (Venables and Ripley, 2002), to ensure the most parsimonious model was selected based on Akaike Information Criterion (AIC) values. Finally, random index selection was used to split the resampled data into 80/20% train/test cohorts for the purposes of producing scores for forms of accuracy. Data splitting ratios used in the literature range from 50/50% to 90/10%, however 80/20% (known as the Pareto principle) is a commonly used split and therefore was chosen for this study (Joseph, 2022). This was done by randomly selecting 80% of the sample to be used as the train dataset, with the remaining 20% reserved for the test dataset. All reported accuracy scores represent the mean average value across 1000 runs of model fitting (using the variables remaining after all filtering steps) under the train/test records split ratio. Visualisations were produced using QGIS software and R.

3. Results

3.1. AES adoption

AES adoption rates were relatively low at both the farm- and field-levels in the Humber case study region during 2019; the proportion of all farms adopting AES on at least one of their fields stood at 11.02%, and the proportion of all fields adopting an AES was 12.81%. There were four schemes that were the most commonly adopted in the study area: SW1 (4–6 m buffer strip on cultivated land), BE3 (management of hedgerows), AB9 (winter bird food) and GS2 (permanent grassland with very low inputs - outside SDAs) in 2019 (see Table 2 for a description of the schemes), which was representative of England as a whole. These schemes represented a range of options based on land use (soil and water (SW1), field edge (BE3), biodiversity and arable land (AB9), and grassland (GS2)) and longevity of agreements (BE3 and GS2 are more permanent features, whilst SW1 and AB9 are more temporary).

The most prevalent of these four AES types were ‘buffer strips’ and ‘hedgerow management’ (Fig. 2A). Whilst ‘winter bird food’ and ‘permanent grassland’ maintained a similar number of active agreements

Table 2
Description of the most common AES adopted in the study area (where annual payment is reflective of 2019).

Countryside Stewardship option	Description and goals	Environmental benefits	Annual amount paid to farmer	Source
SW1: 4–6 m buffer strip on cultivated land	Buffer strip employed on the edges of cultivated fields, between the productive part of the field and an existing feature (e.g. hedgerows, stone walls, woodlands, water bodies) with no evidence of damage (i.e. by vehicles)	Provides new habitat for wildlife (i.e. corridors), protects existing landscape features, improves water quality by preventing surface water runoff	£353/ha	Natural England (2022a)
BE3: management of hedgerows	Hedgerows on boundary lines of shrubs, where hedges are at least 2 m tall and 1.5 m wide	Increases the availability of blossom for invertebrates, provides food for overwintering birds, improves the structure and longevity of hedgerows, and maintains hedgerows as historic landscape features	£8 per 100 m for 1 side of a hedge	Natural England (2022b)
AB9: winter bird food	Seed mix is applied in areas of 0.4–5 ha during spring/summer to provide small seeds throughout winter	Provides small seeds for farmland birds in colder months, and the flowering plants will benefit insects	£640/ha	Natural England (2022c)
GS2: permanent grassland with very low inputs (outside SDAs)	Permanent grassland outside severely disadvantaged areas (SDAs) and below the moorland line, featuring a good cover of flowering grass species, wildflower species, and scattered scrub areas	Increases plant species diversity and vegetation heights, provides nectar and shelter for invertebrates, and increases bird food supply	£95/ha	Natural England (2022d)

since 2016, ‘winter bird food’ started to become more common than ‘permanent grassland’ in 2021, with a percentage increase in uptake of 71.27% between 2020 and 2021. Besides ‘hedgerow management’, other AES relating to hedgerows have seen a substantial incline more recently (Fig. 2B). ‘Hedgerow gapping’ (BN7), whilst initially the most selected for hedgerow option besides BE3, was overtaken by the preference to ‘plant new hedges’ (BN11), which increased by 62.08% from 2020 to 2021. Whilst much lower in number, ‘planting standard hedgerows’ (TE1) and ‘tree guards’ (TE6) displayed the largest percentage increases in uptake between 2020 and 2021 of all options (223.91% and 292.86% respectively). ‘Tree guards’ (TE1) are for use on hedgerows (as well as orchards and parkland trees), and are permitted to be adopted alongside of hedgerows operated under BE3 and ‘planting

