No effect of Agri-Environment Schemes on radar-measured aerial insect abundance at landscape scale in England

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I confirm that the work submitted is my own, except where work which has formed part of jointly authored publications has been included. My contribution and the other authors to this work has been explicitly indicated below. I confirm that appropriate credit has been given within the thesis where reference has been made to the work of others.

Other authors contributing to this work are as follows: Tommy Matthews, David Dufton, Julia Crook, Mansi Mungee, William E Kunin, Ryan R Neely III and Christopher Hassall. The work which is directly attributable to me includes: (i) all analyses, (ii) writing of the manuscript, (iii) all figures and tables, (iv) all supplementary materials. Christopher Hassall and William E Kunin provided supervision throughout. Mansi Mungee, Ryan R Neely III, David Dufton, Tommy Matthews and Julia Crook provided technical support with radar data processing. All authors provided advice throughout the work as well as comments and suggestions to the manuscript.

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The specific contributions made to this work are as follows: Bill Kunin, Chris Hassall and I conceived of the project, building on much work by Mansi Mungee; Bill Kunin and Chris Hassall provided supervision and advice throughout; Julia Crook, David Dufton, Mansi Mungee and Ryan R Neely III wrote and provided software essential to collecting and processing the radar data upon which this work is based; Tommy Matthews provided additional help and support in applying this software and in technical advice on dual-polarisation radar product; Ryan R Neely III provided computational resources via the NERC computing platform, JASMIN. Additional technical support on dual-polarisation radar products was provided by Ryan Neely III, Julia Crook, David Dufton and Maryna Lukach. All previously mentioned contributors provided invaluable comments, help, support and feedback on draft versions of this thesis

Abstract

Agri-environment schemes (AES) commonly represent the largest financial investment in biodiversity conservation at a national or international level, but evidence for AES intervention effectiveness remains equivocal. Here, we develop a novel and general method for assessing the impact of conservation interventions using Weather Surveillance Radar (WSR) to produce spatially explicit time series of aerial insect abundance over 1,597 km^2 of agricultural land in England from 2015-2022. Using this dataset, we evaluated the landscape-scale causal effect of AES across 15 natural experiments involving paired AES and control sites. We find no natural experiment which indicates a positive causal effect of AES on aerial insect abundance at levels of expenditure ranging from £34 km^{-2} to £5,122 km^{-2}. When considering all 1597 km^2 of agricultural land covered by the radars, we also find a weak but significant negative correlation between AES and aerial insect abundance, with stronger, positive relationships between aerial insect numbers and the percentage cover of woodland and semi-natural grassland. Our results provide the most robust evaluation of the benefits of AES and indicate that AES are not working to conserve aerial insects, assuming that WSR accurately captures the landscape-scale abundance of insects from 500-700 m above sea-level. We demonstrate the utility of landscape-scale conservation impact assessment using WSR-measured insect abundance, a technique which may be broadly applicable to problems in insect conservation science.

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Abbreviations

AES: Agri-Environment Schemes

AONB: Area of Outstanding Natural Beauty

BACI: Before-After Control-Impact

CAP: Common Agricultural Policy

CS: Countryside Stewardship

CVP: Columnar Vertical Profile

ES: Environmental Stewardship

ESA: Environmentally Sensitive Areas

EU: European Union

G7: Group of Seven (Canada, France, Germany, Italy, Japan and the United Kingdom)

GAM: Generalised Additive Model

GLMM: Generalised Linear Mixed Model

LCM: Landcover Map

LNR: Local Nature Reserve

LR: Landscape Recovery

NGO: Non-governmental Organisation

NNR: National Nature Reserve

PTA: Parallel Trends assumption

RIS: Rothamsted Insect Survey

SFI: Sustainable Farming Incentive

SSSI: Site of Special Scientific Interest

UKBMS: United Kingdom Butterfly Monitoring Scheme

WSR: Weather Surveillance Radar

ZDR: Differential Reflectivity

Contents

1. Introduction

England is often said to be among the most nature-depleted countries in the world (Mordue et al., 2023). The Biodiversity Intactness Index (one of many measures of this type) ranks the United Kingdom bottom among the G7 and in the 10% most degraded countries internationally (Phillips et al., 2021). Insects dominate terrestrial biodiversity in term of species richness, abundance and biomass (Wagner, 2020). Observed population declines across taxa (Wagner, 2020) are a major cause for concern due to insects' diverse roles in pollination, nutrient cycling, herbivory and predation (Wilson, 1987). Many species of insect, especially smaller species of Diptera and Coleoptera as well as aphids, parasitoid wasps, ballooning spiders and migratory species of dragonfly, butterfly and moth make use of the convective boundary layer (CBL), at 150-1200 m above ground level, for dispersal (Chapman et al. 2004; Bell et al. 2013). Comprising a major section of the terrestrial insect fauna, these species can now be monitored near-continually over large areas using weather surveillance radar (Mungee et al. 2025).

Globally, agricultural expansion is among the most significant drivers of insect declines (Miličić et al., 2021; Dicks et al., 2021). England is unusual internationally in that the vast majority of the country was cleared to make way for agriculture more than 2000 years ago - a process so complete that even the general characteristics of its natural vegetation remain debated by ecological historians (c.f. 'semi-open wood pasture', Vera, 2000; 'wildwood', Rackham, 2000). Nearly 70% of the country's land area is used for agriculture (Marston et al., 2024). As such, the fate of biodiversity in England is tightly linked with that of farming. Major early changes include the British Agricultural Revolution beginning in the 16th century, associated with the enclosure of the commons, increased use of natural fertilisers, new systems of field rotation and selective breeding of animals (Overton, 1996). Despite these developments, the general picture of the English landscape before 1945 is one of continuity. As ecological historian Oliver Rackham (2000) writes: "much of England in 1945 would have been instantly recognisable by Sir Thomas More, and some areas would have been recognised by the Emperor Claudius"; he notes that "almost every" hedge, wood, heath and fen present on ordinance survey maps of 1870 is visible on aerial photographs of 1940, except for relatively minor losses to urban expansion.

This continuity was broken in the second half of the 20th century. The post-war ‘green revolution’ intensification of agriculture had a dramatic effect on the landscape and on biodiversity. Unimproved grassland, once a feature of the English countryside supporting a high diversity of plants and insects, declined by 98% between 1930 and 1984 (Fuller, 1987) and roughly 50% of all hedgerows were destroyed in the 20th century (Barr and Parr, 1994). Intensification was driven in part by incentives and subsidies of various kinds, most significantly the 1947 Agriculture Act and the Common Agricultural Policy of the European Union after accession in 1973 (Robinson and Sutherland, 2002). Recognising rapid losses to intensification, efforts towards species conservation also began during the post-war period. England developed a complex system of designations including National Parks, Areas of Outstanding Natural Beauty (AONB), Environmentally Sensitive Areas (ESA), National Nature Reserves (NNR), Local Nature Reserves (LNRs) and Site of Special Scientific Interest (SSSI), among others (Winter, 2013). Other sites are managed by NGOs such as the Wildlife Trusts, the Royal Society for the Protection of Birds or by private individuals.

However, outside of such protected areas, the primary mechanism by which the state seeks to conserve nature in England is through farm subsidies encouraging nature-friendly farming practices. Since accession to the European Union in 1973, this has occurred through Agri-Environment Schemes (AES). Preceded by some smaller scale-schemes such as Broads Grazing Marsh Conservation Scheme (1985) and Environmentally Sensitive Areas (1987), AES implementation began in earnest in through the Common Agricultural Policy (CAP) in 1991. In this new type of farm subsidy, a portion of funds would be allocated through schemes incentivising the reintroduction or protection of traditional features such as low input grassland and hedgerows. The first major AES in England, the Countryside Stewardship Scheme (CS 1991), allocated a small tranche of the CAP budget to delivering conservation on farmland. In 2005, Countryside Stewardship was replaced by Environmental Stewardship (ES), which was itself replaced in 2016 by a new scheme, also called Countryside Stewardship (CS 2016).

Post-Brexit, Environmental Land Management (ELMs) were introduced, comprising three schemes, including a third iteration of the Countryside Stewardship Scheme (CS 2024), the Sustainable Farming Incentive (SFI) and Landscape Recovery (LR).

The main changes to AES over the last 30 years have been to offer a wider variety of available interventions (‘options’) and to allocate larger portion of the total subsidy to environmental objectives. This process continued following Brexit, when, leaving the CAP, the UK government indicated that farm subsidies will transition away from ‘Pillar I’ payments (made on the basis of land area owned) entirely, moving towards delivering subsidies through AES only, a change billed as “public money for public goods”. *Figure 1* provides an overview of these changes to conservation and farming policy in the United Kingdom (see Simoncini et al., 2019, for a review of changes the CAP).

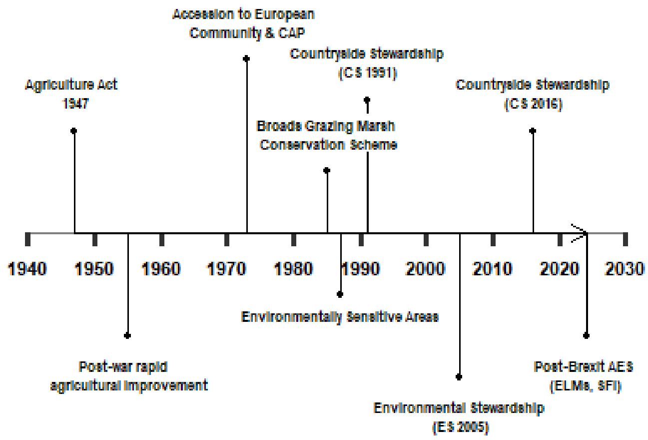

Figure 1. Timeline of major changes to British farming and conservation policy. The 1947 Agriculture Act, coupled with scientific developments in farming issued a significant intensification of British farming. In the following decades, the vast majority of pasture was improved with fertiliser, reducing plant diversity. Hedges were also removed and pesticide use increased. In 1973 the UK joined the Common Agricultural Policy (CAP) of the European Community (later European Union). The protectionism of the CAP along with the 1980s commodity boom caused major overproduction of food, producing the famous ‘butter mountains’ of the 1980s, symbolising post-war intensification. AES policy began in 1991 through the CAP in response to perceived biodiversity losses resulting from intensification. The UK left the CAP with Brexit, marking a shift in UK policy towards more extensive use of AES as a farm subsidy mechanism. In 2024, the ‘pillar I’ basic payment scheme was removed entirely. Now, all subsidies will be delivered through AES, compared to around 25% of the total subsidy in the European Union. Author’s own work.

A major public good these schemes are hoped to deliver is insect conservation. Evidence that they do so effectively is mixed. Studies seeking to assess the efficacy of AES conserving insects typically do so at the scale of individual schemes or farms (Staley et al., 2021). Particularly for Lepidoptera and Hymenoptera, there is a large body of evidence indicating that AES are generally efficacious at fine scales and tend to increase insect abundance and/or richness, when compared to sites or farms where schemes are not present (Dicks et al., 2014; Kleijn et al., 2018; Bladon et al., 2023). However, despite 30 years of targeted AES, farmland insect species such as butterflies have failed to substantially recover since the beginning of standardised monitoring in 1976 (Fox et al., 2021; Fox et al., 2023), suggesting that the demonstrated local enhancement provided by AES fails to translate nationally.

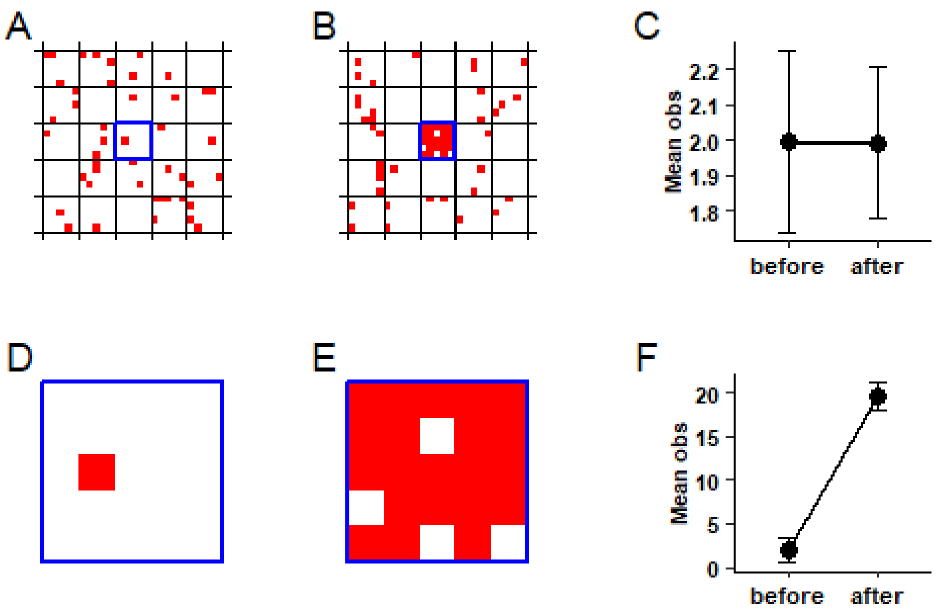

Figure 2. Simulated scale-dependent honeypot effect. The upper (A, B) black-outlined grid represents a landscape comprised of a grid of plots. Red squares represent observable insect foraging activity. A conservation intervention is undertaken in the central plot (A, outlined in blue), causing spatial redistribution of foraging activity (B). The total number of foraging individuals is unchanged when we measure across the whole grid (C). When observations are made at fine scales in the central plot where the intervention was undertaken only (D, E), this leads to a large positive effect estimate (F) while the effect size across all plots is 0 (C). Authors' own work.

This apparent disparity between fine (field) and coarse (national) scale effects has led to increased interest in monitoring the effect of AES at intermediate (landscape) scales, variously defined (e.g. Wood et al., 2015; Staley et al., 2016; Kleijn et al., 2018; Staley et al., 2021; Staley et al., 2022). Kleijn et al. (2018) and Staley et al. (2021) highlight the difficulties with measuring landscape scale insect abundance and separating localized population redistribution from landscape level population change. Typically, surveys of mobile insect taxa seek to infer the effect of AES on insect populations by recording foraging individuals (Kleijn et al., 2018). As mobile taxa (especially pollinators) tend to distribute their foraging activity in response to resource availability, it is challenging to determine if interventions which provide enhanced resources increase the total population size or merely concentrate the existing population spatially around the resource (Kleijn et al., 2018; Staley et al., 2021). Analogously, the presence of a trap or lure may increase the number of individuals one observes at fine scales, but it would be spurious to conclude such an attractant caused an increase in the total size of the population measured. This 'honeypot effect' (Staley et al., 2021) describes the tendency of fine scale surveys of foraging activity to conflate spatial redistribution with effects at the population level (Figure 2). The honeypot effect is an example of a scale-dependent measurement effect. As described by Levin (1992), the scale at which measurements are made conditions which ecological mechanisms are observable; here, a coarse-scale mechanism is of interest (population enhancement) but measurements are made at fine scales (point counts of insects) introducing a "perceptual bias" (Levin, 1992) whereby the finer scale honeypot effect confounds the identification of coarser scale effects of interest (see Discussion). This scale problem is illustrated graphically in *Figure 2*.

