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RESEARCH ARTICLE

Positive impacts of agri-environment schemes on butterflies from multiple evidence sources

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Abstract

1. Agri-environment schemes (AES) provide an important mechanism for environmental improvement with the potential to benefit many taxa, yet evidence of national scale benefits is mixed. Multiple sources of evidence are available to assess AES effects, with different strengths and weaknesses, but most existing studies use a single dataset to evaluate AES impacts.
2. We developed an approach analysing multiple datasets to assess relationships between AES and species abundance, richness and diversity, using the example of butterflies in England. We analysed data from a study specifically designed to assess AES effects (the LandSpAES study) alongside two different citizen science UK Butterfly Monitoring Scheme (UKBMS) surveys. UKBMS surveys were not designed to evaluate AES effects, but they provide better spatial coverage across the agricultural landscapes of England. We compared AES relationships between the three datasets, using a generalised AES gradient method to allow integration of different AES options, including the creation of habitat features such as wildflower strips and the restoration of semi-natural habitats. We assessed AES effects at both local (1 km) and landscape (3 km) scales.
3. We found that AES in the surrounding landscape was positively associated with butterfly community responses in all three datasets and some evidence that local-scale AES was positively associated with butterfly richness. The smaller size of the LandSpAES study led to wider confidence bounds around effect sizes, but the careful design provided assurance that potentially confounding effects were accounted for. The wider spatial coverage of the citizen science datasets increased confidence that results can be extrapolated to the national scale.
4. *Synthesis and applications*. Our results provide support for positive effects of AES on butterflies in England from multiple sources of evidence, providing confidence that these schemes are providing tangible benefits for butterflies. Our recommendations for managers and policy makers are (1) multiple data sources should be

considered for AES monitoring and evaluation, exploiting the strengths of different data types; (2) AES intervention over larger spatial areas than individual fields and farms should be considered when aiming to provide benefits for butterflies.

KEYWORDS
abundance, agri-environment, butterfly, citizen science, data synthesis, landscape scale, survey design

1 | INTRODUCTION

Agri-environment schemes (AES), whereby farmers are paid to implement management for environmental benefits, are important mechanisms for environmental policy delivery in the United Kingdom (UK) and Europe (Batáry et al., 2015; Stewart et al., 2022). As such, it is essential to understand the effectiveness of these schemes. For options targeted towards biodiversity conservation, this includes assessment of the benefits of specific management on target taxa. However, there is also a need to understand the combined impacts of AES intervention across option types and landscapes to provide a national picture of AES effectiveness (Staley et al., 2021). For mobile species, such as butterflies, it is likely that the amount and configuration of AES across the landscape are also important; therefore, we need to consider multiple spatial scales of AES impact.

Some butterfly species have been shown to have more positive population growth on specific sites under AES management compared to nearby non-AES areas (Redhead et al., 2022) or to regional population trends (Kolkman et al., 2022), but this has not been supported across a broader range of sites or species (Oliver, 2014). A recent review suggested most studies assessing community- or population-level responses of Lepidoptera to AES found positive effects (Bladon et al., 2023), but very few studies reviewed aimed to look for effects at national or other larger spatial extents, beyond the individual farm, study site or region. Despite relatively widespread uptake of AES in the UK, the national picture for farmland biodiversity remains one of decline, suggesting AES may not be delivering sufficient benefits at a national scale (Stewart et al., 2022). With the UK implementing new AES after withdrawal from the EU common agricultural policy (Department for Environment Food and Rural Affairs 2024), a solid evidence base to assess the performance of these schemes and enhance their design is needed.

There are several key challenges to overcome when attempting to assess AES impacts at national scales. These include the fact that AES impacts are often found to be context-specific (e.g. Scheper et al., 2015), such that replication across contexts is required to identify general patterns. The ideal data to test AES effects is often lacking (Josefsson et al., 2020; Kleijn & Sutherland, 2003), particularly at large spatial scales. Ideally, data would be professionally collected before and after AES implementation, at a large number of study sites, across a nationally representative range of AES uptake, across multiple landscapes and contexts, and over long time scales to assess population trends.

In England, the data available to assess AES impacts on butterflies come from either targeted studies specifically designed to detect AES effects and conducted at local or regional scales (e.g. Redhead et al., 2022; Staley et al., 2022) or by utilising existing national scale monitoring effort which is not designed specifically for AES impact detection (e.g. Oliver, 2014). Targeted studies are designed specifically to look at AES effects and provide high-quality data where confounding variables are carefully controlled for. The cost of obtaining such data means sample sizes are low, and this comes at the expense of representativeness when the aim is to make inference at national scales. Citizen science data can provide large sample sizes, long time series and wide spatial coverage, but the lack of design to specifically test the impact of AES means it can be challenging to separate AES impacts from the effects of confounding variables (Oliver, 2014). Although the wide spatial coverage of citizen science data can increase representativeness, volunteer-led schemes are often biased towards more ecologically interesting areas and away from more typical farmland (Brereton et al., 2011; Ruck et al., 2024; Tulloch et al., 2013).