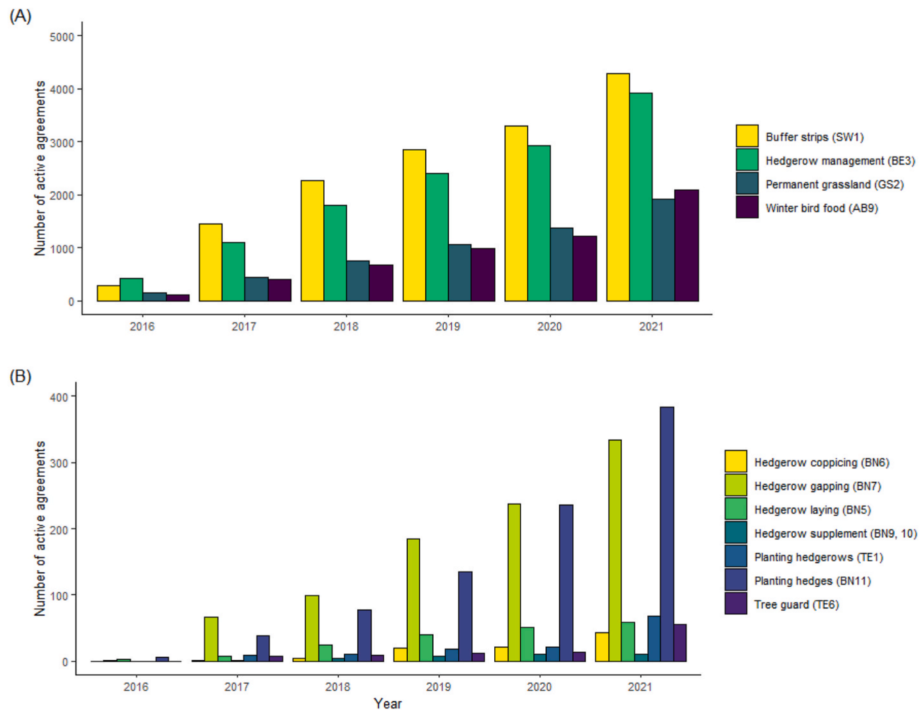

Fig. 2. Number of active agreements of (A) the top four most commonly adopted schemes between 2017 and 2021 ('Flower rich margins and plots' (AB8) AES was more common than 'winter bird food' (AB9) in 2016), and; (B) hedgerow-related schemes from 2016 to 2021. Figure created using *ggplot2, ggthemes* and *ggpubr* packages in R (Wickham, 2016; Arnold, 2021; Kassambara, 2023).

standard hedgerows' (TE1) on the same field.

3.2. *Logistic regression modelling*

3.2.1. *Significant predictors of AES adoption*

Farm/field characteristics. The results show that all (general and specific) AES at farm-level and field-level besides 'hedgerow management' and 'winter bird food' were predicted by larger farm sizes (farm all: $F = 2.03$, $p < 0.001$; field all: $F = 0.33$, $p < 0.001$; SW1: $F = 0.34$, $p < 0.001$; GS2: $F = 0.35$, $p < 0.001$ respectively) (Fig. 3). 'Buffer strips', 'hedgerow management', 'winter bird food' and all AES at field-level were also predicted by larger field sizes ($F = 0.37$, $p < 0.001$; $F = 0.09$, $p < 0.05$; $F = 0.36$, $p < 0.001$; $F = 0.28$, $p < 0.001$ respectively). Contrastingly, the 'permanent grassland' AES was predicted by smaller field sizes ($F = -0.64$, $p < 0.001$). Lastly, 'hedgerow management', and all AES at field- and farm-level were attributed with (farm's) fields that had lower economic sizes ($F = -0.50$, $p < 0.001$; $F = -0.11$, $p < 0.01$; $F = -1.24$, $p < 0.001$ respectively). Meanwhile, 'buffer strips' and 'winter bird food' were more likely to be adopted on fields that belonged to farms with higher economic sizes ($F = 0.19$, $p < 0.05$; $F = 0.13$, $p < 0.05$ respectively).