If AES are to contribute to the recovery of insects nationally and/or enhance the delivery of ecosystem services such as pollination, it is desirable that landscapes with a high level of AES investment act as a population source - providing additional habitat from which insects can reproduce and disperse into the wider landscape. Previous studies (Gabriel et al., 2010; Kleijn et al., 2018; Staley et al., 2021) extrapolate point measurements to estimate landscape scale abundance in various ways. Here, we take a complimentary approach, using Weather Surveillance Radar (WSR) to directly measure landscape-scale insect abundance.

WSRs are designed to monitor meteorological phenomena. However, the capacity of radar to detect non-target biological scatterers has been known since the advent of radar in the 20th century; many types of radar system can relay ecologically relevant information, including specially designed ecological radars. A major emerging source of ecological data is dual-polarisation WSR. Many countries have networks of these radars where they are used to measure weather patterns and generate forecasts, covering much larger areas than dedicated ecological radars. Newer dual-polarisation WSRs are capable of simultaneously transmitting and receiving orthogonal beams of vertically and horizontally polarized radiation. The data products derived from dual-polarization WSR returns are capable of characterising the size, shape and potentially species of aerial bioscatterers (Stepanian et al., 2016), and as such much more ecologically relevant information can be extracted (Matthews et al. 2025).

Recent work (Mungee et al., 2025) has developed and tested the application of dual-polarisation WSR to monitor UK aerial insect abundance at regional and national scales. These methods involve first dividing radar data into Columnar Vertical Profiles (CVPs; cylinders of air space with a diameter of 5 km) arranged in a grid pattern around each radar, facilitating ecological analysis of a radar data over a fixed area. Then, a filtering procedure is used to select scatters identifiable as insects and estimate total insect abundance. Here, we apply these methods to assess the landscape-scale impact of AES intervention over farmland in England using a before-after-control-treatment (BACI) framework coupled with matching. For each CVP we quantify AES expenditure using two measures: measure A (including all biodiversity-related options) and measure B (including only insect-related options). We develop a procedure to match AES treated CVPs with substantial increases in AES expenditure to control CVPs with no change in AES expenditure, based on both landcover similarity and pre-treatment insect abundance trend. This two-stage matching means that one can credibly make the key BACI ‘parallel trends’ assumption, that the insect abundance trend ‘would have been’ parallel in the post-treatment period had the treatment not occurred (i.e. the control unit serves as a credible counterfactual case). We identify a series of natural experiments using this procedure. Separately, we also examine the association between two measures of AES expenditure (measure A, including all biodiversity-related options and measure

B, including only insect-related options) and aerial insect abundance using a series of Generalised Linear Mixed Models. Our results provide the first direct assessment of the landscape-scale impact of AES and provide a template for future impact assessment studies applying WSR. We discuss the policy implications of our findings with reference to the structure of agricultural subsidies in the United Kingdom. We provide detailed instructions on WSR data processing and impact assessment, adapting methods from atmospheric science and econometrics respectively.

2. Methods

Full details are provided in Supplementary Information. In overview, our procedure is comprised of the following steps: (i) extract biological data from UK weather surveillance radar archives, (ii) process those data into CVPs; (iii) estimate insect abundance within each CVP; (iv) quantify the biodiversity-related and insect-related AES spend in each CVP to identify potential treatment and control CVPs, (v) match control to treated CVPs based on similarity in terms of landcover and pre-treatment insect abundance trends, (vi) conduct before-after-control-impact analyses to identify the effect of AES intervention for each pair and (vii) separately produce generalised linear mixed models describing the correlation between landcover and insect abundance. We summarise some methodological steps for clarity in the main text, but further technical details on data processing, sensitivity analyses, generalised additive models, quantifying AES spend and BACI design choices are provided in the Supplementary Information.

All code and data required to produce analyses and figures are available via Figshare (https://doi.org/10.6084/m9.figshare.30489188.v1).

2.1 Data processing

The UK Met Office operates a network of nine C-Band (wavelength ca. 5.3 cm), dual-polarization monostatic radars in England, providing complete meteorological airspace coverage over the country. Due to the low reflectivity of insects relative to some meteorological phenomena, insects can usually only be detected up to a range of 30 km from each radar. This gives approximately 16% airspace coverage for England (Figure 3).

Raw polarimetric data are freely available via the Centre for Environmental Data Analysis archive (*https://archive.ceda.ac.uk/*). Following a procedure developed in Lukach et al. (2024) and Murphy et al. (2020), raw polarimetric radar data were processed into 12 x 12 grids of CVPs surrounding each radar (Figure 3; Figure 4). Each CVP is a cylinder with a diameter of 5 km separated into 200 m height bands (Figure 5 illustrates a single CVP height band). The process of generated CVPs is detailed in SI section 7.1.1. Below ca. 500 m above sea level (variable between radars), data coverage is limited as the radar beam can often intersect with ground-level clutter such as trees, hills and buildings. Mungee et al. (2025) find that aerial insect abundance is increasingly decoupled with ground-level processes at higher elevations. To maximise the amount of clutter-free data available while minimising height band elevation, we analyse a 500 m – 700 m height band only. We focus on a window of generally observed high insect activity in England, between 15th April to 30th October across years 2014 to 2022 (Figure 6.)

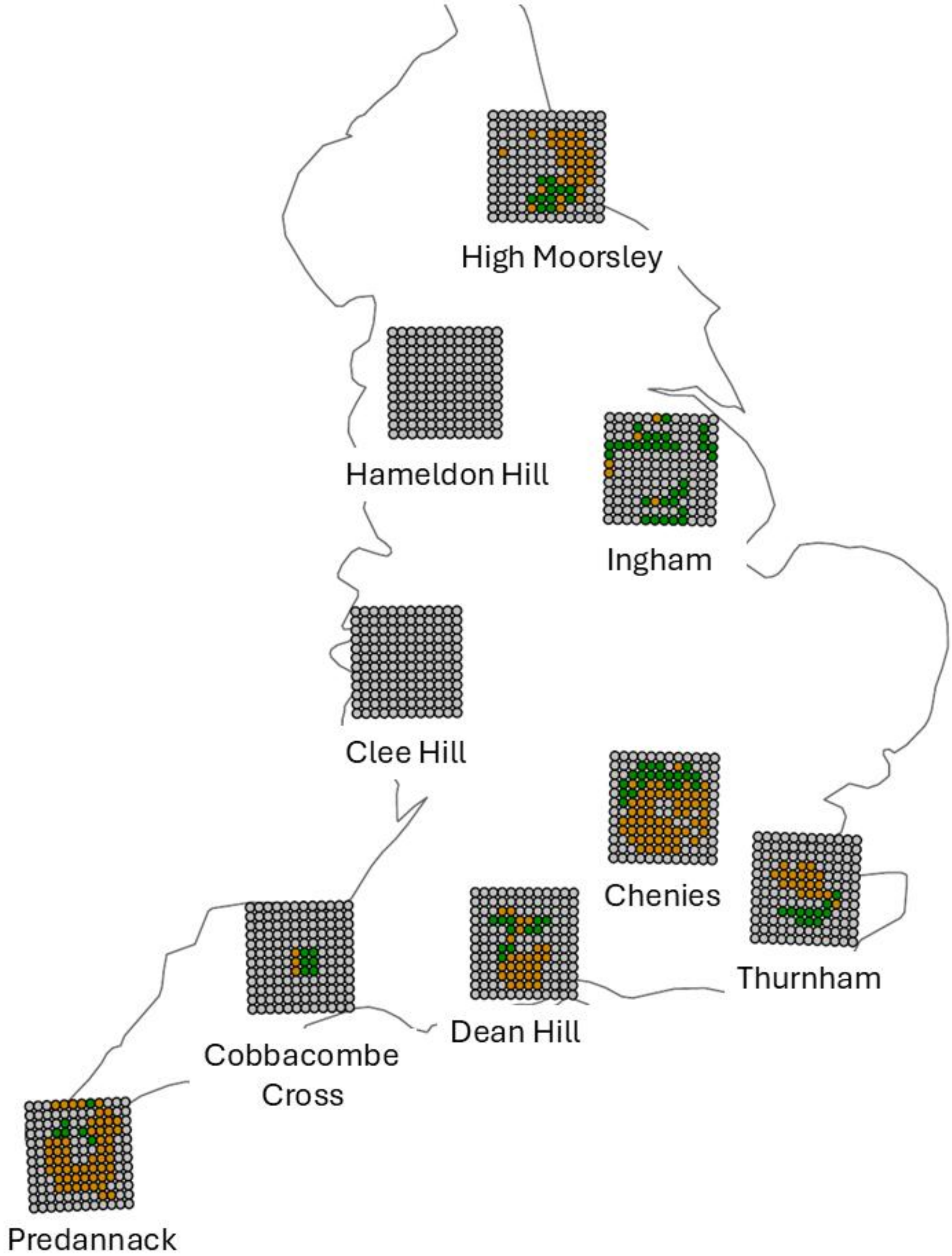

Figure 3. Positions of included CVPs. CVPs over 75% agricultural cover are shown in green, CVPs without 75% agricultural cover are shown in orange. CVPs for which no data was available at the 500-700 m height band due to obstruction or ground clutter are shown in grey. Authors' own work.

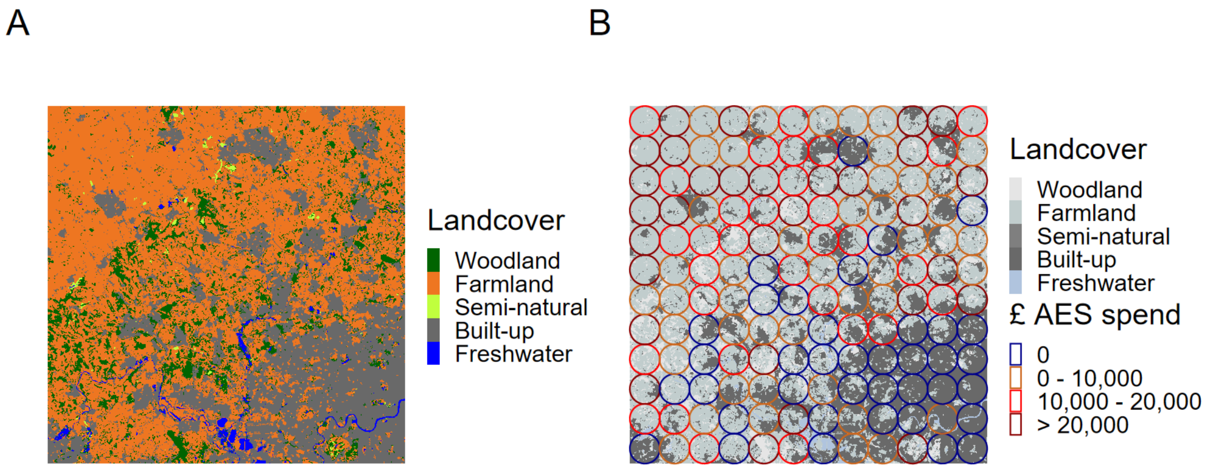

Figure 4. Landcover for CVPs surrounding the Chenies radar (A) and insect related Agri-Environment scheme spend by CVP at the Chenies Radar (B). Semi-natural corresponds to all non-woodland, non-urban and non-farmland cover. Authors' own work.

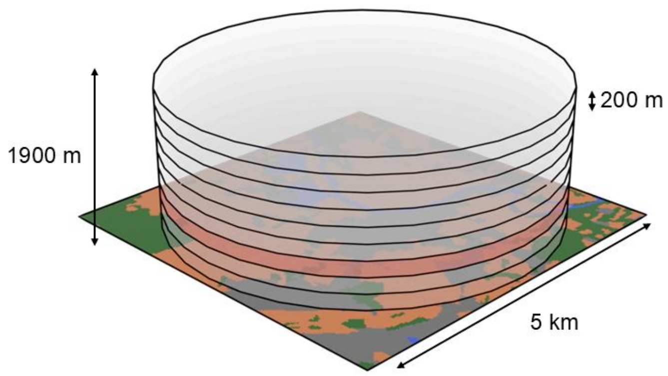

Figure 5. Diagram illustrating the spatial dimensions of a single CVP, Chenies 40. The 500-700 m height band is indicated in red. A corresponding landcover map is shown beneath. Drawn to scale. Authors' own work.

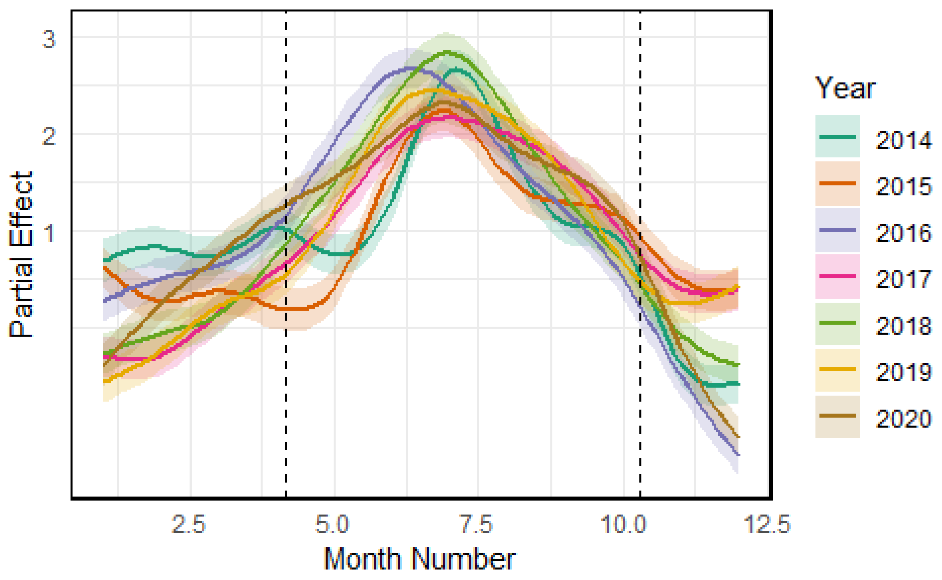

Figure 6. Intra-annual variation in maximum differential reflectivity (ZDR) across CVPs at the Chenies radar. ZDR characterises the ratio of height to width of objects in the radar beam and is routinely used to separate more spherical meteorological objects (rain drops) from more irregular biological objects (birds, bats, insects). Intra-annual variation in ZDR aligns with generally observed variation in insect abundance in the United Kingdom. We selected the period between the dotted lines for further analysis. Smoothed trend lines were produced using Generalised Additive Models (see Supplementary Information for details).Partial effect indicates the estimated contribution of a single smooth term, in this case month by year. Authors' own work.

Following Mungee et al. (2025), we then filter radar returns within each CVP to include only signals attributable to aerial insects, producing a measure of the total back-scattering area of arthropods (cm^2) in each CVP (see Supplementary Information). The process of estimating insect abundance is detailed in SI section 7.1.2. We separate measurements between those covering nocturnal (1900 to 2300 UTC) and diurnal (0800 to 1400 UTC) diel periods, selecting the highest insect reflectivity value for each period for further analysis. Selecting the highest value within nocturnal from diurnal windows separated by buffer period in helps to prevent any double-counting between nocturnal and diurnal measures. We convert this maximum insect-reflectivity figure to a measure of insect abundance by dividing the area by the estimated Radar Cross Section (σ) of a single insect, defined here as

4.52×10^{-4} cm^2 (see Mungee et al., 2025 and Supplementary Information). The result is a dataset providing one diurnal and one nocturnal estimate of maximum insect abundance each day for each CVP. In spatial resolution each measurement has a diameter of 5km and covers airspace between 500m and 700m above ground level.