Choices about data used to evaluate AES effects are generally presented as mutually exclusive (i.e. to invest in a targeted survey or to exploit citizen science data) and most individual AES evaluation studies use a single data source (e.g. Boetzl et al., 2021; Kolkman et al., 2022; Löffler et al., 2023; Meier et al., 2024; Oliver, 2014; Panassiti et al., 2023; Redhead et al., 2022). Given the difficulties in identifying an ideal dataset to evaluate AES effects, we consider that bringing together multiple datasets to answer the same question allows us to benefit from the different strengths of separate datasets. If consistent positive effects across multiple datasets are found, then this provides good evidence that AES are providing benefits to butterflies and that these effects can be seen at national scales. To enable multiple datasets to be analysed to consider AES effects on butterflies in England, we designed a common analytical framework which could be applied to data from both a targeted study (the LandSpAES study) and two citizen science surveys in England.

The LandSpAES study was designed to provide high-quality, targeted evidence of the impact of landscape-scale AES intervention on mobile species, including butterflies (Staley et al., 2022). LandSpAES is a pseudo-experimental study (i.e. AES were not randomly allocated; Christie et al., 2019) which uses a carefully constructed design to allow the effects of local (within a 1 km × 1 km areas) and landscape (the surrounding 3 km by 3 km area) scale AES to be separated. The design reduces the potential for confounding landscape variation to obscure AES effects by replication across six regions with contrasting landscape characteristics (Staley et al., 2022). However, the high cost of the survey means a limited number of survey locations are monitored that are not representative of conditions across all of England.

Data on butterflies from across England are also available from the long-running UK Butterfly Monitoring Scheme (UKBMS), one of the UK's largest structured citizen science schemes. This scheme supports volunteers to survey transect routes for butterflies on a repeated basis and data from this scheme inform trends in butterfly populations across the UK. The UKBMS includes a number of different component surveys including the Wider Countryside Butterfly Survey (WCBS), which was designed to increase understanding of trends in butterflies outside of the high-quality habitats volunteers tend to prefer (Brereton et al., 2011). These citizen science surveys provide a potentially useful resource to understand AES effects as they provide a large volume of data and cover a broad range of English agricultural landscapes. However, the lack of an AES-focused design means the potential for confounding effects is much higher.

We assessed AES impacts on butterflies in England from the LandSpAES, UKBMS and WCBS datasets. Our key questions were as follows:

1. Are similar relationships between butterfly community responses (abundance, diversity and richness) and AES implementation observed in all three datasets when analysed under a common framework?
2. Do relationships vary with the spatial scale of AES considered (a 1 km 'local' area vs. a 3 km 'landscape' area)?
3. Is there evidence of an overall positive impact of AES on butterflies?

2 | MATERIALS AND METHODS

2.1 | Datasets

2.1.1 | LandSpAES data

The LandSpAES project ran from 2017 to 2022 and assessed whether key mobile taxa were affected by the quantity of AES management, measured at local and landscape scales, specifically considering impacts beyond option, farm or AES agreement boundaries, and across multiple taxa. To enable this, a novel AES gradient approach was developed (Staley et al., 2021, 2022) using information on the spatial extent, expected benefit per species group and payments for each option to derive a continuous AES score. The AES gradient score methodology (described in detail below) allows landscapes with different characteristics and expected biodiversity impacts to be compared in terms of AES intervention on a common scale. For example, it allows an upland landscape with a small number of spatially extensive options such as reduced stocking and a lowland landscape with small areas of resource-rich options such as flower-rich margins to be placed on the same scale.

Fifty-four 1 km squares were selected to maximise the contrast between AES gradient scores in the local (1 × 1 km) area and in the wider landscape (surrounding 3 × 3 km) to enable separation of AES effects at different spatial scales. The selection process (described in detail in Staley et al., 2021) used a weighted random methodology to select squares from all factorial combinations of low, medium and high AES gradient scores at local and landscape scales (i.e. nine squares, see Figure S1) within each of six regions with homogenous background landscape characteristics (National Character Areas, hereafter NCAs), giving 54 cells in total. These NCAs included both upland and lowland landscapes (Figure 1) and were chosen to represent a diversity of farmed landscapes across England. The design enables the interaction between local- and landscape-scale AES to be assessed, to investigate whether butterflies respond more positively to local AES in landscapes with less AES implementation.