Landscape characteristics. Environmental landscape features either had positive or no affiliations with AES, both at field- and farm-level. Firstly, all AES were predicted by the percentage cover of rivers surrounding farms ($F = 0.24$, $p < 0.05$). Overall AES was also predicted by the presence of rivers nearby at the field-level ($F = 0.37$, $p < 0.001$) as well as for 'buffer strips', 'permanent grassland' and 'winter bird food' specifically ($F = 0.74$, $p < 0.001$; $F = 0.91$, $p < 0.001$; $F = 0.25$, $p < 0.05$ respectively). Furthermore, all AES at field-level - bar 'buffer strips' - showed a significant interaction with small woody features: overall AES, 'hedgerow management', 'permanent grassland', and 'winter bird food' were predicted by the presence of small woody features in the surrounding area ($F = 0.23$, $p < 0.001$; $F = 0.25$, $p < 0.05$; $F = 0.79$, $p < 0.001$; $F = 0.68$, $p < 0.001$ respectively).

Designated sites. At the field-level, all AES besides 'permanent grassland' were predicted by the presence of Nitrate Vulnerable Zones (NVZ) (field all: $F = 0.18$, $p < 0.001$; SW1: $F = 0.39$, $p < 0.001$; BE3: $F = 0.40$, $p < 0.001$; AB9: $F = 0.60$, $p < 0.001$). The presence of Sites of Special Scientific Interest (SSSI) negatively predicted the adoption of 'hedgerow management' AES ($F = -0.95$, $p < 0.001$), however overall AES at the field-level were positively predicted by SSSI presence ($F = 0.59$, $p < 0.001$). In terms of Ecological Focus Areas (EFAs), 'buffer strips', 'hedgerow management', 'winter bird food' and overall AES at the field-level were more likely to be adopted on fields that had a higher number of EFAs adopted ($F = 0.44$, $p < 0.001$; $F = 0.24$, $p < 0.001$; $F = 0.44$, $p < 0.001$; $F = 0.20$, $p < 0.001$ respectively). Furthermore, overall farm-level AES were more likely to be adopted on farms that also featured EFAs ($F = 0.66$, $p < 0.001$). On the contrary, 'permanent grassland' at field-level was predicted by a lower number of EFAs ($F = -2.38$, $p < 0.001$).

Agricultural land classification quality. Field-level overall AES was predicted by very good ($F = 0.47$, $p < 0.001$), good to moderate ($F = 0.70$, $p < 0.001$) and poor ($F = 0.77$, $p < 0.001$) quality agricultural land, signifying that they were the most likely to be adopted on poorer quality land. Whilst this was supported by the farm-level model, which indicated that AES presence was unlikely to occur on very good quality agricultural land ($F = -0.15$), this finding was not significant. Furthermore, 'buffer strips' were more likely to occur on very good quality land ($F = 0.39$, $p < 0.05$) but even more so on good to moderate quality land ($F = 0.59$, $p < 0.001$). Lastly, 'permanent grassland' was more commonly adopted on poor quality agricultural land ($F = 0.86$, $p < 0.001$).

3.2.2. *Classification accuracy scoring*

Based on the mean average of 1000 runs with an 80% train set, the field-level logistic regression model achieved an overall classification accuracy rate of 61.64%. The model correctly predicted 57.00% real-world adopting fields as AES adopters, and 66.28% of real-world non-adopting fields as AES non-adopters. Meanwhile, the proportion of predicted adopter fields that were real-life AES adopters stood at 62.81%, with the figure again slightly lower for AES non-adopting fields at 60.68% in the case of the proportion of predicted non-adopting fields