2.2 Analysis

We calculate two measures of AES spend in the Countryside Stewardship and Environmental Stewardship Schemes in England: (A) including all biodiversity conservation related options and (B) including only options for which published evidence or expert opinion suggests are beneficial to butterflies or other pollinating invertebrates, as reviewed by Staley et al. (2021). Included options are detailed in Supplementary Tables 1 and 2.

We analyse the relationship between AES spend (measures A, B) and insect abundance in a Generalized Linear Mixed Model (GLMM) framework using R package glmmTMB (Brooks et al., 2017; McGillycuddy et al., 2025).As our insect abundance metric was derived from total reflectivity (rather than counts per se) we model log-transformed insect abundance using a Gaussian distribution rather than the Poisson or negative binomial models typically used to model counts in ecology. As high AES intervention tends to occur within CVPs covering agricultural land, we account for potential covariance between agricultural landcover and AES intervention by including only CVPs dominated by agricultural land-use. We sought to identify agricultural CVPs for analysis, striking a balance between selecting CVPs which are dominated by agriculture and including as many CVPs in analyses as possible. We identified 96 CVPs with over 75% combined coverage of ‘arable and horticultural’ and ‘improved grassland’ landcover (Figure 3; Figure 4) using the 2022 CEH land cover map (LCM; Marston et al., 2024). Implementing such a cutoff introduced artificial collinearity between landcover variables, hampering model interpretability. As such, after initial model fitting, we exclude farmland coverage covariates from subsequent models to resolve this multicollinearity issue. We conduct sensitivity analysis using different cutoff levels, finding that the relationships between variables other than AES spend were similar across cutoff levels (Supplementary Information section 7.3)

In total, we fit three GLMMs. Model one, used to describe the interannual trend in insect abundance, includes random effects for CVP and month of the year and an interaction term between time of day (factor: nocturnal or diurnal) and Year (factor: 2014-2022).

Eq. 1

$$\log\left(1 + Abundance_{ijkm}\right) = \beta_0 + \beta_1 \,\mathrm{Time\_of\_day}_{ijkm} + \beta_2 \,\mathrm{Year}_j + \beta_3 \left(\mathrm{Time\_of\_day}_{ijkm} \times \mathrm{Year}_j\right) + b_{\mathrm{CVP},i} + b_{\mathrm{Month},k} + \varepsilon_{ijkm}$$

We then fit two additional models to describe the relationship between annual AES spend and insect abundance. Model two includes (1) a random effect for CVP to account for repeated measures; (2) crossed random effects for month and year to account for temporal trends; (3) landcover covariates: woodland (combined coniferous and broadleaf woodland cover), seminatural grassland (including acid, neutral, calcareous and heather grassland cover), and built-up cover (including urban and suburban landcover); (4) a time of day (factor: nocturnal or diurnal) variable; and (5) the total annual expenditure in AES measure A, including all biodiversity-related options. Model three was fit with identical covariates to model two but substitutes AES measure B for AES measure A.

Eq. 2

$$\log\left(1 + Abundance_{ijkm}\right) = \beta_0 + \beta_1 \,\mathrm{AES}_{ijkm} + \beta_2 \,\mathrm{Time\_of\_day}_{ijkm} + \beta_3 \,\mathrm{Woodland}_{ijkm} + \beta_4 \,\mathrm{Built\_up\_gardens}_{ijkm} + \beta_5 \,\mathrm{Seminatural}_{ijkm} + b_{\mathrm{CVP}_i} + b_{\mathrm{Year}_j} + b_{\mathrm{Month}_k} + \varepsilon_{ijkm}$$

Equation 2 corresponds to model 2 including measure A AES and model 3 including measure B AES. Diagnostics for each model were checked throughout the modelling process using R package DHARMa (Hartig, 2024) and for multicollinearity using VIFs implemented in R package performance (Lüdecke et al., 2021). All VIF values were between 1.00 and 1.03. Models 2 and 3 describe the correlative association between AES spend and insect abundance but fall short of identifying any putative causal relationship due to factors which drive both AES intervention and insect abundance. For example, agricultural intensity is likely to causally affect both insect abundance and the degree of AES intervention. In highly productive systems the opportunity cost incurred by undertaking AES interventions (especially those which reduce the area of land under cultivation) is likely to be higher, and therefore AES intervention is disincentivised in high intensity systems with respect to lower intensity systems (e.g. organic farming is associated with less agriculturally favoured areas; Gabriel., et al. 2009). Such confounding obscures the true effect of AES intervention.

To isolate the causal effect of insect-related AES on aerial insect abundance we identify a series of pseudo-experiments which we analyse in a Before-After Control-Impact (BACI) framework. BACI facilitates identification of the causal effect of AES intervention by eliminating time-invariant confounding (e.g. agricultural intensity) and time-varying confounding occurring simultaneously in the treated and control units (e.g. weather- or climate-driven interannual variability). This means that all fixed confounding, such as landcover and site history, which affects the absolute level of insect abundance in the CVP is removed. It does so by using the change in insect abundance between the before and after period in the control CVP as the 'counterfactual case' – what 'would have happened' in the treated CVP, had the intervention not occurred. The critical assumption in BACI analyses is that of 'parallel trends' (Supplementary Information). The parallel trends assumption (PTA) states that the treatment unit would have followed the same trend as the treatment unit had the intervention not occurred (i.e. if plotted, their trajectories would have been parallel). If we cannot credibly make the PTA, the difference between the outcome at the control and treatment unit may be caused by both the diverging trend and the (potentially) the treatment, such that the causal effect cannot be identified. We can increase our confidence that the PTA holds by ensuring that the treatment and control units are (1) nearby, such that they are subjected to similar time-varying confounding like weather; (2) similar to one another in terms of landcover, meaning that they might be expected to respond similarly to treatment and non-measured time-varying confounding, such as how favourable a particular year is for insects; (3) following parallel trends in the pre-treatment period that might be expected to continue into the post-treatment period if the intervention does not occur or has no effect. BACI design choices and theoretical justification for matching is discussed more fully in Supplementary Information section 7.4.

We develop a two-stage matching process to identify pairs of treatment and control CVPs which are nearby to one another, similar in terms of land-cover and show parallel trends in the pre-treatment period in order to meet the PTA credibly. Firstly, for each potential treatment CVP (receiving some non-zero level of AES intervention), we identify a pool of candidate control CVPs based on landcover similarity. To be included in the pool, candidate control CVPs needed to be located within the scanning space of the same radar and match (within 15%) landcover of the treated CVP, in terms of: (1) agricultural landcover (LCM classes 'arable and horticultural' and 'improved grassland'), (2) combined urban and suburban cover, (3) combined broadleaf and coniferous woodland cover and (4) semi-natural grassland cover (including neutral, calcareous, acid and heather grassland). Landcover for each CVP was extracted from the CEH landcover map (Marston et al., 2024). A cutoff of 15% was selected to select CVPs which are broadly similar in landcover configuration. However, since BACI analysis controls for all pre-treatment differences between CVPs which affect the absolute level of insect abundance, it was not critical that CVPs match exactly in terms of landcover (see Supplementary Information section 7.4.3). For each candidate treatment-control pair, we then calculate a trend similarity score which describes how closely aligned the insect abundance trend is between the treatment and control units (see Supplementary Information). For each treated CVP, we select the control CVP with the lowest similarity score for further analysis.

For each candidate pair produced by matching on landcover and pre-treatment trend, we then model insect abundance using a series of dynamic BACI models (similar conceptually, but distinct to those presented in Wauchope et al., 2021). These models are similar to traditional BACI models but also including terms for Time and Time Since Treatment, which allows one to estimate the divergence between treatment and control in each year of data separately (Supplementary Figures A1-9 and B1-9). This model specification is well suited to conservation impact assessment we are able to detect lagged treatment effects and assess the PTA based on results corresponding to the pre-treatment period. We calculate robust (Eicker–Huber–White) standard errors using R packages lmtest (Zeileis and Hothorn, 2002) and sandwich (Zeileis, 2004; Zeileis et al., 2020). We include candidate BACI pairs which are not significantly different from one another in any pre-treatment year (Time Since Treatment variable) as an additional test to ensure trends to not diverge in the pre-treatment period. For comparisons which meet these criteria, our final effect size estimate is calculated using a traditional BACI model, interacting dummy variables describing the treatment period (before or after treatment) and intervention (treatment or control). To account for recent work in econometrics examining the pitfalls of dynamic BACI analyses with staggered treatment intervention, we present each BACI comparison separately as an assessment of a particular level of AES intervention (Supplementary Information section 7.5).

3. Results

Table 1. Number of included insect abundance estimates for each included radar in England.

Radar	Years covered	# Estimates	BACI site pairs
Thurnham	2017-2022	6429	1
Chenies	2014-2022	5589	12
Dean Hill	2017-2022	1371	0
High Moorsley	2017-2022	1221	1
Ingham	2018-2022	887	0
Cobbacombe Cross	2018-2022	447	0
Predannack	2014-2022	322	1

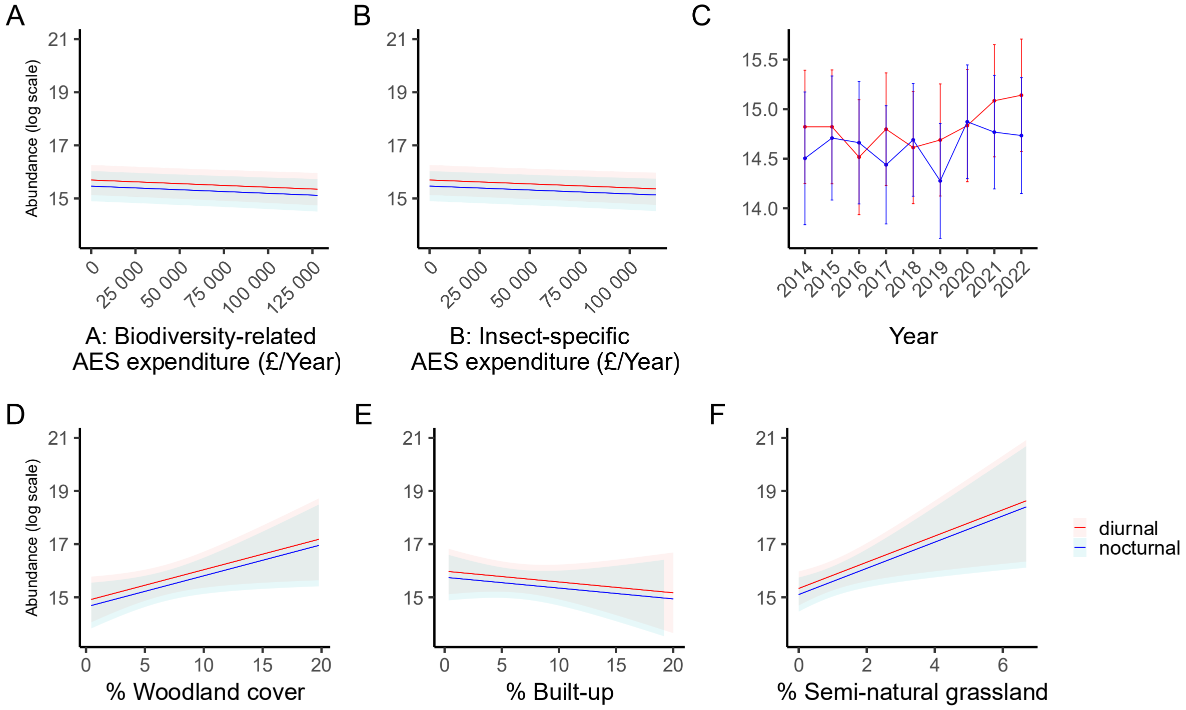

Figure 7. GLMM results indicating the associative relationship between WSR-measured aerial insect abundance and landcover variables. A total of 96 agricultural CVPs are analysed. AES measure A, including all biodiversity related AES options and AES measure B, including only insect-related AES options were both significantly negatively related to insect abundance. However, in both cases the slope coefficient was extremely small (A, B)l. Semi-natural (F) and woodland landcover (D) was significantly positively related to insect abundance, while built-up cover was unrelated to insect abundance (E). Insect abundance across agricultural CVPs varied through the period covered, not displaying a clear trend (C).Authors' own work.

We evaluate the correlative relationship between AES spend and insect abundance across 96 agricultural CVPs (Table 1), covering a total of 1884.96 km^2 over 1.63×10^4 scans. We record a total of 5.25×10^{12} aerial insects. Daily CVP estimates of insect abundance varied between 1.88 x 10^5 and 8.42 x 10^{10}. Diurnal insect counts were 20.53% greater than nocturnal insect counts (β = -0.22; $p <$ 0.001). Two radars, Clee Hill and Hameldon Hill had insufficient coverage at 500m and were not included in the analysis.

Annual AES expenditure varied between £ 0 and £ 1.28×10^5 for AES measure A and between £ 0 and £ 1.13 x 10^5 for AES measure B. In Generalised Linear Mixed Models, AES measure A, including all biodiversity related AES options, was significantly negatively associated with insect abundance (β = -2.71×10^{-6}, SE = -9.80×10^{-7}, p = 0.0057). AES measure B, including only insect-related AES options, was also significantly negatively associated with insect abundance (β = -2.94×10^{-6}, SE =1.08×10^{-6} p = 0.0066). The effect size in both cases was very small: for measure A this corresponds to 2.67% fewer insects per £10,000 of AES expenditure. For measure B, this corresponds to ca. 2.89% fewer insects per £10,000 of AES expenditure.

Insect abundance was significantly positively related to both woodland cover (β = 11.709, SE = 5.494, p = 0.033) and semi-natural grassland cover (β = 49.347, SE = 19.276, p = 0.010). Built up cover was unrelated to insect abundance (β = -4.076, SE = 5.382, p = 0.449). Full results are given in Figure 7 and Table 2.

Table 2 Generalised Linear Mixed Model results showing the associative effect of agri-environment intervention (measures A and B) and landcover for agricultural CVPs (over 75% combined arable and improved grassland landcover

Model	Term	Estimate	Standard Error	Statistic	P value
Model A	**Intercept**	**16.824**	**0.641**	**26.243**	**<0.001**
Model A	**Annual Spend (A)**	**-2.71×10^{-6}**	**9.80×10^{-7}**	**-2.763**	**0.006**
Model A	**Nocturnal**	**-0.229**	**0.0338**	**-6.784**	**<0.001**
Model A	**Woodland Cover**	**11.709**	**5.493**	**2.131**	**0.033**
Model A	Built-up Cover	-4.076	5.382	-0.757	0.449
Model A	**Semi-natural Cover**	**49.347**	**19.276**	**2.560**	**0.010**
Model B	**Annual Spend (B)**	**-2.94×10^{-6}**	**1.08×10^{-6}**	**-2.716**	**0.007**

3.1 Causal effect

We identified a total of 18 candidate pairs with either AES measure meeting all matching criteria. Three pairs selected by the matching procedure were removed, two contained visually diverging trends in the pre-treatment period and one pair was removed due to model failure, leaving 15 pairs. No comparison showed a significant positive effect of agri-environment intervention on insect abundance (Figure 8) for either measure A (including all biodiversity related options) or measure B (including only insect-related AES options). One comparison, pair 42, indicated a significant negative effect of AES intervention. No excluded pair showed a significant multi-year effect of AES intervention. There was a large degree of overlap between the groups of BACI comparisons between the two measures; CVPs with expenditure in measure

B also tended to have expenditure in measure A (all measure B options are included in measure A).