Six mobile taxon groups were monitored within survey squares (butterflies, bees, moths, hoverflies, birds and bats) annually between 2017 and 2021 (excluding 2020 when field survey was not possible due to the COVID-19 pandemic; Staley et al., 2022). Here we focus on butterflies, which were recorded to species along fixed transect routes within a 5 × 5 × 5 m hypothetical box, known as a 'Pollard walk'. Key characteristics of the butterfly surveys conducted within LandSpAES are shown in Table 1.

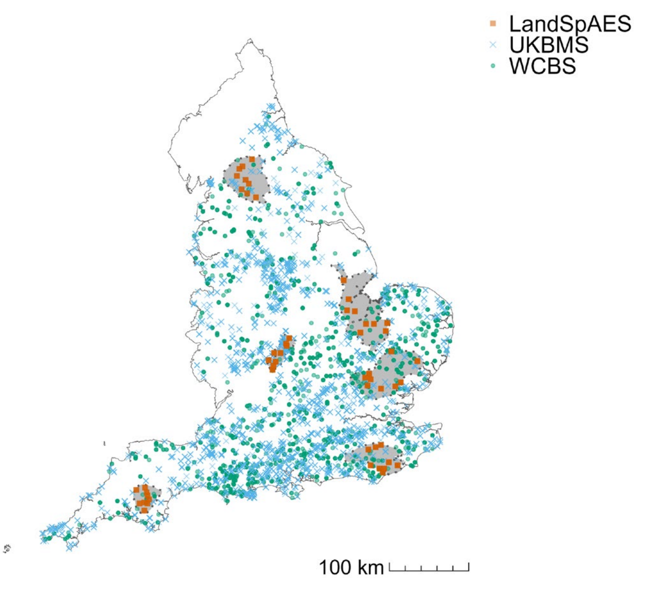

FIGURE 1 Map of survey locations in England used in this study belonging to three datasets: the UK Butterfly Monitoring Scheme (UKBMS); Wider Countryside Butterfly Monitoring Scheme (WCBS); LandSpAES study. Shaded grey areas show the National Character Areas in which LandSpAES sites are situated (Yorkshire Dales, The Fens, Dunsmore and Feldon, South Suffolk and North Essex Clayland, High Weald, Dartmoor). Citizen science transects outside of farmed landscapes were not included in the analysis and are not shown on the map.

TABLE 1 Key characteristics of data sources included in the analyses.

Feature	LandSpAES	UKBMS	WCBS
Number of unique survey sites	54	1207	730
Design rationale	Designed to detect relationships between mobile taxa and AES gradients at local and landscape scales in six regions	Designed to assess abundance change over time in UK butterfly populations	Designed to assess abundance change over time in UK butterfly populations with a focus on wider countryside species
Survey method	Pollard walk	Pollard walk	Pollard walk
Transect length	2 km	Variable (50 m to 12 km)	2 km
Transect placement	Representative of a 1 km square	Surveyor choice	Representative of a 1 km square
Repeat visits between May and August	3–4 (median = 4)	1–66 (median = 16)	1–10 (median = 2)
Years of data per square (2017–2019 plus 2021)	3–4	1–4	1–4

2.1.2 | UKBMS and WCBS survey data

The UKBMS is a citizen science scheme monitoring populations of butterflies across the UK since 1976, using several types of survey. The original and most widely adopted survey type is a standard transect walk (hereafter termed 'UKBMS') where a fixed-line route is established by the recorder and walked weekly from the start of April to the end of September annually (Pollard & Yates, 1993). These transects vary greatly in length and are more typically located, historically at least, in areas of good quality semi-natural habitats. In 2007, the WCBS was developed to produce unbiased abundance indices and trends for wider countryside species, through more representational coverage of habitats (such as farmland) that dominate much of the UK but were historically under-represented in UKBMS sites (Brereton et al., 2011). WCBS sites are randomly selected 1 km squares within which butterflies are recorded on two parallel 1 km transects. WCBS transects are visited at least twice per year, primarily in July and August. WCBS and LandSpAES transects are both designed to sample a 1 km square, whereas UKBMS transects can extend across multiple 1 km squares. We assigned a 1 km grid reference to UKBMS transects for analysis using the transect mid-point grid reference. Key dataset properties are summarised in Table 1.

The distributions of UKBMS and WCBS sites in 2017–2019 and 2021 are shown in Figure 1, showing a much greater coverage of England compared to LandSpAES sites. We excluded any UKBMS and WCBS sites that were not predominantly farmland using criteria previously applied during LandSpAES square selection (>30% of combined urban, suburban and freshwater coverage or >50% combined broadleaved and coniferous woodland coverage; Staley et al., 2016; Rowland et al., 2017).