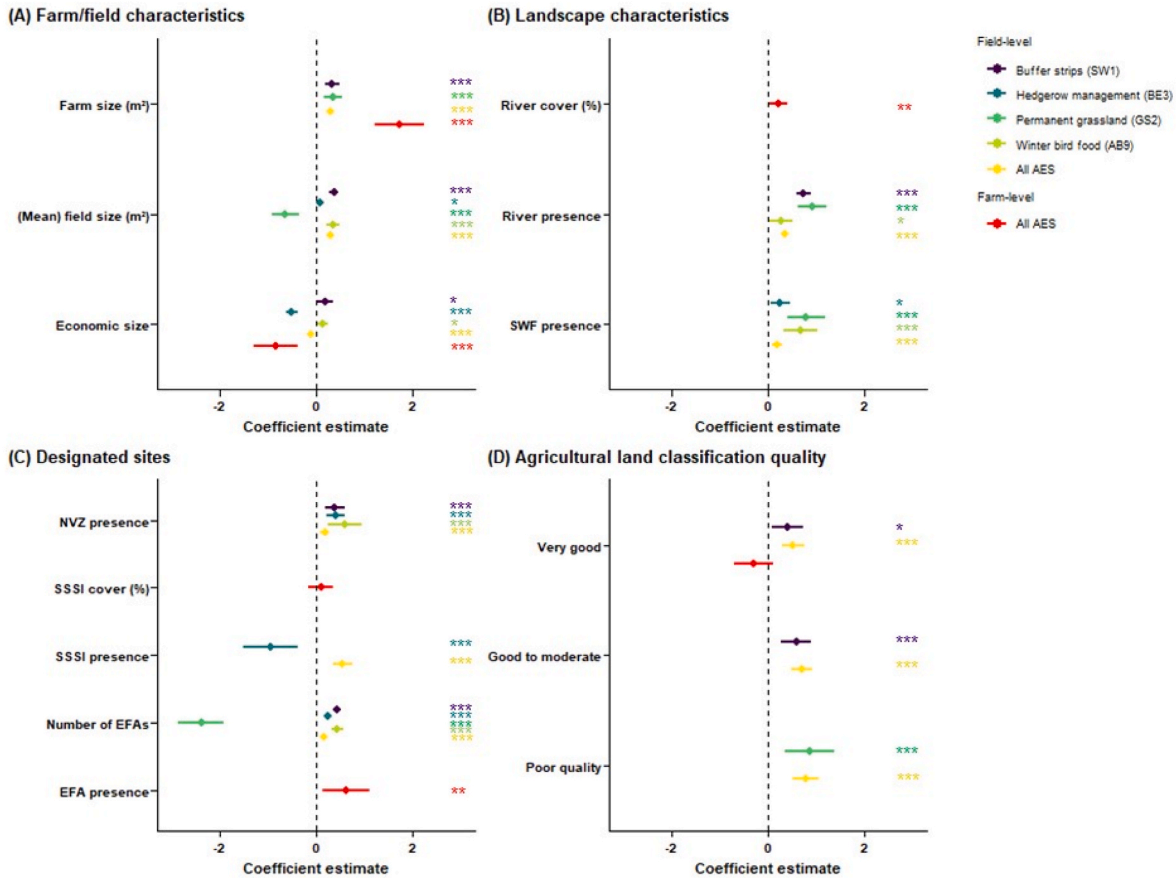

Fig. 3. Field- and farm-level model coefficient estimates (see Supplementary Material Tables A1 and A2 for full table outputs) for (A) farm/field characteristics; (B) landscape characteristics; (C) designated sites, and; (D) agricultural land classification quality. Bar widths represent a 0.95 confidence interval and significant P-values are represented by asterisks; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$. Figure created using *ggplot2, ggprism, jtools* and *ggsci* packages in R (Wickham, 2016; Dawson, 2022; Long, 2022; Xiao, 2023).

that were actually AES non-adopters. As such, for fields, the false negatives rate was 39.32%, the false positives rate was 37.19%, and the total misclassification rate was 38.36%.

When looking at the most commonly adopted AES, all average overall classification accuracy rates were higher than that of the overall field-level model. The accuracy rates were 71.79% for the buffer strip (SW1) model, 58.79% for the 'hedgerow management' (BE3) model, 73.89% for the 'permanent grassland' (GS2) model and 68.12% for the 'winter bird food' (AB9) model.

The farm-level logistic regression model achieved a mean average overall classification accuracy rate of 72.10%. The model correctly predicted 67.30% real-world adopters as AES adopters, and 77.08% of real-world non-adopters as AES non-adopters. Meanwhile, the proportion of predicted adopters who were real-life AES adopters stood at 74.70%, with the figure for AES non-adopters at 70.17% in the case of the proportion of predicted non-adopters who were actually AES non-adopters. As such, for farms, the false negatives rate was 29.83%, the false positives rate was 25.30%, and the total misclassification rate was 27.90%.

4. Discussion

The objective of this research was to delineate the spatial drivers of AES in the Humber case study region. Accordingly, this analysis found that farm and landscape characteristics, designated sites and land quality determined where farmers allocated AES, and that the relationships with these determinants do indeed differ depending on the scheme at focus.