Figures showing dynamic BACI model results (including individual effect estimates for each year of data) are presented in Supplementary Information Figures A1-15 and B1-15. Dynamic BACI model results for a single pair are presented in Figure 9. Results for the three excluded models are included in Supplementary Information Figures C1-3.

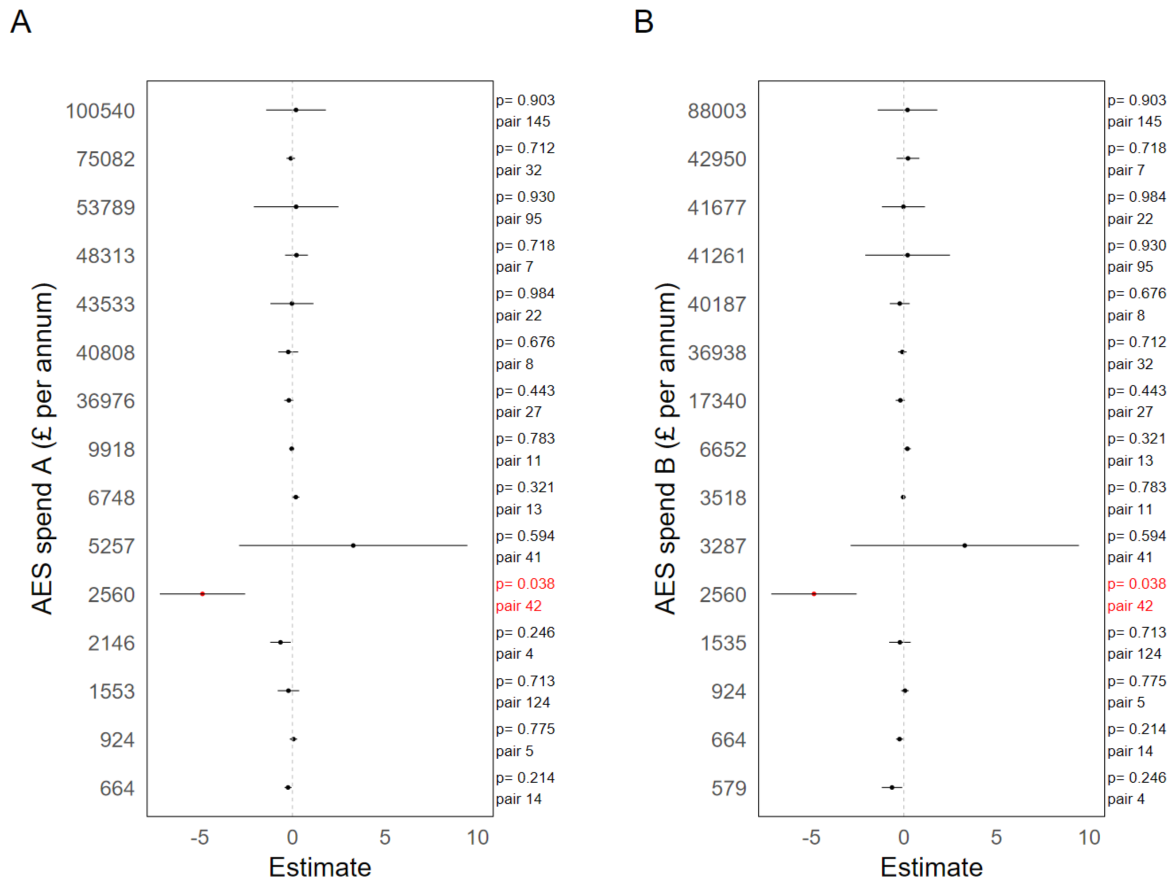

Figure 8. Forest plot showing the BACI effect size for each pair identified and selected by the matching procedure. No comparison pair showed a significant effect in response to AES intervention. This was consistent across all levels of AES intervention tested for both measures A and B. Error bars indicate standard errors. Authors' own work.

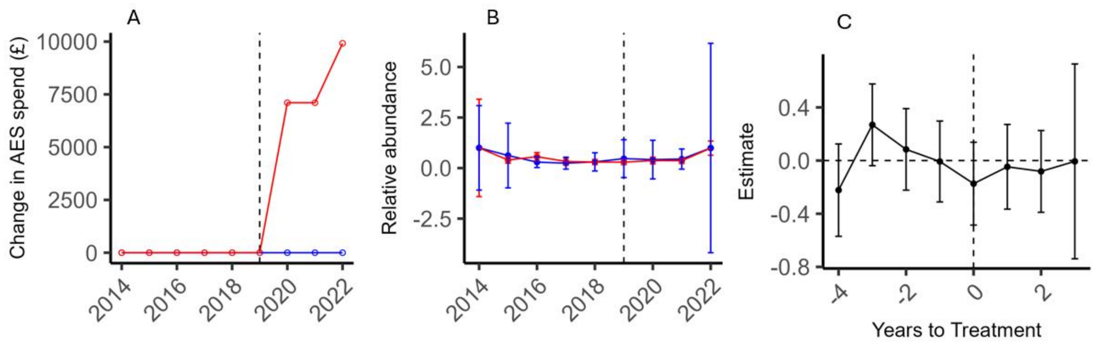

Figure 9. Plots showing results for pair 11, one of 15 included BACI pairs, showing the trend in AES spend (A), the trend in insect abundance in each CVP (B) and the dynamic BACI model results showing time-since treatment (C). All other BACI pairs are included in Supplementary Figures A1-15 and B1-15. Error bars indicate standard errors. Authors' own work.

4. Discussion

Conservation of farmland insect species is a primary objective of Agri-Environment Schemes across the Global North, such as the Common Agricultural Policy of the European Union. In England, many options contained within these schemes are specifically targeted at conserving once-common insect species, especially butterflies and other pollinators, but also other groups. To judge these schemes effective, it is necessary to demonstrate that AES intervention enhances insect abundance beyond the 'option' scale - not simply within or immediately surrounding the plot where intervention has been undertaken. We apply a novel approach to impact assessment using BACI methods borrowed from the difference in difference (DiD) literature in econometrics. These approaches are design based: by using within estimation, one can isolate the causal effect of AES intervention, removing confounding from comparing sites which are not alike in fixed observable characteristics, such as landcover and landscape history (see Supplementary Information sections 7.4 and 7.5). Using these methods, we find that insect-related AES intervention in England had no causal effect on landscape-scale aerial insect abundance measured by weather surveillance radar. We also find no evidence for a positive relationship between aerial insect abundance and insect-related or biodiversity-related AES spend across agricultural CVPs. We find a negative relationship between AES spend and insect abundance, albeit with an extremely shallow slope and arguably of negligible practical significance. These findings were consistent between AES aimed at biodiversity generally (measure A) and insects specifically (measure B) and between diurnal and nocturnal diel periods.

Previous work generally reports positive associations between AES and insect abundance at fine spatial scales, especially when measurements are made within intervention (at fine scales), such as areas within patches of sown flowers (Dicks et al., 2014; Kleijn et al., 2018; Bladon et al., 2023). However, on-the-ground studies that have assessed the effect of landscape scale AES uptake (variously defined) are more equivocal than those that survey ‘within’ interventions such as sown flower mixtures. Staley et al., (2022) sampled across a range of sites in England representing two sets of contrasts in AES uptake. Sites were classified as high, medium or low local (1x1km) AES uptake, and also as high, medium or low in terms of landscape (3x3km) AES uptake, producing nine separate contrasts. Across groups, their results are mixed. They find a positive correlation between the abundance of (1) butterflies and (2) moths and AES uptake at the landscape (3x3km) scale. They find no such correlation for other groups tested, including bees and hoverflies. Using a measure of bumblebee reproduction, consistent with many previous studies, Carvell et al. (2015) find that within 1ha or 0.25ha areas of sown flower mixture, bumblebee reproduction was increased in comparison to areas where flowers were not sown. However, they find that this effect does not translate to the landscape scale: reproduction was not significantly higher at transects outside the sown area (within 1km) when compared to areas surrounding control sites, where flowers were not sown. They do, however, observe a significant increase in reproduction when comparing the landscape scale effects of 1ha to 0.25ha flower patches (but not when compared to zero intervention). For bees, the best evidence that insect-directed AES can enhance insect population size comes from the application of molecular techniques. Contrary to Staley et al., (2022), Wood et al. (2015) effectively demonstrate that higher level stewardship options directed at pollinators increased bumblebee colony numbers in Hampshire and Sussex.

Importantly, we measure species not typically collected in AES surveys, which predominantly study butterflies, bees, and hoverflies. The aerial insect fauna is less well understood than the terrestrial insect fauna, however, small species of

Hemiptera (aphids, psyllids); various Diptera; Hymenoptera of Ichneumonoidea and Chalcidoidea; and Coleoptera families Nitulidae and Staphylinidae have been recorded at WSR-detectable heights (Chapman et al., 2004). We demonstrate that the abundance of aerial insect communities, comprised of groups such as these, are not affected by AES intervention.

However, our analyses are subject to a number of caveats due to the nature of WSR data. Because insects travelling in the convective boundary layer will be affected by the wind, our insect abundance estimates are likely to be affected by spillover between CVPs. Two aspects of our methodology help to ameliorate this issue. Firstly, we take the maximum insect-attributable reflectance value for each diel period within each CVP. We expect the effect of spillover to be less pronounced on the maximum value than on a diel mean value because it seems likely that spillover has a relatively constant influence on insect abundance (dependent on wind), working to make the mean values of adjacent CVPs more similar to one another. This means that while taking the maximal value may help to isolate local processes, we cannot discount the impact of spillover between high and low AES intervention areas. Secondly, our CVPs are large, with a diameter of 5 km. Since spillover should affect areas close to the perimeter of CVPs most dramatically, and the ratio of surface area to volume decreases with size, we expect that the effect of spillover will contribute a smaller proportion of insects to the overall estimate when the spatial resolution is coarse. Another caveat to consider contamination from birds. While methods are well developed to isolate meteorological from biological scatterers, methods are less well developed for resolving taxonomic groupings within the biological community. Our method to isolate birds from insects relies on ZDR thresholding (Supplementary Information) which is likely to include contamination from birds, especially less oblate species. Ongoing work seeks to improve techniques to isolate birds from insects in weather surveillance radar data (discussed below; Matthews et al. 2025). Another caveat is the concentration of natural experiments around the Chenies radar, which includes a large majority of the included BACI analyses. While this may undermine the generality of our findings, land surrounding the Chenies radar is among the most variable areas of the county, including parts of the Greater London area, green belt and the New Forest. Our results also cover a substantially larger area than all previous AES studies, even with the relatively small number of natural experiments included. Additionally, our Generalised Additive Models, covering all CVPs across all dual-polarisation radars in England, find no positive effect of AES intervention. Finally, while aerial insects comprise a major section of the terrestrial insect fauna (Chapman et al. 2004; Bell et al., 2013) AES target species, such as honeybees and bumblebees, appear unlikely to travel in the convective boundary layer. We are therefore unable to directly assess the impact of AES for these species using WSR. On the other hand, if low-flying and aerial species are expected to respond in a similar fashion to conservation interventions like AES, WSR-measured insect abundance may be used as an indicator for the effect of conservation interventions on insects more generally.

4.1 Policy implications

Agri-environment schemes now account for 50% of the total UK government expenditure (£876 million) on biodiversity conservation (Defra, 2024). Our results indicate such interventions have failed to increase or slow the decline of aerial insects in England. The failure of AES to conserve insect at national scales is also borne out by the continued decline of farmland insect species, such as butterflies (Fox et al., 2023), despite large public expenditure on their conservation through AES. These schemes have objectives beyond conservation. AES also aim to subsidise food production and conserve of non-biodiversity traditional landscape features, such as drystone walls and archaeological sites. Success in these objectives should be evaluated on their own merit.

A major deficiency of AES policy as related to biodiversity conservation is a lack of spatial planning (Banerjee et al. 2021). While there are some differences in available options and payment levels in Countryside Stewardship and Environmental Stewardship schemes for farms above the moorland line and for those in Severely Disadvantaged Areas, Entry-Level Stewardship in both schemes does not involve spatial planning of any type. This includes a large majority of agreements undertaken in both schemes (a smaller tranche of budget in these schemes is allocated to Higher Level Stewardship which involves closer collaboration and outcome assessment from Natural England.) In practice the existing incentive structure for Entry Level Stewardship means that conservation action is incentivised where the opportunity cost (profit forgone from crops or livestock) is lowest (Banerjee et al.

2021). One would therefore expect participants to undertake conservation activities in the most marginal areas of their individual holding, which may or may not adjoin existing habitat areas or AES interventions of other landholders. Reserve design principles based on island biogeography theory (Diamond, 1975) suggest large, circular, contiguous reserves (or areas of other conservation intervention) are more effective than those which are small and isolated. It therefore seems likely that an alternative AES strategy incorporating these principles could gain more for an equivalent amount of investment. For example, woodland creation options could be prioritized in areas of farmland adjacent to existing woodland.

Further objections to AES come from the ‘land sparing versus sharing’ literature (e.g. Collas et al. 2023). In this perspective, conservation interventions are conceptualised as either ‘sharing’ land between food production and conservation objectives (e.g. ‘wildlife-friendly’ farming, organic farming, AES), or ‘sparing’ interventions, where intensive food production enables agriculture and conservation to be separated. The central argument of land sparing relates to yield (Phalan et al. 2016). It is argued that land sharing interventions, such as AES, typically reduce yield and therefore require larger areas of land to maintain food production. On the other hand, it is argued that high yield intensive farmland requires less land space for the same level of production, potentially freeing up land for natural habitat (Phalan et al. 2016). As some species are specialists of agricultural land, one must weigh up the costs and benefits expected for the agricultural ‘winners’ (those species for which population sizes equal or larger when agriculture is present) against the ‘losers’ (species for which population sizes are equal or larger when agriculture is not present; Hulme et al., 2013). Typically, a modelling approach is used to estimate the magnitude of expected population change for each species in various scenarios using population-yield curves. A cost-benefit calculation can then be conducted accounting for the number of species that stand to benefit from the hypothetical sparing scenario. Most studies of this type find that more species stand to benefit from land sparing than sharing (e.g. Hulme et al., 2013; Williams et al., 2017).

The strongest case for land sparing can be made in areas of the globe where natural areas are substantially more diverse than agricultural ones, yield gaps are large and agriculture is actively expanding, for example at the expense of tropical and subtropical forest (e.g. Hulme et al., 2013; Williams et al., 2017). Here, a clear policy prescription is to designate natural areas while encouraging intensification which can maintain food production while reducing agricultural expansion (Phalan et al., 2016). The situation in the UK (and some of Europe) is different in that these areas have been extensively managed for agriculture for thousands of years (Rackham, 2000) and a large proportion of species under conservation concern are dependent on extensive agricultural management (Feniuk et al., 2019). For Poland, Feniuk et al. (2019) suggest a 'three-compartment' strategy to conserve farmland-dependent species comprising intensive farmland, spared natural areas but also areas of very low-yielding high nature value farmland. This three-compartment strategy has also been positively evaluated for British bird species (Finch et al., 2019).