2.2 | Calculation of response variables

Total butterfly abundance, species richness and Shannon diversity index were calculated for each transect in each dataset in each year, aggregating across all visits between May and August. We excluded visits outside this window, which covers the LandSpAES survey period. Our analysis assesses the effect of AES on the butterfly community observed across the year and thereby includes potential AES effects on turnover throughout the year. Summaries of each response variable for each dataset are shown in Table S1.

Most butterflies were recorded to species in all three datasets; however, in a few cases, aggregates were used for species which were particularly difficult to identify in the field. It was usually possible to allocate aggregates to species level based on the proportions of the two constituent species observed in each square, as recommended in the UKBMS field guidance (UKBMS 2024). Where this was not possible, the aggregate taxon was used across datasets for consistent taxonomic resolution. A list of species recorded is provided in Table S2.

2.3 | Survey effort

Key differences between the datasets include the total transect length and the number of repeat visits per year. Failing to account for these differences in survey effort could obscure variation due to AES. We calculated the number of unique visits between May and August (regardless of whether any butterflies were seen) for all datasets, and transect length for UKBMS transects, to include as covariates in analyses.

2.4 | AES gradient calculation

We calculated AES gradients using the approach described in Staley et al. (2016) with updated AES uptake data. As described above, this approach uses the spatial extent of options, expected benefit per species group derived from an evidence review and payments (sometimes provided as points) for each option to derive a continuous AES score for a 1 km unit. Option extents were derived from AES uptake data for Environmental Stewardship and Countryside Stewardship, accessed from the Natural England Open Data Geoportal (https://naturalengland-defra.opendata.arcgis.com/). These include all types of AES option present from 2017 to 2021, including legacy Entry and Higher Level Stewardship, and Countryside Stewardship options from 2016 onwards, made spatially explicit at the level of the field centroid where the AES option was located. The benefit score was obtained by scoring each option for benefit to multiple mobile taxon groups as a function of the strength and quality of available evidence (Staley et al., 2016, 2021). Scheme points or payment rates per unit option were derived from the relevant AES handbooks (Table S3).

All three elements were multiplied for each option type and then summed across all options present to give a single AES gradient score per year for each 1 km square in the three butterfly datasets. The AES gradient score has arbitrary units and ranges from 0 (no AES present) to over 40,000 (multiple beneficial options widely present). The 3 km gradient scores were then derived by taking the mean score of the surrounding eight cells for each 1 km square. The AES gradient scores were calculated identically for all three datasets providing a consistent measure of AES that is specifically designed to be relevant for mobile taxa including butterflies. Across England, the AES options included in the gradients included the creation of resource-rich habitat features such as wildflower strips, the restoration of semi-natural habitats such as species-rich grassland, and the adoption of less intensive management activities (e.g. reduced stocking density or reduced fertiliser application). A full list of AES option types included in the gradient calculations is provided in Table S3.

AES uptake data have some limitations in the accuracy and precision with which AES options are recorded, but comparison against AES gradients measured from field data obtained during the LandSpAES project showed good correspondence (average correlation of 0.78; Staley et al., 2021).

2.5 | Environmental covariates

To account for potentially confounding factors, we constructed three variables representing broad gradients of climate, landscape and habitat across England. We calculated these variables from three separate principal components analyses (PCAs), each containing 6–8 variables at 1 km resolution selected to be likely influences on butterfly populations. Details and sources of environmental covariate data are given in Table S4. From each PCA, we then extracted the first axis score for each transect location as a new variable to include in our models of butterfly responses. We chose PCA as a pragmatic method of distilling the large number of potentially important variables into a small number that could be included in any dataset model (Graham, 2003). PCA axes had no or weak correlations with AES scores (Table S5).

2.6 | Statistical analysis

A unified model structure was derived which could be applied to each butterfly response and dataset to enable a fair comparison of results. There were six key model components:

1. The response variable, which was either butterfly species richness, diversity or abundance, is described above. Richness responses were modelled as Poisson, abundance as negative binomial and diversity as Gaussian with an exponential transformation.
2. The AES gradient terms for local, landscape and an interaction between local and landscape gradients.
3. Terms for survey effort. In all models a term was included for the number of visits between May and August, and in UKBMS models, a term was included for transect length.
4. The three PCA gradients representing key variation in climate, landscape and habitat.
5. A term for survey year.
6. A random term for survey square identity, to account for repeated visits to the same 1 km square. Preliminary analysis investigated whether temporal autocorrelation could be estimated, but this was not possible due to the small number of years and missing data from 2020.