The most commonly adopted AES in the Humber were 'buffer strips' (SW1), 'hedgerow management' (BE3), 'winter bird food' (AB9) and 'permanent grassland' (GS2). 'Planting standard hedgerows' and 'tree guards' (of which are used on new hedgerows) displayed the largest percentage increase in uptake from 2020 to 2021 (223.91% and 292.86% respectively), alongside of 'plant new hedges', which also drastically increased during this period (62.08%). As a result of a decline in hedgerow numbers, the government introduced a target this year to create or restore 30,000 miles of hedgerows by 2037, and 45,000 miles of hedgerows by 2050 under the new Environmental Improvement Plan 2023; Biffi et al., 2022; DEFRA, 2023b). As 'hedgerow management' is only applicable to established hedgerows (i.e. over 20 m in length), there is likely to be a surge in the uptake of the SFI equivalent of this AES ('hedgerows standard'). Understanding the allocation of 'hedgerow management' according to spatial components at the field-level is therefore useful in highlighting where environmental measures will be placed under the new ELMs system.

Farm size positively predicted overall AES adoption at the field- and farm-level. The implementation of specific schemes, including 'buffer strips' and 'permanent grassland', at the field-level was also more likely on larger farms. This finding is generally corroborated in the literature, where AES uptake has been associated with larger farms in Italy (Defrancesco et al., 2008), Ireland (Hynes and Garvey, 2009), Germany (Paulus et al., 2022), Austria (Leonhardt et al., 2022), Wales (Hounsome et al., 2006), England (Coyne et al., 2021) as well as multiple other EU member states (Lastra-Bravo et al., 2015; Pavlis et al., 2016; Zimmermann and Britz, 2016; Ruto and Garrod, 2009). Whilst there is ambiguity in defining small and large farms across literature, Wilson and Hart

(2000) also found that out of 19 EU countries, in thirteen countries (including the United Kingdom) it was more common for farmers to be AES-participating if they owned farms that were larger than the regional average size. In describing this inclination and according to interview campaigns held in the Humber case study, large family-owned estates were found to profit more from AES as they cover larger areas and have the resources to employ personnel to run the schemes (Wittstock et al., 2022).

Field size was also important in AES allocation, with the likelihood of adoption higher on larger fields. This was true of overall AES at the field-level, however no significant relationship was highlighted between mean field size and AES adoption at the farm-level. There was some disparity across specific schemes at the field-level and their association with field size; ‘buffer strips’, ‘hedgerow management’ and ‘winter bird food’ were more common on larger fields, however ‘permanent grassland’ was more likely to be selected for on smaller fields. Field size has been explored relatively less than farm size in the literature, however the opposite effect was found in Germany, whereby field size had a negative effect on overall AES application, but the German AES species-rich ‘permanent grassland’ was found to increase on larger fields (Paulus et al., 2022). This highlights that farmer choices relating to AES are country-specific, and, where practical, should not be generalised owing to the vast array of farming systems present across the EU. In explaining why grassland is more frequently located on smaller fields, it is important to note that the ‘permanent grassland’ scheme is the only one of the four focussed on in the Humber analysis that is required to occupy the whole parcel (except when located with GS1). Furthermore, farmers with larger estates may be adopting the ‘permanent grassland’ AES on their smaller fields as it is easily-implemented on smaller, potentially irregularly shaped, areas.

Economic size had a negative impact on overall field- and farm-level AES. In regards to field-level schemes, ‘hedgerow management’ also occurred more commonly on low-yielding farms, whilst ‘buffer strips’ and ‘winter bird food’ were featured on fields that belonged to farms with larger standard outputs. The tendency to place AES measures on unproductive areas is supported in the literature (Lastra-Bravo et al., 2015; Zimmermann and Britz, 2016; Früh-Müller et al., 2019; Paulus et al., 2022). Scheper et al. (2013) highlighted that AES are most effective when implemented in resource-poor landscapes dominated by arable land where they readily create large ecological contrasts. Whilst this may be true, if AES are only being applied to low-quality fields (i.e. 11.02% of all fields) then a large number of (resource-rich) fields are not being targeted for AES adoption, thus lowering overall ecological benefits resulting from a low adoption rate and subsequent poor connectivity. In deciphering why farmers place AES on unproductive land, Lastra-Bravo et al. (2015) suggested that adoption compensates for the income lost due to the lower productivity of the land, and that it can offset some of the risks associated with agricultural production. Furthermore, according to the aforementioned case study interviews, farmers with estates located on very productive land generally saw AES participation as a loss of potential income, and family-run farms perceived AES as a steady, albeit low, income for less productive parts of their land (Wittstock et al., 2022). This suggests that ‘winter bird food’ and ‘buffer strips’ occurred on fields that belonged to farms with larger economic outputs because they paid the largest amounts of the four explored in this analysis, which was enough to counteract income lost through AES participation (Table 2).