How farm subsidies fit in with land-sparing conservation strategies is an open question in need of further research. A subsidy-based three compartment policy may involve removing AES and returning to CAP pillar-1-type or market-based subsidy structures incentivising intensification in high-yielding areas or farm types (for instance intensive production of cereals in fertile arable areas like East Anglia) while farmers in less productive areas could be paid to spare land or conduct high-nature value farming. Land sparing or high-nature value farming could for instance be delivered in the manner of Higher-Level Stewardship or Landscape Recovery schemes through which larger scale agricultural conservation arrangements are currently made through AES. A proposal of this type has been evaluated as more cost effective than AES policy (Collas et al. 2023). However, farm subsidies are not the only mechanism through which the state can seek to manage land for conservation. The Nature Conservancy, a forerunner of Natural England (NE), was invested with powers to acquire and hold land in 1949, leading to the establishment of the country's national nature reserves through Compulsory Purchase Orders (CPOs; Sheail 1996). Since that time, NE has become a non-departmental public body ('quango') under Defra; while the body retains the ability to acquire land for conservation through CPOs, this power is rarely used (Shrubsole, 2020). Similar bodies have been used to great effect elsewhere. For example, in New Zealand, the Department of Conservation owns and manages ca. 30% of the country for conservation (Towns et al., 2019) and in the US, national parks are federally owned. Whether such a strategy is cost-effective in England will naturally depend on the value of the land considered for CPO. For example, the state can accomplish the temporary creation of a hectare (100m by 100m, over 25 years) of species-rich grassland through the 2024 ELMs AES for a total of £16,150, whereas the typical value of a hectare of agricultural land in (comparatively marginal) areas such as the North East and Tees Valley, as of 2019 was £16,000 (Defra, 2019). In less marginal areas, land values are higher, up to £26,000 per hectare (Defra, 2019). This comparison illustrates how AES can be conceptualised as 'renting' conservation outcomes from landowners; in the long-term, especially in marginal areas, public ownership of land may be a more cost-effective solution.

4.2 Weather Surveillance Radar as a conservation impact assessment tool: the importance of scale

WSR insect monitoring increasingly recognised as a technique capable of addressing the existing gaps in existing insect monitoring techniques (Bauer et al. 2024). Here, we demonstrate a novel approach by which WSR can be used to evaluate conservation interventions. Examples of conservation interventions in the UK potentially amenable to assessment using WSR include rewilding, streetlighting reductions, afforestation, extreme weather events and agricultural changes such as organic management, winter wheat, and pesticide bans, among others.WSR is unique among insect survey techniques as measurements are made at extremely coarse spatial scales and resolutions. In a classic article, Levin (1992) alerted ecologists to problems of scale arising the fact that measurements are typically made at scales that are smaller than the scales at which ecological mechanisms operate. Consideration of scale is crucial in conservation biology as different ecological mechanisms operate at different observational scales (Levin, 1992; Estes et al., 2018) and the method by which data is collected imposes a 'perceptual bias, a filter through which the system is viewed' (Levin, 1992).

We can contrast the scale of WSR and traditional insect surveys using several useful scale measures reviewed by Estes et al. (2018): spatial resolution, spatial extent, temporal resolution and temporal duration:

1. The spatial resolution of a measurement describes the area covered by a single spatial replicate (Estes et al., 2018). In typical surveys, insects are collected by point or transect counts (e.g. Pollard walks used in the UK

Butterfly Monitoring Scheme) or by using various kinds of traps and lures (e.g. light traps, malaise traps, pan traps, suction traps). The spatial resolution of these measurements is fine as samples cover a relatively small area. For example, data collected through the UK Butterfly Monitoring Scheme (Pollard and Yates, 1993) has a 2-dimensional resolution equal to a 5 m strip covering the length of the transect (e.g. 0.005 km^2 for a 1 km transect). For point measurements, such as those made using light traps in the Rothamsted Insect Survey (RIS), the resolution of a measurement varies between species as moth species appear to differ in their attraction to light based on mobility (O’Connell-Booth et al., 2024). However, a recapture experiment suggests the range of a moth trap is around 10 - 27 m based on taxonomic family (Merckx and Slade, 2014). An attraction range of 27 m corresponds to a resolution of 0.00229 km^2. Here, WSR-measured insect abundance is measured at a spatial resolution of 19.63 km^2 (each CVP was produced with a diameter of 5 km), 8500 times larger than the single light trap.

2. Spatial extent is a measure of the total area encompassed by all spatial replicates (Estes et al., 2018). Around 112 light traps make up the RIS network, meaning the spatial extent of the survey is 0.256 km^2, whereas 15 met office radars cover the United Kingdom, equating to ca. 42400 km^2 in extent.

3. Temporal resolution also differs between traditional and WSR surveys. RIS light traps are typically emptied nightly, giving a temporal resolution of 24 hr. Here, we analyse a maximum of two measurements per day, one each representing daily and nightly maximum reflectivity. However, the maximum temporal resolution of WSR is potentially much finer, as these radars produce scans roughly every 5 minutes. Combining spatial and temporal resolution gives a third measure, scope, encompassing the total number of discrete measurements that make up a survey. One year of WSR data has a potential maximum scope of ca. 2.27 x 108 whereas the RIS light trap network has a scope of ca. 40,880.

4. The temporal duration of the RIS is 1964 to the present, whereas WSR insect data is available from the onset of dual-polarisation weather radar. In the United Kingdom this is around 10 years, varying between radar stations

5. To the measures provided by Estes et al. (2018) we can add fifth measure, taxonomic resolution, describing the precision of species identification. Traditional surveys have a fine taxonomic resolution, typically identifying to species, whereas WSR currently has a coarse taxonomic resolution, capable of distinguishing only insect from non-insect, although ongoing work seeks to improve this (Matthews et al., 2025). We are not aware of an agreed metric for taxonomic resolution; however potentially useful measure could describe the number of taxonomic groupings an identification method can resolve. For example, 1 divided by the total number of distinguishable taxonomic groupings in Operational Taxonomic Units (OTUs) is a metric that measures the resolving power of an identification technique. This metric is preferable to total number of species identifiable in that it scales with the information extracted by the measure rather than the total number of species in the system and generalises higher and lower-level taxonomic identification capacity. Here, the taxonomic resolution of WSR by this metric is 0.5 as two groupings can be produced: insect and non-insect. Using this metric, traditional surveys making use of a proscribed list of species from which surveyors can select from have a taxonomic resolution of $\frac{1}{\text{length of species list}+1}$ as individuals can be classified as any species appearing on the list or alternatively as none of the species on the list.

Overall, WSR has coarse spatial resolution, large spatial extent, fine temporal resolution, short temporal duration and coarse taxonomic resolution in comparison to traditional entomological surveys. For Levin (1992) there is no single correct scale at which to view a system as different mechanisms are observable at different scales. However, it is logical to match the scale of the measurement technique to the scale of the phenomenon of interest (Levin, 1992). This is well illustrated using a significant space-time diagram produced by Steele (1978), which shows how particular sampling techniques are suited to investigating variability in particular phenomena. For example, the coarse-scale fish-stock survey is suited to investigating variability in fish stocks, which occurs at coarse scales, but less well suited to evaluating changes in phytoplankton populations, which occurs at finer scales than fish stock surveys are capable of detecting.

Here, the coarse spatial resolution of WSR data is not well suited to assessing fine-scale phenomena such as insect flower visitation. On the other hand, WSR's fine temporal resolution means it can be used to examine both multi-year trends and sub-daily variation in insect abundance (Mungee et al., 2025). Its large spatial extent also makes it well suited to assessing national insect abundance trends (Mungee et al., In 2025). For example, if survey data from the RIS light trap network (Macgregor et al., 2019) is used to infer national trends in insect abundance for the UK, which has an area of ca. 244,376 km^2 , the survey's extent is spatially extrapolated by a factor of ca. 9.54×10^5 whereas 1848 CVPs fall over land in the UK, meaning that the extrapolation factor is much lower, at ca. 6.68. On the other hand, the long temporal duration of the RIS reduces the influence of weather-related interannual variation in insect abundance, meaning these data are well suited to assessing species trends (Macgregor et al., 2019).

The coarse spatial resolution of WSR-CVP measurements (circles of diameter 5km) is well suited to assessing the impact of large-scale conservation interventions, such as AES. The 'honeypot effect' (described above) is an example of this type of scale mismatch problem in terrestrial ecology. On-the-ground surveys of insects, such as FIT counts and Pollard walks are well suited to capturing fine-scale processes such as foraging activity and individual movement as these survey methods produce data at fine resolution. However, when seeking to investigate a coarser (larger) scale process, like a change in the total size of an insect population, fine scale processes such as individual movement are effectively measurement noise. The surveyor may seek to reduce the influence of this very fine scale noise on survey result by, for instance, summing species counts along the length of a transect. This is effectively coarsening the resolution of the sample. As we coarsen the resolution of the sample fine scale mechanisms (individual actions of insects) become less and less influential in determining the final figure; the signal to noise ratio increases. The honeypot effect describes the tendency of fine-scale surveys to conflate fine-scale movement of individuals with a change in the population size, a coarser scale process. One way to address this effect is to coarsen the resolution of the effect size estimate, for example by sampling both inside and outside of the intervention of interest (in the manner illustrated in *Figure 2* panels A, B and C), potentially requiring a large survey effort. Alternatively, freely available coarse-scale measures of insect abundance collected with WSR can be used.

Overall, weather surveillance radar alters the ‘vision’ of the observer, which can now comprise three spatial dimensions plus time, collecting information on insect dynamics at scales not possible using traditional methods. This technique is well suited to assessing coarse scale ecological processes. As many conservation interventions seek to enhance insect abundance at the ‘landscape’ scale, WSR is well placed to become a central tool for conservation impact assessment in coming years.

4.3 Future research

To enhance WSR as a conservation impact assessment tool, future work could seek to develop methods to improve taxonomic resolution, capable of distinguishing insect species or morphotypes from one another. Matthews et al. (2025) identifies two approaches to increasing the taxonomic resolution of dual-polarisation WSR: top-down, data driven approaches, and bottom-up, simulation-based approaches. Top-down approaches are those which seek to reconcile a priori understanding of aerial biodiversity with patterns observable directly from WSR data, usually through the use of a statistical or machine learning algorithm. Whilst top-down approaches represent our current best attempt to partition WSR data into finer taxonomic groupings, they are fundamentally limited by a lack of ground-truth data labelled at finer taxonomic resolution. For example, Lukach et al. (2022) uses an unsupervised spectral clustering algorithm to identify four clusters attributable to distinct biological morphotypes, but the biological interpretation of these clusters is limited. Alternatively, a bottom-up approach involves using simulation to reconstruct the scattering properties of various species one may observe using WSR. For example, Mirkovic et al. (2016) use the simulation software WIPL-D to estimate the 3D radar scattering properties of bats and bat aggregations. Matthews et al. (2025) proposes the creation of a library of such simulated animal scattering properties, analogous to the traditional ID-guide, potentially facilitating finer scale taxonomic resolution in

WSR studies. Work in this area is ongoing but in future may facilitate the identification of particular species of volant animal from WSR data.

From a causal inference perspective, another potential future direction for research is development of spatial matching algorithms to select CVP locations. Many methods are available for statistical matching (Ho et al., 2007), primarily developed and used in the fields of econometrics, epidemiology and political science, although they are potentially broadly applicable to problems in conservation science. Among the available methods, including exact, propensity score, nearest-neighbour, cardinality and optimal matching, it is unclear what the benefits and drawbacks are to each in an ecological setting. Here, we use methods developed by Lukach et al. (2024) to generate CVPs in a 60 x 60 km grid surrounding each radar location. This is a convenient way to obtain coverage of a fixed spatial area surrounding a radar. We then seek to match CVPs from the grid to one another using both landcover and pre-treatment insect abundance trend. A potential improvement to this approach would be to generate “pre-matched” CVPs - for example, one could identify a location for a treatment CVP surrounding a conservation intervention, then seek to identify where to spatially arrange a set of control CVPs to minimise difference between treatment and potential control CVP in confounders of interest, irrespective of any existing grid. For example, one could create CVPs which cover relatively homogeneous areas of land. This approach would minimise confounding from small areas of other land uses unavoidably included when CVPs are arranged in a grid pattern.

5. Conclusions

We demonstrate a novel approach to assessing the impact of large-scale conservation interventions on insects using weather surveillance radar. The technique allows the landscape-scale impact of conservation interventions on insects to be measured directly for the first time. Using this approach, we find that Agri-Environment Schemes in England had no impact on aerial insect abundance at coarse (ca. 20 km^2) spatial scales measured by WSR across intervention levels from £664 to £100,540 per annum for all biodiversity-related options (measure A) and between £579 and £88,003 including only insect-related options (measure B). We find no evidence for a positive relationship between AES and insect abundance, GLMMs indicated a weak but statistically significant negative relationship. Our results are subject to a number of caveats, discussed above, including spillover from adjacent CVPs and potential contamination from birds. The matched-BACI assessment approach described here is broadly applicable to a variety of coarse-scale insect conservation intervention such as rewilding, streetlight reductions and changes to agricultural practice.

Agri-environment subsidies are the primary mechanism by which the UK government seeks to deliver insect conservation. In 2023, AES replaced CAP-style basic payments entirely. Over 50% of the total budget allocated to conservation is spent through these schemes (Defra, 2024), yet we detect no benefits for aerial insects at landscape scale. Alternative strategies, such as 'three compartment' land sparing (Feniuk et al., 2019) and the state acquiring land through CPO should be seriously considered.

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7. Supplementary Information

7.1 Data processing

7.1.1 Columnar Vertical Profiles

Vertical-looking radars have long been used for the study of insects (Chapman et al. 2002). VLRs produce a thin vertical beam (10-100 m in diameter; see Figure 1. in Chapman et al. 2002) which can be used to extract information describing the abundance and diversity of entomofauna passing above a site (e.g. Wotton et al. 2019). These radars are typically operated at a fixed position, naturally providing a description of a fixed area above a particular site at which the radar is operated. In contrast, WSRs cover a much larger area but collect data in plan position indicator (PPI) mode, rotating 360° in azimuth and transmitting pulses in a narrow beam. Over a ca. 5-minute scanning cycle, several rotational scans are produced with the beam oriented at different elevation angles (Lukach et al., 2024). One major limitation of PPI-mode data for ecological application is that it does not provide a clear picture of radar returns with height above a 'site' of interest (Murphy et al., 2020). Columnar Vertical Profile (CVP) methodology provides a solution to this issue. CVPs, developed by Murphy et al. (2020), provide a 3-D 'columnar chunk' of the atmosphere, facilitating analysis of polarimetric radar variables within a fixed area. In brief, to produce a CVP, returns are azimuthally averaged over the user-defined CVP area for each elevation scan, then, every azimuthally averaged point within the CVP range is projected onto a height axis above the point (See Figure 1 in Lukach et al., 2024). Following a procedure developed by Mungee et al. (2025), raw dual polarisation radar data were processed into 12 x 12 grids of CVPs divided into 200 m vertical height bands. For each of the nine dual-polarisation weather surveillance radars in England, we produced a grid of 144 discrete columns, each divided into a set of 200 m height bands. Here, we analyse a single height band at 500 – 700 m above sea-level. This height band was selected to minimise the influence of ground clutter (trees, hills, buildings) which intersect with the radar beam, while also minimising the distance of the height band to the ground. Previous work (Mungee et al. *in press*) has shown radar-measured insect abundance at this elevation is coupled to landcover and correlated with ground-level measures of insect abundance from light and suction traps.