Linear or generalised linear mixed effect models were run using brms package v2.18.0 (Bürkner, 2017) as an interface to Stan (Carpenter et al., 2017; rstan v2.26.13). All models were fitted using four chains and 2000 iterations, of which 1000 were warm-up, and examined for convergence using the R-hat statistic (Vehtari et al., 2021), effective sample size and graphical checks. Recovery of the data was examined using graphical posterior retrodictive checks (Gabry et al., 2019).

To test whether coefficients from the AES terms were similar between individual dataset models (e.g. whether the 1 km AES effect estimated for LandSpAES was the same as the 1 km AES effect estimated for UKBMS), we calculated pairwise differences between 1000 draws from the posterior distributions of the parameters. If the 95% highest posterior density interval (HPDI) overlapped zero, then we concluded that the two coefficients were similar. All code to run the models is available at https://github.com/NERC-CEH/AES-multiple-evidence-paper. This study did not require ethical approval.

3 | RESULTS

AES had a significant positive relationship with butterfly community variables, particularly at the landscape (3 km) scale (Figure 2; Table 2). We found evidence that the landscape gradient was positively associated with butterfly community responses in all three datasets, although there was variability between responses and datasets in the strength of evidence. Relationships between landscape AES intervention and butterfly abundance were most strongly supported by LandSpAES and WCBS, but positive relationships with richness were more evident in the analysis of UKBMS and WCBS. A positive relationship with diversity was only found for WCBS.

Mixed evidence was found for effects of the local (1 km) AES gradient, which had a positive effect on richness in both UKBMS and WCBS analyses, but a negative relationship with butterfly diversity