The Agricultural Land Classification (ALC) analysis relates to economic size by underpinning land productivity and potential yield. Overall AES at the farm-level was negatively associated with very good land quality, whilst AES at the field-level had the highest estimate for occurring on poor quality land. This was synonymous to the finding relating to economic size, supporting the notion that AES are generally placed on unproductive land. In terms of specific AES, ‘permanent grassland’ was also expected on poor quality land, whilst ‘buffer strips’ were estimated to most commonly occur on good-to-moderate land. Of the four AES explored, ‘buffer strips’ were most likely to be placed on more productive and higher quality land. Again, this supports the notion that the £353/ha farmers received for ‘buffer strip’ implementation was enough to persuade farmers to incorporate this AES onto their more productive, higher quality land. Meanwhile, farmers are likely to allocate low quality land to ‘permanent grassland’ as it takes up a whole parcel, rendering the field non-arable.

River cover and presence positively predicted farm- and field-level AES adoption respectively. ‘Winter bird food’, ‘permanent grassland’ and ‘buffer strips’ were also more commonly integrated on fields featuring or located near to rivers. Despite much research into the AES implications on water quality in the UK (Haygarth et al., 2012; Kay et al., 2012; Poole et al., 2013; Jones et al., 2017), this is the only study in the UK to have reviewed AES placement in proximity to the river network. According to scheme requirements, ‘buffer strips’ are encouraged to be adopted next to “trackways that channel runoff water directly to a watercourse” (Natural England, 2022a) whilst ‘permanent grassland’ should be “on parcels adjacent to a permanent watercourse” (Natural England, 2022d). Conversely, ‘hedgerow management’ is not required to reside besides water sources (Natural England, 2022b). However, as Jones et al. (2017) commented when reviewing the positioning of AES options in relation to river networks, the decisions of the farmers are often influenced by a variety of social, economic and practical factors.

Presence of small woody features increased the likelihood of overall AES adoption at the field-level, but it was not a significant predictor at the farm-level. ‘Hedgerow management’, ‘permanent grassland’ and ‘winter bird food’ were also predicted by the presence of small woody features in-field, or in the surrounding area. Rivers and small woody features not only break up the landscape, causing more heterogeneity and disruption, but also make land hard to manage. Paulus et al. (2022) suggested that placing AES in areas adjacent to water bodies and forest edges indicates that farmers are using hard-to-reach, marginal areas for these schemes. The notion that AES are allotted to peripheral, marginal and difficult to manage fields is supported in the literature (Schmidtner et al., 2012; Uthes and Matzdorf, 2013; Hodge et al., 2015; Zimmermann and Britz, 2016; Früh-Müller et al., 2019; Brown et al., 2021; Paulus et al., 2022). Furthermore, Batáry et al. (2011) and Scheper et al. (2013) commented that AES options should be implemented in structurally simple landscapes for ecological effectiveness. The lack of ‘buffer strips’ located near to small woody features indicates that this AES is not as commonly implemented on marginal fields, which is in line with the finding that ‘buffer strips’ are also placed on more productive land.

Nitrate Vulnerable Zones (NVZs) presence predicted a higher likelihood of AES at the field-level, but not at the farm-level. ‘Winter bird food’, ‘hedgerow management’ and ‘buffer strips’ were also more commonly present on fields within NVZs. Dragosits et al. (2015) suggested that ‘buffer strips’ could be spatially targeted near to sensitive habitats or designated sites to help reduce nitrogen flow into semi-natural systems, and Carnell et al. (2018) supported this finding by identifying that ‘buffer strips’ achieved ~35% reduction in total NH_3 (which was the most out of all AES sampled). Due to the nature of these schemes, it is likely that they do not require nitrogen fertilisation (unlike ‘grassland management’). Furthermore, NVZs have limitations on the amount of nitrogen permitted for application and farmers must produce nutrient budgets. This suggests that these AES were selected for NVZ fields to combat the issue of nitrate pollution.