7.1.2 Calculating Insect Abundance

We use methods developed by Mungee et al. (2025) to estimate insect abundance through time in each CVP. First, meteorological signals are removed using a depolarization ratio (DR) filtering method developed by Kilambi et al. (2018). DR (crudely, a measure giving an indication of scatterer shape irregularity) is calculated from two polarimetric variables: differential reflectivity (ZDR; the log of the ratio of horizontal to vertical power of returns) and co-polar correlation coefficient ρhv (a measure of sample uniformity, how much the scattering properties of the sample vary between radar pulses). This process identifies meteorological signals where the signal is from relatively spherical scatterers (ZDR close to zero) and does not vary strongly from pulse to pulse. Intuitively, rain is comprised of relatively spherical droplets which are similar to one another. As insects and birds tend to be substantially more oblate, irregular and variable in shape than hydrometers, DR filtering provides a method to remove radar volumes comprised of more uniform distributions of relatively spherical scatterers. Following Kilambi et al. (2018), a minimum DR threshold of -12dB is applied here. Next, a second filtering step removes meteorological signals with higher DR (as caused by hail, graupel and very heavy rain) by specifying a reflectivity threshold of 45 dBZ (Kilambi et al., 2018). The body plan of arthropods are typically more elongated than that of birds, meaning insects typically produce higher ZDR values (e.g. see Stepanian et al., 2016, using

S-band radar). Following Mungee et al. (2025), we therefore separate birds from insects using a ZDR threshold of 3dB to exclude birds while retaining as many arthropod signals as possible. This threshold inevitably excludes some insects – for example, those tilted up or downwards such that they project more in the vertical direction will have low ZDR. However, insect metrics produced using this threshold have been shown to be coupled to landcover and correlated with ground-level insect abundance (Mungee et al., 2025)

We sought to restrict our analysis to a period of high insect activity in England. In England, on-the ground observed insect activity generally peaks during summer (e.g. for moths between July and August; see Figure 1. in O'Connell-Booth and Kunin, 2024). We note that maximum ZDR displays seasonal variation characteristic of biological activity (Figure. 6), albeit with a wider (several month) peak than is observed for individual insect groups, such as moths. We take seasonal ZDR to function as a crude proxy for insect activity in unfiltered radar data. In our focal region above England, we expect insects to be the most frequent cause of high ZDR as results from S-band radars show that insects generally take substantially higher ZDR values than birds or meteorological phenomena (see Figure 9 in Stepanian et al., 2016; Table A4 in Gauthreaux et al., 2020; note that there may be some differences in absolute ZDR values between S- and C-band radars). The maximum value of ZDR can therefore work as a crude proxy for the presence of this high-ZDR mode issued by the presence of aerial insects. The match between observed variation in insect abundance in England and variation in maximum ZDR provides an indication that this approximation functions as expected.

Using this ZDR variation (Figure 6.) we identified a window of high insect activity between 15th April to 30th October and restrict our analyses to this period. We also restrict our analysis to two scans per 24-hour period: one diurnal scan, taken between 8:00 and 14:00, and one nocturnal scan, taken between 19:00 and 23:00 corresponding to diel peaks in activity for diurnal and nocturnal insects respectively.

After these filtering steps, we then calculate an estimate of insect abundance for each CVP in the 500 – 700 m height band based on the return with maximum reflectivity in each of the nocturnal and diurnal windows. We first converted radar reflectivity factor (Z) to the more biologically meaningful radar reflectivity (η) using the equation: η (dB) = Z (dBZ) + β, where β equals to 26.58 for UKMO C-Band radars (Equation 19 in Chilson et al., 2012; Mungee et al. 2025) and converted this value to linear units (cm^2/km^3). We multiplied radar reflectivity by the total CVP height band volume, yielding the total back-scattering area of arthropods (cm^2) within this volume. To estimate abundance from backscatter area, we divide by the estimated Radar Cross Section (σ) of a single insect, defined here as 4.52×10^{-4} cm^2 (see Mungee et al. 2025).

7.2 Generalised Additive Models

We also produce a GAM model describing seasonal and interannual variation in maximum ZDR. These models were used to generate Figure 6 and select the seasonal window for analysis described above. We extract the maximum daily ZDR value per day in each CVP across the available data. To analyse within-year seasonal variation in maximum ZDR (Fig. 6) at the Chenies radar, we interact month number with year, and include a random effect for CVP ID. This model describes seasonal variation within Chenies radar CVPs separately for each year from 2014-2022 (Eq.3). To describe interannual variation in maximum ZDR, we produce a time variable describing the number of months since January 2014. Using a factor 'by' smooth with 100 knots, we interact CVP ID with month number to describe interannual variation within each CVP separately. This corresponds to Model I in Pedersen et al. (2019), with separate smooths with shared 'wiggliness' for each CVP.

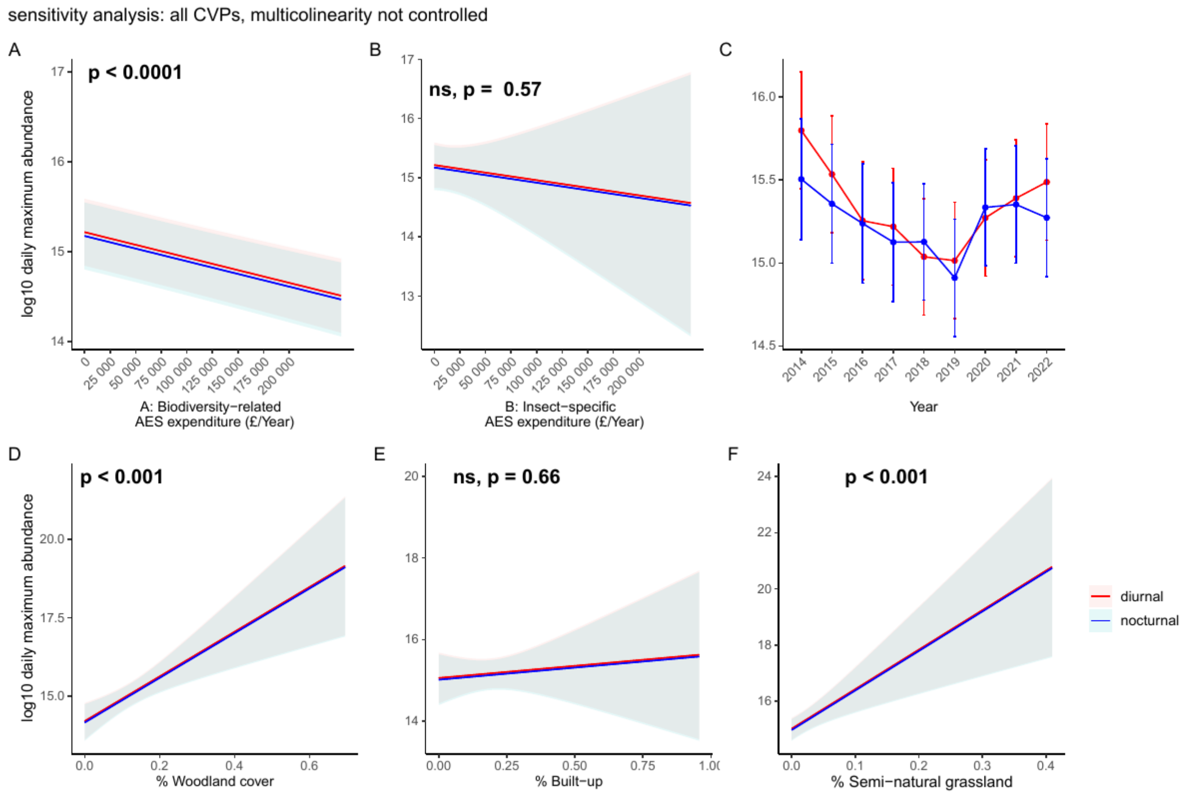
Eq.3

$$ZDR_i = \beta_0 + f_{\mathrm{Year}_i}(\mathrm{Month_i}) + b_{\mathrm{ID}_i} + \varepsilon_i$$

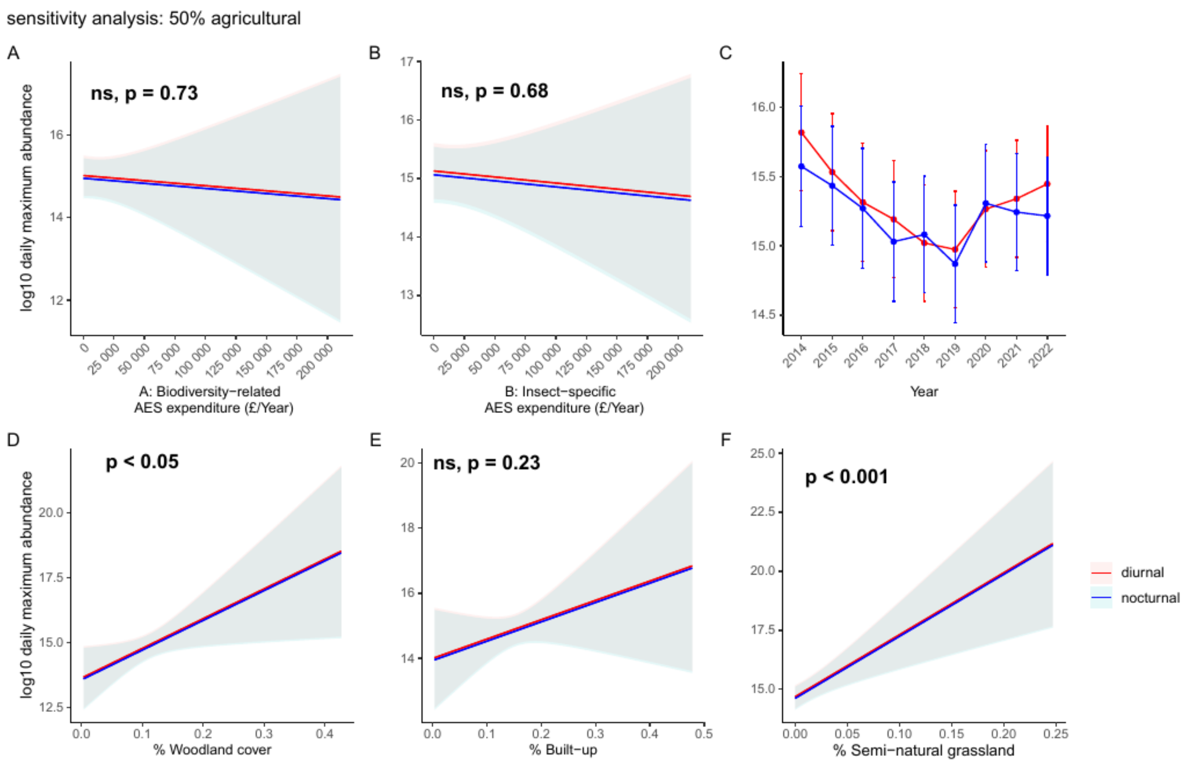
7.3 GLMM sensitivity analysis

We produce descriptive statistics and analyse the associative relationship between AES spend (measures A, B) and insect abundance using a Generalised Linear Mixed Modelling framework. To control collinearity between agricultural landcover (combined cover of improved grassland and arable and horticultural cover; Marston et al. 2024) and AES intervention, we include only agricultural CVPs in these models – those with over 75% agricultural cover.

To determine sensitivity of these models to the specific percentage threshold cutoff for inclusion, we conduct a sensitivity analysis. We produce models including all CVPs (no agricultural cutoff) and including all CVPs with over 50% agricultural landcover. In the model including all CVPs, AES measure A intervention was significantly negatively associated with insect abundance. We detect multicollinearity in these models, AES expenditure was correlated to agricultural cover. This is to be expected as AES can be placed only on agricultural land. While this model cannot distinguish between AES intervention and agricultural landcover due to multicollinearity, we expect a portion of this negative association is attributable to a negative association between farmland and insect abundance. In this model woodland cover and semi-natural cover was significantly positively related to insect abundance and built-up cover was unrelated to insect abundance (SI Figure 1). In the model including only CVPs with over 50% agricultural cover (SI Figure 2) positive associations between insect abundance and semi-natural landcover and between insect abundance and woodland cover remained, but the significant negative relationship between AES measure A and insect abundance did not. In the 75% cutoff model included in the main paper, significant positive relationships between semi-natural cover and insect abundance and between woodland cover and insect abundance remained. Multicollinearity between AES intervention and farmland cover was removed. However, in this model farmland showed multicollinearity with other landcover variables. We therefore removed the farmland cover variable from the model. In this final model including the 75% agricultural cutoff, removing the farmland cover variable introduced a very small significant negative relationship between AES intervention and insect abundance. The beta coefficient for the AES variables was extremely small ($\beta > -0.00001$) compared to other landcover variables (semi-natural cover: $\beta = 49.34$; woodland cover: $\beta = 11.71$). Overall, sensitivity analyses indicate that relationships between insect abundance and semi-natural cover and woodland cover present in unfiltered models were consistent throughout models, but the large negative relationship between AES and insect abundance emerged as an artefact of multicollinearity between agricultural cover and AES intervention; the relationship between insect abundance and AES was non-significant using a 50% agricultural cutoff and significant but very small using a 75% cutoff. We therefore proceed with the 75% cutoff model.



SI Figure 1. Sensitivity analysis including all CVPs (no agricultural cutoff) with multicollinearity uncontrolled. In these models there was a significant negative association between AES and insect abundance which we attribute to multicollinearity between AES intervention and farmland area. Authors' own work.



SI Figure 2. Sensitivity analysis, GLMM model results including only CVPs which were over 50% agricultural. Authors' own work.

7.4 Impact assessment

7.4.1 Quantification of AES spend

We calculate the annual spend on biodiversity-related revenue AES between 2014 and 2022 using the Environmental Stewardship (2005) and Countryside Stewardship (2016) agreement area datasets available through the Natural England geodata portal service.

We calculate two measures of AES spend: (A) including all biodiversity conservation related options and (B) including only options for which published evidence or expert opinion suggests are beneficial to butterflies or other pollinating invertebrates. AES measure A was calculated by including all revenue options, aside from those aimed at (1) educational activities, such as school visits; (2) access enhancement, such as through the construction of gates or styles; (3) maintenance or weatherproofing of farm buildings and (4) maintenance or protection of archaeological sites, historical features, stone walls and engineered water bodies. AES measure B uses a more stringent set of criteria, including only biodiversity-related options demonstrated by published evidence or expert opinion to benefit either butterflies or pollinating invertebrates, as reviewed and scored by Staley et al. (2021). We place options into the broader groupings provided by Staley et al. (2021) based on option name and description provided by DEFRA. All options not falling into scored categories were also removed, which includes all options excluded by measure A. Supplementary Table 1 lists Countryside Stewardship options included in each measure. Supplementary Table 2 lists Environmental Stewardship options included in each measure. We calculate the annual expenditure on revenue options by each measure per CVP by month using the payment rates contained in the 4th edition Environmental Stewardship Entry Level and Higher-Level Stewardship handbooks and in the Countryside Stewardship 1st January 2016 handbook.

Of the selected options, 97.71% CS records and 97.32% of ES records contained necessary information for inclusion, including near-exact ("parcel-level") spatial location and information on the size or quantity of the option. Additionally, the percentage cover of 21 CEH landcover classes were extracted from the UK CEH Land Cover Map 2023 (Marston, 2022).