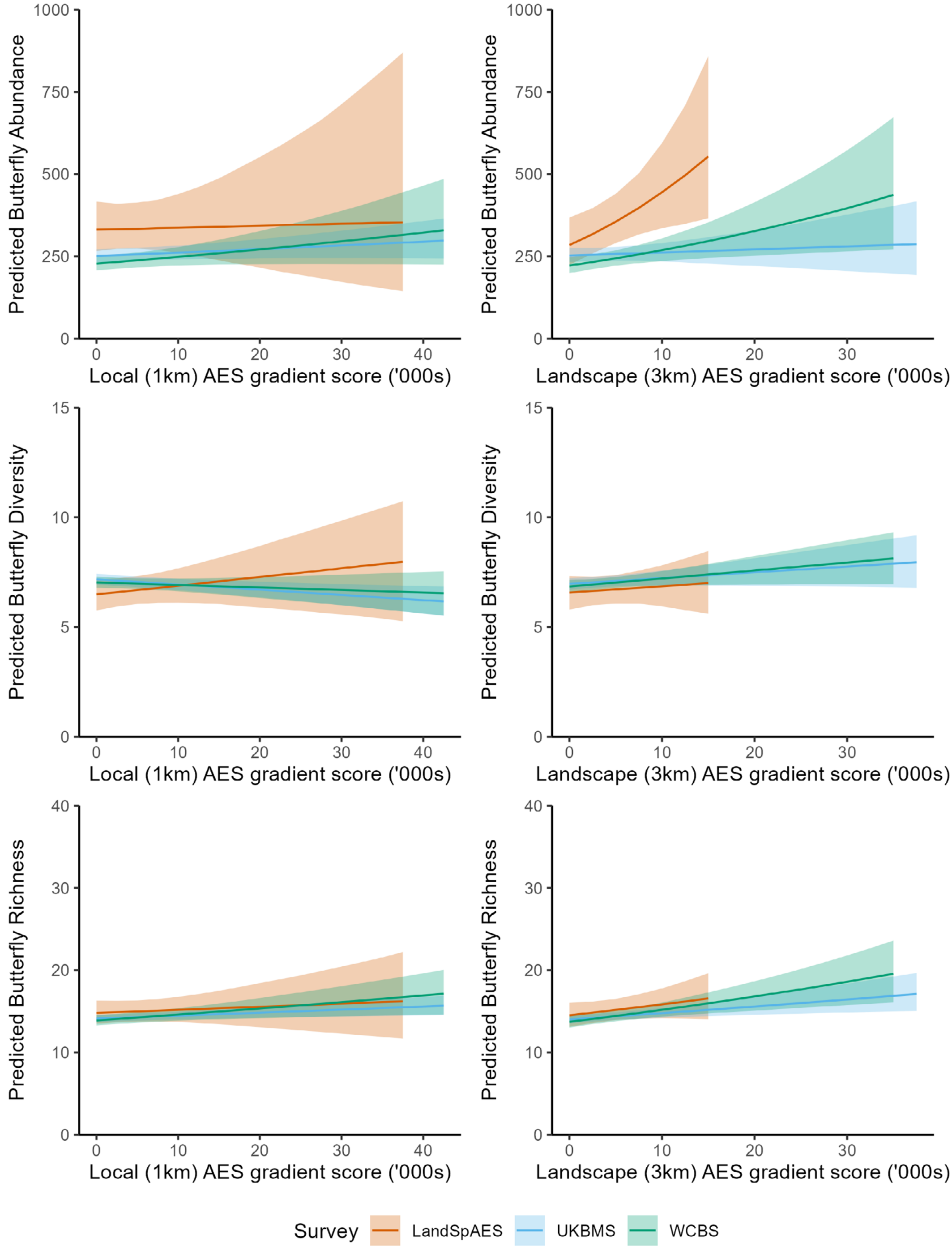

FIGURE 2 Predicted relationships between local (1 km) and landscape (3 km) AES gradients and total butterfly community abundance, diversity and richness for each of the three butterfly datasets considered (UKBMS, UK Butterfly Monitoring Scheme; WCBS, Wider Countryside Butterfly Survey; LandSpAES study). Shannon diversity is exponentially transformed.

in the UKBMS analysis. There was no evidence that local AES positively impacted butterfly abundance in any dataset.

Interaction effects, where the effect of local AES is mediated by the level of AES in the surrounding landscape, were only found in analyses of WCBS data. These analyses suggested that the effect of local AES on both butterfly richness and abundance was highest in low AES landscapes (Table 2). In all cases, credible intervals around the estimated effects were widest for models using LandSpAES data, reflecting the smaller sample size available. LandSpAES also had less coverage of very high landscape AES scores, due to a small number of very highly scoring UKBMS and WCBS squares, with the vast majority of 1 km squares having landscape AES scores of less than 20,000 (Figure S2).

Despite some differences in significance, the overall similarity of responses between datasets is demonstrated by the HPDI tests which showed no significant differences between most datasets (Table 3). The one case where the HPDI test showed that the datasets did not agree was between LandSpAES and UKBMS for landscape-scale AES effects on butterfly abundance. LandSpAES showed a strong positive relationship between butterfly abundance and the landscape AES gradient, whilst UKBMS data showed no significant relationship (Figure 2; Table 2). There was a slight trend towards greater differences between UKBMS and the other datasets, although in all cases responses using UKBMS and WCBS data were not statistically different from each other. A version of Figure 2 showing data points is provided in Figure S3.

4 | DISCUSSION

Our results demonstrate that combining multiple data sources provided a broad consensus on relationships between AES and butterfly community responses. The results showed high similarity between the estimated relationships when compared pairwise between the data sources and, in several cases, the observed relationships were very similar across all three datasets, for example the positive relationship between landscape AES and butterfly richness.

4.1 | AES effects on butterflies

We found more evidence of landscape-scale (3 × 3 km) AES effects on butterflies than effects of local AES (within a 1 km square). This would suggest that the mobility of butterflies, and their relatively high ability to disperse and exploit the floral resources and larval

TABLE 2 Results of models of butterfly abundance, diversity and richness against AES local, landscape and interaction effects. Mean covariate estimates are shown alongside standard errors in brackets.

		Local AES (1 km)	Landscape AES (3 × 3 km)	Local × landscape AES interaction
Abundance	LandSpAES	0.005 (0.070)	**0.212 (0.095)**	0.030 (0.072)
	UKBMS	0.020 (0.013)	0.017 (0.030)	0.001 (0.009)
	WCBS	0.045 (0.024)	**0.103 (0.038)**	**−0.213 (0.011)**
Diversity	LandSpAES	0.231 (0.220)	0.223 (0.317)	−0.233 (0.218)
	UKBMS	**−0.117 (0.042)**	0.130 (0.093)	−0.003 (0.03)
	WCBS	−0.057 (0.063)	**0.193 (0.098)**	−0.022 (0.028)
Richness	LandSpAES	0.012 (0.028)	0.045 (0.035)	−0.005 (0.032)
	UKBMS	**0.013 (0.004)**	**0.029 (0.011)**	−0.006 (0.003)
	WCBS	**0.026 (0.011)**	**0.055 (0.016)**	**−0.013 (0.005)**

Note: Bold indicates significant effects where the 95% credible interval does not include zero.

TABLE 3 95% highest posterior density intervals (HPDIs) for each combination of models and covariates.