The presence and cover of Sites of Special Scientific Interest (SSSIs), another designated site examined in this analysis, positively predicted the occurrence of AES at the field- and farm-level respectively. Conversely, ‘hedgerow management’ was more commonly adopted on fields that were not within an SSSI. The initial finding is supported in the literature, where option uptake is generally higher within SSSIs (Natural England, 2021). The latter results regarding the ‘hedgerow management’ AES may have been because SSSI sites require Natural England’s consent to plant, manage or change hedgerows (Natural England, 2022b).

The presence and number of Ecological-Focus Areas (EFAs) increased the likelihood of AES implementation at the farm- and field-level respectively. ‘Winter bird food’, ‘hedgerow management’ and ‘buffer strips’ also had a positive association with EFA numbers at the field-level. In 2019, ‘hedgerow management’ was allowed to overlap with EFA hedges, avoiding the issue of ‘double funding’, however, ‘buffer strips’ was not permitted to overlap with EFA margins (DEFRA, 2020). As a result, ‘buffer strips’ would have been allocated to fields featuring fallow, catch crops, nitrogen-fixing crops and hedgerow EFAs, whilst ‘hedgerow management’ and ‘winter bird food’ would have also been located next to margin EFAs. The negative association between ‘permanent grassland’ and total number of EFAs was again opposed by Paulus et al. (2022), which found that a German ‘permanent grassland’ AES was positively related to EFA presence. In the UK, EFAs are only required on arable land larger than 15 ha, meaning that the smaller fields of ‘permanent grassland’ are exempt from claiming for EFAs. This again highlights the difficulty in drawing comparisons between specific AES types across countries, and is heavily policy-dependent.

As with any regional study, the extent to which these findings can be applied across time and space is inherently limited. This study revealed interesting dynamics in biophysical drivers of AES, in addition to reproducing claims on the importance of farm characteristics in AES adoption. However, further studies are needed across multiple political and physical geographies in order to generalise this claim with higher levels of dependability. Additionally, the fact that farms and fields adopting legacy AES schemes such as Environmental Stewardship could not be sufficiently recognised in this study means that farms and fields actually enacting AES options were not accurately recorded as such in this data, limiting the ability to best differentiate between AES adopting and AES non-adopting farms and fields.

Research on agri-environment schemes is mostly published in academic journals based in the West, and is often situated in contexts within Europe, North America and Oceania (Scheper et al., 2013; Batáry et al., 2015; Brown et al., 2021). As a result, it is crucial to highlight the importance of research examining agri-environment interventions outside the Global North context (see Jones et al., 2020), including in Brazil (Siqueira et al., 2021), Tanzania (Kwayu et al., 2014), Costa Rica (Sierra and Russman, 2006; Chan and Daily, 2008), and the Ningxia Hui Autonomous Region of China (Zhang et al., 2008). While the findings of this research in the UK’s Humber region make a valuable contribution to the thinking and collective evidence base of policymakers internationally as well as in Britain, it is critical to stress that research from the Global North cannot speak for the full diversity of experiences and priorities which will influence the appropriate composition of agricultural policy elsewhere. As highlighted earlier, the nature of this research is highly context-dependent, and thus an increase in research relating to agri-environment measures from the Global South would contribute unique, valuable insights the literature could otherwise overlook.

5. Conclusion

This analysis highlighted that ‘buffer strips’ (SW1), ‘hedgerow management’ (BE3), ‘winter bird food’ (AB9) and ‘permanent grassland’ (GS2) were the most commonly adopted schemes of 2019 in the Humber case study, which was also representative of farmers preferences in England as a whole. Whether and how the allocation of these AES depend on spatial variables is important in understanding where schemes will likely continue to be placed, highlighting if policy is adequately targeting farmers. With the exception of ‘buffer strips’, the most prevalent AES, which showed more of a tendency to be located on fields that were more profitable and featured better land quality, AES were generally placed on unproductive, marginalised and vulnerable land.

With the increase in planting new hedgerows and the government’s hedgerow target, the ELMs equivalent of ‘hedgerow management’ will likely see a rise in uptake in the upcoming years. As such, if hedgerows are continued to be limited to unproductive, marginalised, nitrate vulnerable and unprotected land, as found in this study, vast amounts of agricultural land will not have been targeted efficiently. Should the government wish to accomplish its hedgerow targets by 2037 and 2050, this paper suggests that the new ELMs policy is made suitable for all farmers, and attention is given to those that manage more productive, high-valued agricultural land.

Credit author statement

Rosemary Wool: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **George Breckenridge:** Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Guy Ziv:** Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Arjan Gosal:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, 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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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