7.4.2 Before-After Control-Impact and Difference in Differences

To isolate the causal effect of insect-related AES on aerial insect abundance we identify a series of pseudo-experiments which we analyse in a Before-After Control-Impact (BACI) framework. Difference in Differences (DiD), widely used in econometrics and other fields of observational science, is equivalent to the "standard" BACI in the simplest "two treatment, two time-period" case. Many extensions to DiD (and therefore BACI) are available, designed accommodate more complex pseudo-experimental designs. As these designs are formally identical in the simplest case, we refer to these DiD methods as extensions as species of the BACI approach here (for further discussion of econometric methods in conservation science, see Supplementary Information to Wauchope et al. 2021; Larsen et al. 2019).

BACI methods rely on constructing a valid counterfactual case: 'what would have happened in treated units had the treatment not occurred'. The degree to which a particular control unit serves as an effective counterfactual case depends on the confidence with which the evolution of the post-treatment outcome at the control unit can serve as a representation of the expected evolution of the outcome variable at the treatment site had the intervention not occurred (the parallel trends assumption). A key test of this assumption is that the outcome variable in the treatment and control sites follow ‘parallel trends’ or ‘common shocks’ during the pre-treatment period.

7.4.3 Matching

Given a pool of 291 CVPs, we sought develop an analysis pipeline to select a subset of optimally matched contrasts for analysis. We trialed several approaches, including matching on pre-treatment landcover covariates using R package MatchIt (Ho et al 2007), constructing local groups of CVPs using spatial K-means clustering and a series of approaches to matching based on pre-treatment trend, assessing each approach by the degree to which the resulting matched pairs were (1) similar in terms of landcover, (2) near one another and (3) displayed parallel trends in the pre-treatment period.

The most performant approach involved two stages of matching. First, potential treatment and control CVPs were matched based on landcover using a form of caliper matching. For each treatment CVP, we identify a subset of potential control CVPs belonging to the same radar which match the treatment CVP in terms of landcover. Each control CVP needed to match (within 15%) landcover of the treated CVP, in terms of the following class groups: (1) agricultural landcover (LCM classes ‘arable and horticultural’ and ‘improved grassland’), (2) combined urban and suburban cover, (3) combined broadleaf and coniferous woodland cover and (4) semi-natural grassland cover (including neutral, calcareous, acid and heather grassland.) Additionally, we require that potential matches belong to the same radar to eliminate radar-specific confounding and effectively restrict the maximum distance between CVP pairs to c.60km. We also require that pairs share at least three years of pre-treatment data to facilitate evaluation of the ‘parallel trends’ assumption.

Within this subset of potential control CVPs identified by landcover matching, we develop a method to identify pairs which satisfy the parallel trends assumption. For each CVP, we normalised insect abundance by the mean insect abundance in the first year of available data for that CVP, thus generating an index of insect abundance suitable for inter-CVP comparison. This produced a measure of the year-to-year trend in abundance within the CVP.

$$(1)\ Abundance\ Index_{ij} = \frac{Abundance_{ij}}{Mean(Abundance_{i1})}$$

Where $Abundance_{ij}$ is the mean abundance in CVP *i* at year *j*. We then quantified a similarity score (calculated in the same manner as Euclidean distance) between treatment and potential control units using the formula

$$(2)\ Similarity\ score = \sqrt{\sum_{j=1}^{n} (Index_{j\ treated} - Index_{j\ control})^2}$$

For each treated CVP, we then calculated the similarity score in the pre-treatment period for each candidate control CVP. For each treated CVP we select the control unit with the smallest similarity score in pre-treatment indexed insect abundance as a potential counterfactual case.

<u>Theoretical justification for matching methods</u>

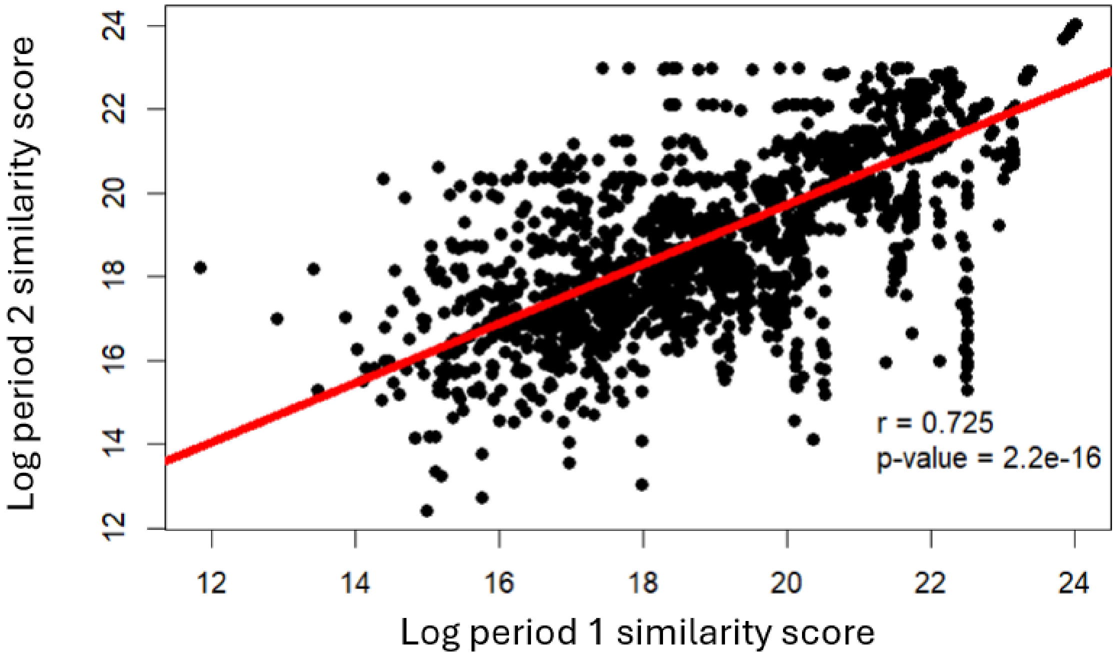
In econometrics, matching based on pre-treatment time-invariant covariates (hereafter: covariate matching) is a common practice. This may be counterintuitive: as a form of within-estimation (Larsen et al. 2019), BACI methods are designed to eliminate time-invariant confounding, allowing comparison between groups which are not alike. However, much theoretical and empirical work in the DiD literature advises practitioners to adhere to the ‘pre-treatment criterion’ and generally account for as many informative observed time-invariant covariates as possible through matching (Ham and Miratrix, 2024; Zubizarreta et al. 2014; Shpitser et al, 2012; Ding and Miratrix, 2015). This work suggests that where a field of potential controls is available, it is preferable to select control units which are as similar as possible to treated units (save for the treatment) in order to credibly meet the parallel trends assumption (PTA) in the post-treatment period (Ham and Miratrix, 2024).

In contrast to covariate matching, matching based on the response variable in the pre-treatment period (outcome matching) is not always preferable and may at times inflate bias. Ham and Miratrix (2024) analyse a set of trade-offs involved with outcome matching. Firstly, outcome matching may inflate bias by artificially increasing the similarity between pre-treatment trends in treated and control units, tending to select controls whose trajectory does not match that of the general population. It is easy to understand that in cases where a treated unit displays an ‘unusual’ trend, with exceptionally high or low values with respect to the general population (perhaps owing to measurement error), bias can be generated by a regression to the mean effect if these outcomes are used for matching. Ham and Miratrix (2024) argue matching based on pre-treatment outcomes is beneficial if (1) outcomes provide a reliable indication of unobserved confounders and (2) if this signal is stable between the pre- and post- intervention periods.

Which unobserved confounders may we wish to control for by pre-treatment outcome matching in an ecological context? Unlike many outcomes studies in econometrics (such as house prices or employment), insect population trends proceed in regular cycles (Figure 6). These cycles are driven by seasonal variations in insect abundance interacting with mechanisms including density-dependence, predator-prey dynamics, as well as weather and climatic conditions in current and previous years. These mechanisms interact with anthropogenic factors (such as insect decline drivers and conservation interventions) to generate the characteristic highly variable cycles (which is also observed in seasonal variation in ZDR, Figure 6).

These mechanisms mean that (separate from any intervention) some years are more ‘favourable’ to insects than others, characterised by high or low relative abundance. We note that inter-year relative favourability varies between CVPs, such that a ‘poor’ year in any particular CVP may not be relatively poor in other CVPs belonging to the same radar. In sum, we wish to select matched pairs of CVPs for which relatively poor and relatively abundant years coincide. Additionally, we want to avoid matching a CVP in which insects are on a particular multi-year trend (for example, locally declining) to a CVP where a different trend is present.

Does the similarity score between pre-treatment outcomes stably measure the co-incidence of interannual variation in insect abundance and effectively match trend? A simple test of the stability of the measure could be conducted by testing the correlation between pre- and post- treatment similarity score between CVPs. For each candidate treatment and control comparison, we divide yearly mean insect abundance into two periods of equal length (period 1, standing in for pre-treatment outcomes, and period 2, standing in for post-treatment outcomes.) We calculate the similarity score between period one outcomes in the candidate control and treatment CVPs and the similarity score between period two outcomes in the treatment and control CVPs. If pre-treatment outcomes stably measure coincidence of interannual variation, period 1 similarity score should be highly correlated with period 2 similarity score. We compute this using Pearson correlation and fit a linear model to the log transformed data. Similarity score one was highly correlated with similarity score two ($r = 0.725$, $p < 0.0001$), indicating that pre-treatment outcomes are a stable measure. This trend stability measure indicates that matching on pre-treatment trend is justified in this case.



SI Figure 3. Correlation between pre- and post- treatment similarity score between candidate pairs of CVPs. Authors' own work.

7.4.5 Estimating dynamic treatment effects

For each pair produced by the above matching procedure, we additionally test the PTA using a linear two-way fixed effects model (TWFE; Goin & Riddell, 2023; also termed 'within estimator' or 'least squares dummy variable model', Larsen et al.

2019). There has been much recent discussion around the pitfalls of TWFE with staggered treatment rollout (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021) but note that TWFE models remain unbiased when there is no staggered treatment rollout, as in the single pair comparisons used here (see Simulation 2 in Baker et al. 2022; Rüttenauer and Aksoy, 2024).

Wauchope et al. (2021) highlight that standard BACI designs (which compare the average pre- and post-treatment values only) can often benefit from inclusion of dynamic treatment effects which can capture trend change by estimating immediate and lagged treatment effects separately. This can be implemented using interaction terms in the standard ordinary least squares BACI model (see Wauchope et al. 202l, Box. 1). Alternatively, one can use the TWFE specification, as below. The two specifications are equivalent when the design includes two time-series only (Goin & Riddell, 2023; Larsen et al. 2019). For each potential control-treatment pair, we specified the model:

$$(3)\ Y_{ijk} = a_0 + \sum_i a_i \cdot I[CVP_i] + \sum_j \beta_i \cdot I[Year_j] + \sum_k \gamma_k \cdot I[Years\ to\ Treatment\ ] + \epsilon_{ij}$$

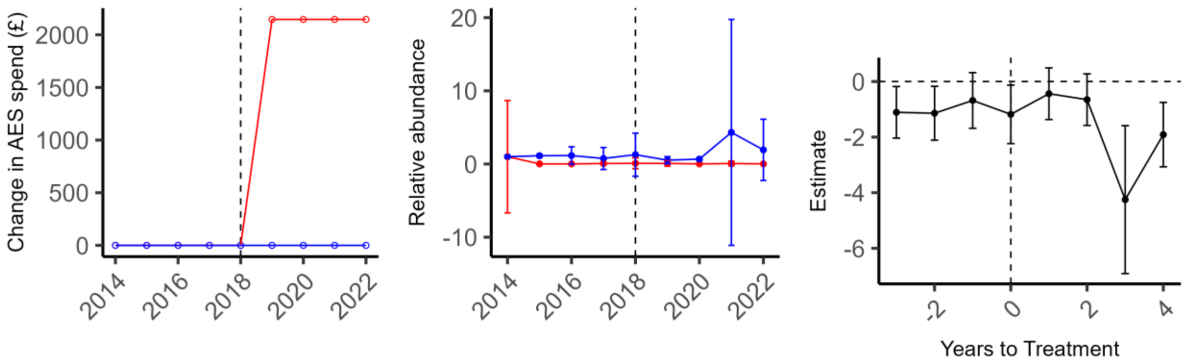
where Y is the outcome indexed insect abundance. The model includes fixed effects for CVP (αi) and Year (βj) (Goin & Riddell, 2023). Dynamic effects of intervention are captured on coefficients on Years to Treatment parameter (γk), which encodes the number of years before or after the first year of intervention (t=1), for which all never treated control time periods are coded as 0. We exclude all CVP pairs where the treatment and control outcomes are significantly different for any pre-treatment year, thus selecting only comparisons for which parallel trends hold. Preliminary models indicated heteroskedasticity between CVPs and between treatment and control groupings. Heteroskedasticity does not produce biased OLS estimates but does cause biases in standard errors (Hanck et al. 2018); as such we calculate robust standard errors (Eicker–Huber–White standard errors) using R packages lmtest (Zeileis and Hothorn, 2002) and sandwich (Zeileis, 2004; Zeileis, et al., 2020). The dynamic BACI models are presented in SI figures A1-15 and B1-15. We exclude three pairs from the final analysis. Two of these pairs included visually diverging trends after matching. A model failure occurred in the third pair. The three excluded pairs are included in SI figures C1-3

To produce the final effect size estimates we then calculate the overall average effect of the intervention for each comparison using standard BACI models including interaction terms for treatment (treated, control) and time (before, after) to produce a single effect size estimate for each comparison. These figures are included in the main text results and in Figure 8.