Response	Dataset 1	Dataset 2	AES 1 km	AES 3 km	Interaction
Abundance	LandSpAES	WCBS	−0.183–0.108	−0.097–0.306	−0.098–0.186
	LandSpAES	UKBMS	−0.162–0.119	**0.007–0.397**	−0.115–0.169
	WCBS	UKBMS	−0.078–0.030	−0.179–0.010	−0.005–0.050
Diversity	LandSpAES	WCBS	−0.140–0.751	−0.568–0.703	−0.637–0.210
	LandSpAES	UKBMS	−0.096–0.774	−0.581–0.726	−0.652–0.196
	WCBS	UKBMS	−0.211–0.092	−0.321–0.200	−0.059–0.103
Richness	LandSpAES	WCBS	−0.076–0.046	−0.082–0.068	−0.052–0.075
	LandSpAES	UKBMS	−0.058–0.056	−0.057–0.086	−0.063–0.063
	WCBS	UKBMS	−0.036–0.010	−0.063–0.013	−0.004–0.019

Note: Bold indicates that the HPDI does not overlap zero, indicating a significant difference in slopes.

foodplants provided by AES options, means that they are responding to AES at a landscape scale. Larkin and Stanley (2021) found that landscape-level farming intensity, defined by the amount of improved versus semi-natural grassland within a 2 km radius, had a stronger influence on butterfly community composition than a field-scale proxy for AES, but did not find effects on butterfly richness, diversity or abundance. This difference could be due to their use of a proxy for AES at the local scale, and a measure of farming intensity at the landscape scale that is not necessarily related to AES interventions (Larkin & Stanley, 2021). Stronger responses to landscape-level AES might also be expected given the higher mobility of the butterfly species in our study, which were dominated by mobile, wider countryside species. In addition, the use of a consistent method to calculate AES intervention at two spatial scales may have allowed better spatial attribution of relationships between AES and butterflies, compared to previous studies (e.g. Panassiti et al., 2023). However, we found the positive effect of landscape AES on abundance was not observed in the UKBMS dataset. UKBMS includes more high-quality semi-natural sites (Roy et al., 2015) with nationally scarce, but potentially locally highly abundant, habitat specialist species such as the Chalk Hill Blue (*Polyommatus coridon*). Although these species may respond to targeted AES (e.g. Brereton et al., 2008), they may show weaker relationships with the generalised AES gradients used here, particularly if the transect habitat is already of high quality.

Although interaction effects were not supported in most models, we did find some evidence from the WCBS survey that the effect of local AES was highest in low AES landscapes. This might indicate that resources provided by AES are more important for butterfly populations when the landscape is impoverished in AES options (Scheper et al., 2015). A similar effect of organic farming on butterflies has been observed, whereby the benefits are greater in conventional landscapes (Rundlöf et al., 2008). Whether this is an attraction effect (e.g. reflecting species movement to high resource areas) or a population effect relies on future assessment of change over time, although there is evidence that AES uptake at landscape scales equivalent to those used here is correlated with more positive long-term population trends (Redhead et al., 2022).

We found only one negative relationship, between UKBMS measured diversity and the local AES gradient. Because UKBMS is biased towards semi-natural sites where rare and specialist species are likely to be present, this may inflate diversity in landscapes which are managed in ways other than those supported by AES (e.g. specialist management of nature reserves). Alternatively, the finding could reflect AES supporting proportionally higher abundances of more common, generalist species (Aviron et al., 2011; Batáry et al., 2015), leading to a small decrease in observed diversity.

4.2 | Dataset comparison

As recognised by other authors, there are significant challenges in designing studies to assess AES effects (Redhead et al., 2022, Josefsson et al., 2020). Individually, many datasets will fail to overcome at least some of these challenges (e.g. lacking an AES-focused design, lacking data prior to AES implementation, lacking accurate AES intervention data). Using multiple data sets with different strengths and weaknesses is one way of tackling these shortcomings. Identifying similar patterns across multiple datasets provides confidence that observed patterns are both real (i.e. not influenced by confounding factors) and representative (i.e. effects can be extrapolated beyond small, focused, study areas).

By analysing multiple datasets using a common analytical approach, we were able to make direct comparisons between coefficients estimated using each dataset. By ensuring that we defined community responses, AES gradients and model structures in comparable ways, we can conclude that differences between analyses are likely to be due to the design and properties of each dataset. For example, we found that relationships in LandSpAES data were much more uncertain (i.e. had wider confidence bounds) than relationships observed using the citizen science datasets due to the smaller size and likely lower power of the LandSpAES data (Jennions & Møller, 2003). However, the targeted design of the LandSpAES study, which was designed to accurately attribute AES effects, provides high confidence that relationships are not influenced by confounding variables.

Citizen science data is a useful source of information for understanding national scale impacts of drivers such as AES due to the large volume of data available and wide spatial coverage. The challenge for analyses of this data is in accounting for confounding factors and potential biases, which if not fully accounted for could lead to incorrect inference about the impacts of AES (Johnston et al., 2023; Ruck et al., 2024). Our analytical framework included some of these potentially confounding variables in the models via the PCA approach, and comparison with LandSpAES data provided confidence that most confounding variables were accounted for. We did not account for the known bias of UKBMS towards good quality sites in our models, partially explaining why UKBMS results were the most divergent. In addition, UKBMS transects are not restricted to 1 km squares (Table 1), resulting in lower confidence in the spatial attribution of the AES gradient scores and the environmental covariates for UKBMS butterfly data.

4.3 | Caveats and limitations

Few AES studies are designed in an optimal way, using a before–after comparison, because monitoring usually starts after the AES scheme (Christie et al., 2019; Josefsson et al., 2020). Our study does not include a before–after comparison and cannot rule out higher AES uptake in higher quality areas influencing our results. Repeated monitoring after a scheme has started can help to identify whether AES impacts population trends, for example whether AES ameliorates declines in the wider landscape (Redhead et al., 2022; Roth et al., 2008). Citizen science provides an ongoing source of monitoring effort (e.g. Oliver, 2014), but researchers lack control over when and where revisits are conducted. Ideally, citizen science data would be used alongside longer-term surveys designed to look for effects of AES over time.

Our AES gradient approach incorporates AES across multiple types of farmland systems and landscapes and provides insight into whether AES as a whole are providing benefits to butterflies. The generalised nature of this gradient approach also means it could be adapted to AES contexts in other countries, instead of using total option area as a metric of landscape AES (e.g. Meier et al., 2024; Zingg et al., 2019). However, the generalised approach means it is more difficult to link specific options to benefits to butterflies across diverse landscape types. For example, high butterfly abundance in lowland arable landscapes may be linked to a high density of sown flower margins, whereas in upland landscapes such as the Yorkshire Dales, high butterfly abundance may be more influenced by landscape diversity, habitat heterogeneity and low impact management (Löffler et al., 2023).

An important caveat to our approach is that it uses data from citizen science schemes that are broadly comparable to designed studies. Butterflies have well-designed national-scale structured monitoring in England, and the LandSpAES protocols were specifically designed to enable comparability (Jarvis et al., 2021). The approach is likely to be most successful for other taxa which have structured citizen science schemes; where only opportunistic citizen science data is available, more complex methods of comparing and integrating data would be required (Johnston et al., 2023).

5 | CONCLUSIONS AND RECOMMENDATIONS

We found good support for a positive impact of landscape-level AES intervention on butterflies across a targeted survey designed to assess AES effects and national-scale citizen science datasets. This indicates that the positive relationships with butterfly abundance and richness hold across multiple conditions, and we can assume they are representative nationally. These results suggest that AES has a potentially significant role in supporting butterfly abundance across lowland and upland landscapes in England. The finding that butterflies appear to respond more strongly at the landscape scale suggests that managers and policy makers should consider supporting AES intervention across spatial areas beyond those of individual fields and farms to create landscapes of high AES uptake. This could be implemented by encouraging or incentivising clusters of neighbouring farmers to take up beneficial options (Meier et al., 2024). Current AES schemes in England include both the Sustainable Farming Incentive, which aims to incentivise very widespread uptake of easily applied AES options, and Landscape Recovery, which aims to support multiple landowners across a landscape to implement more targeted environmental improvement actions. Creation of landscapes of beneficial options under both schemes could be positive for butterflies.

To quantify the impacts of AES requires efficient monitoring and evaluation. Here we showed the benefit of using both targeted and citizen science monitoring to understand AES impacts at national scales and would recommend future monitoring and evaluation consider both forms of evidence. We suggest building points of commonality into new surveys for easier comparability with existing datasets, for example using a 1 km cell basis and using standardised protocols. Understanding the impact of AES at national scales will benefit from exploiting multiple datasets, ensuring that we make the most of the data available.

AUTHOR CONTRIBUTIONS

Joanna T. Staley, Susan Jarvis, Gavin Siriwardena and Susanna Phillips conceived the ideas and designed methodology; Marc Botham, John W. Redhead, Emily Upcott and Morag McCracken provided access to and processing of the data; Fiona Seaton and Susan Jarvis analysed the data; Susan Jarvis, Fiona Seaton, Marc Botham and Joanna T. Staley led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available from Zenodo https://doi.org/10.5281/zenodo.15131293 (Jarvis et al., 2025). Code to run models and create outputs is also archived on Zenodo at https://doi.org/10.5281/zenodo.15879871 (Jarvis & Seaton, 2025).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. LandSpAES study design conceptual figure.

Figure S2. (a, b) Distribution of landscape scale AES scores in each dataset.

Figure S3. Version of Figure 2 showing data points.

Table S1. Data summaries of butterfly response data from three datasets.

Table S2. List of all species recorded in datasets used in this study.

Table S3. Payment rates or points per option included in gradient calculations.

Table S4. Table of environmental data sources used in the PCA analysis.

Table S5. Correlations between PCA axes and AES gradient scores.

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