7.5 Individual BACI comparison

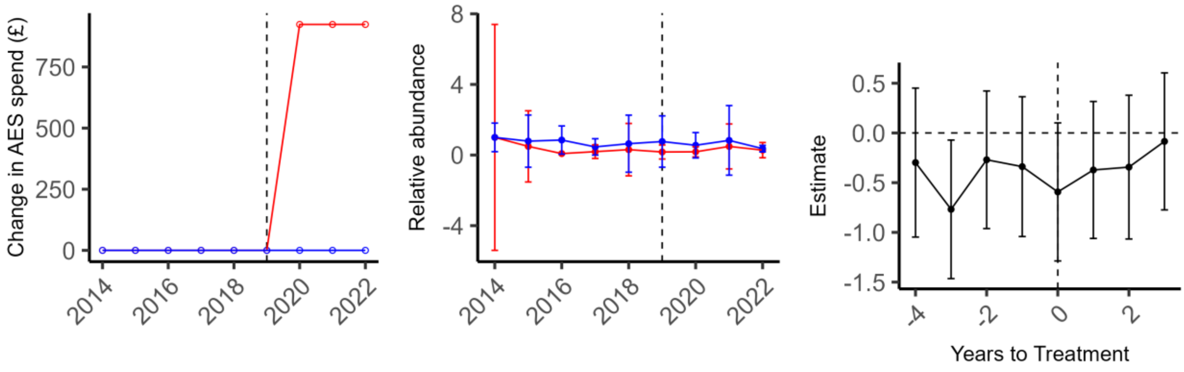
7.5.1 Measure A

SI Figure A. Dynamic BACI model results for each comparison included for AES measure A. From left to right, plots show (1) AES spend per year in the CVP; (2) the normalized trend in insect abundance in the control and treated CVP and (3) dynamic BACI model results. Time to treatment shows years relative to the first increase in AES spend (Time to treatment = 1). Red lines correspond to the treated CVP, and blue lines correspond to the control CVP in each plot



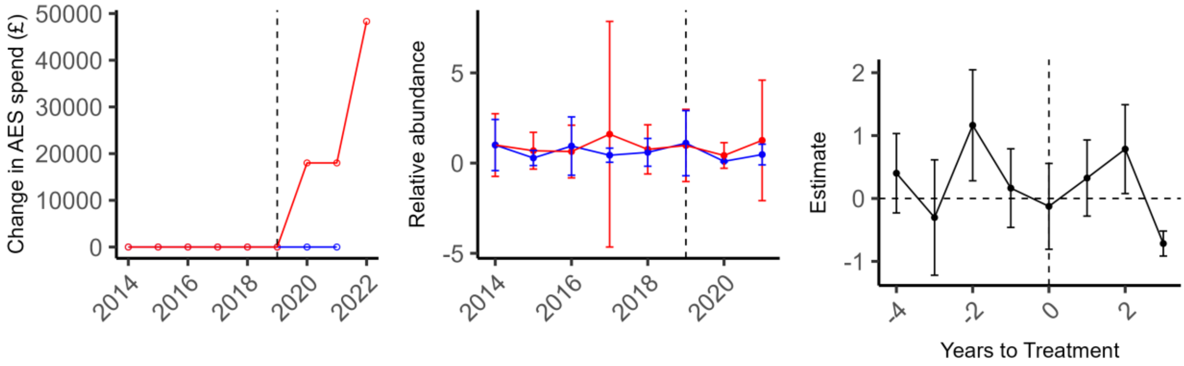
Years to Treatment	estimate	std.error	statistic	p.value
-3	-1.10	0.93	-1.20	0.2300
-2	-1.10	0.97	-1.20	0.2400
-1	-0.68	1.00	-0.68	0.5000
0	-1.20	1.10	-1.10	0.2600
1	-0.44	0.93	-0.47	0.6400
2	-0.65	0.93	-0.70	0.4800
3	-4.20	2.70	-1.60	0.1100
4	-1.90	1.20	-1.60	0.1000

SI Figure A1. Pair 4, including Chenies 29 (treatment) and Chenies 32 (control)



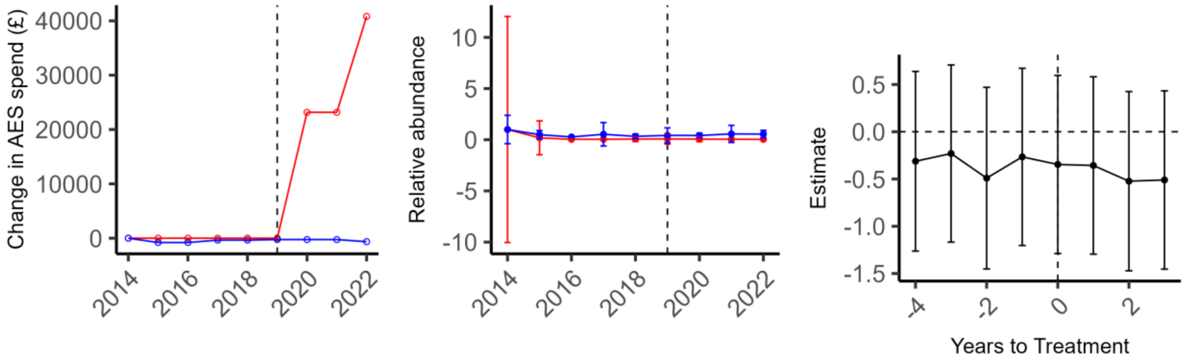
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.300	0.75	-0.40	0.6900
-3	-0.770	0.70	-1.10	0.2700
-2	-0.270	0.69	-0.39	0.7000
-1	-0.340	0.70	-0.48	0.6300
0	-0.590	0.69	-0.85	0.3900
1	-0.370	0.69	-0.54	0.5900
2	-0.340	0.72	-0.48	0.6300
3	-0.085	0.69	-0.12	0.9000

SI Figure A2. Pair 5, including Chenies 31 (treatment) and Chenies 42 (control).



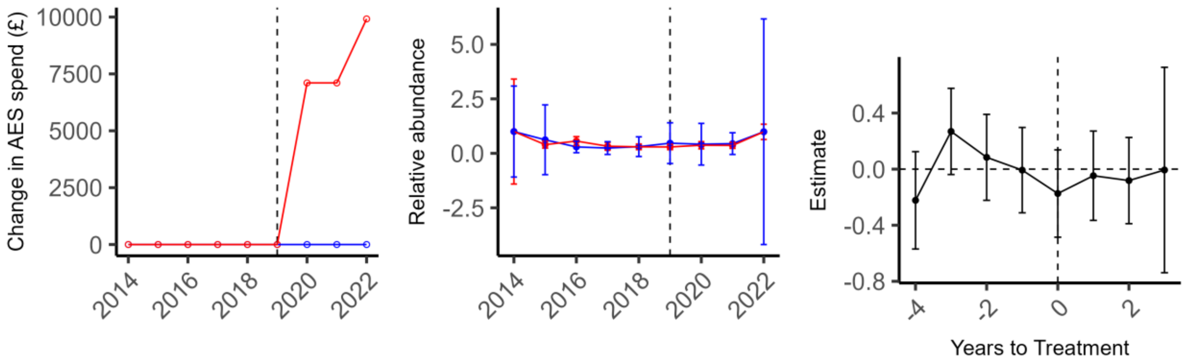
Years to Treatment	estimate	std.error	statistic	p.value	
-4	0.40	0.63	0.64	0.5200	
-3	-0.30	0.92	-0.33	0.7400	
-2	1.20	0.88	1.30	0.1900	
-1	0.16	0.62	0.26	0.7900	
0	-0.13	0.68	-0.18	0.8500	
1	0.32	0.61	0.54	0.5900	
2	0.78	0.71	1.10	0.2700	
3	-0.72	0.20	-3.60	0.0003	*

SI Figure A3. Pair 7, including Chenies 40 (treatment) and Chenies 39 (control).



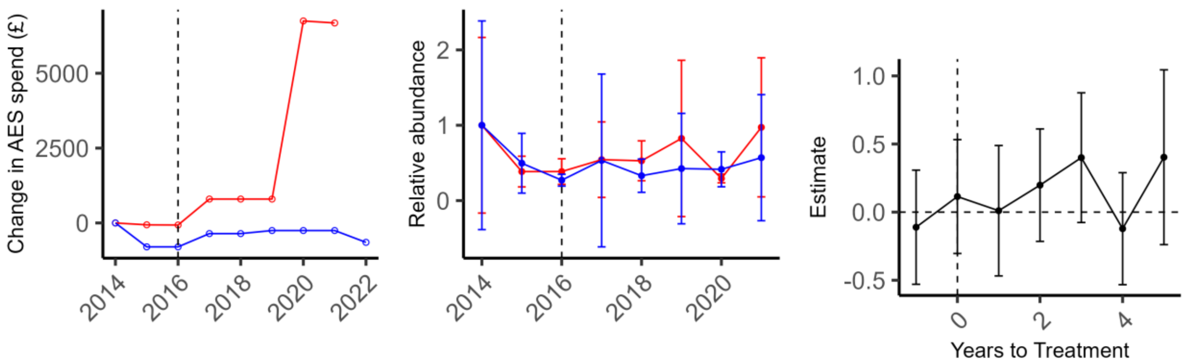
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.31	0.95	-0.33	0.7400
-3	-0.23	0.94	-0.25	0.8100
-2	-0.49	0.96	-0.51	0.6100
-1	-0.27	0.94	-0.28	0.7800
0	-0.35	0.94	-0.37	0.7100
1	-0.36	0.94	-0.38	0.7000
2	-0.52	0.95	-0.55	0.5800
3	-0.51	0.94	-0.54	0.5900

SI Figure A4. Pair 8, including Chenies 41 (treatment) and Chenies 75 (control).



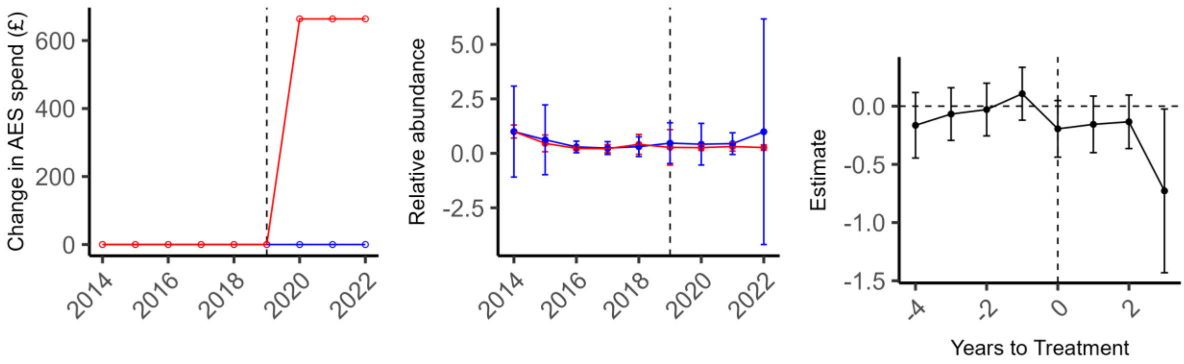
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.2200	0.35	-0.6400	0.5200
-3	0.2700	0.31	0.8700	0.3800
-2	0.0840	0.31	0.2700	0.7800
-1	-0.0071	0.30	-0.0230	0.9800
0	-0.1700	0.31	-0.5600	0.5800
1	-0.0470	0.32	-0.1500	0.8800
2	-0.0820	0.31	-0.2700	0.7900
3	-0.0062	0.73	-0.0084	0.9900

SI Figure A5. Pair 11, including Chenies 53 (treatment) and Chenies 43 (control).



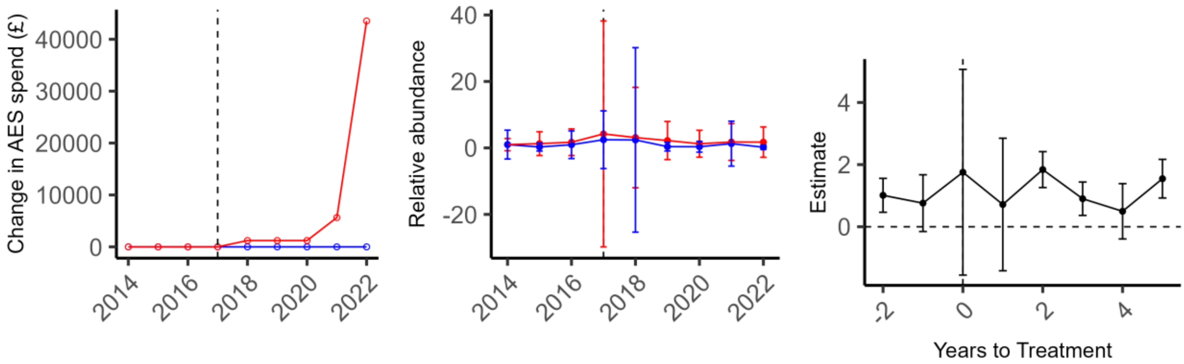
Years to Treatment	estimate	std.error	statistic	p.value
-1	-0.11	0.42	-0.260	0.7900
0	0.11	0.42	0.270	0.7800
1	0.01	0.48	0.022	0.9800
2	0.20	0.41	0.480	0.6300
3	0.40	0.48	0.840	0.4000
4	-0.12	0.41	-0.300	0.7700
5	0.40	0.64	0.630	0.5300

SI Figure A6. Pair 13, including Chenies 63 (treatment) and Chenies 75 (control).



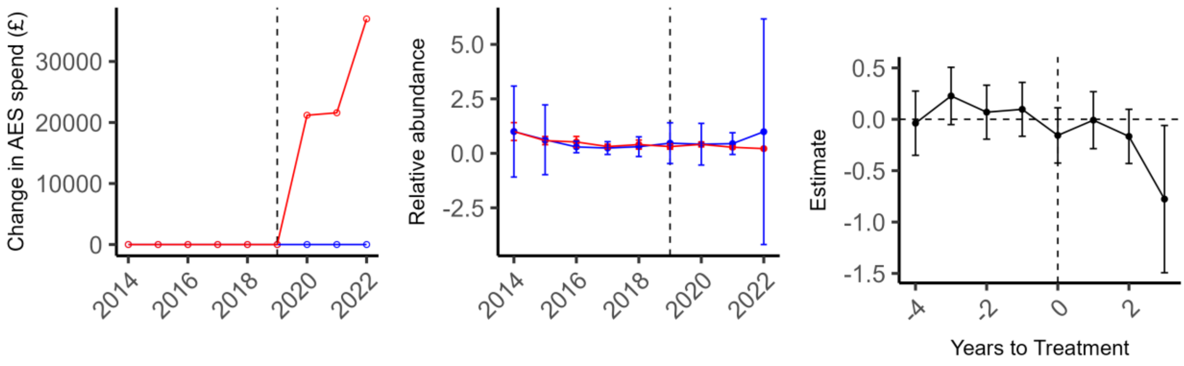
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.160	0.28	-0.58	0.5600
-3	-0.068	0.23	-0.30	0.7600
-2	-0.029	0.23	-0.13	0.9000
-1	0.110	0.23	0.47	0.6400
0	-0.190	0.24	-0.80	0.4200
1	-0.160	0.24	-0.64	0.5200
2	-0.130	0.23	-0.58	0.5600
3	-0.730	0.70	-1.00	0.3000

SI Figure A7. Pair 14, including Chenies 64 (treatment) and Chenies 43 (control).



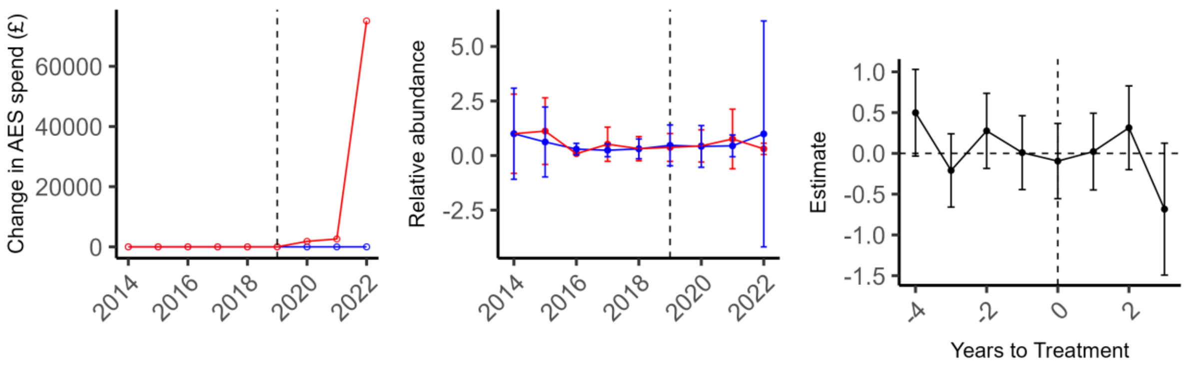
Years to Treatment	estimate	std.error	statistic	p.value	
-2	1.00	0.55	1.90	0.0640	
-1	0.76	0.91	0.83	0.4100	
0	1.80	3.30	0.53	0.6000	
1	0.72	2.10	0.34	0.7400	
2	1.80	0.58	3.20	0.0015	*
3	0.90	0.54	1.70	0.0930	
4	0.50	0.89	0.56	0.5800	
5	1.50	0.62	2.50	0.0130	*

SI Figure A8. Pair 22, including Chenies 81 (treatment) and Chenies 30 (control).



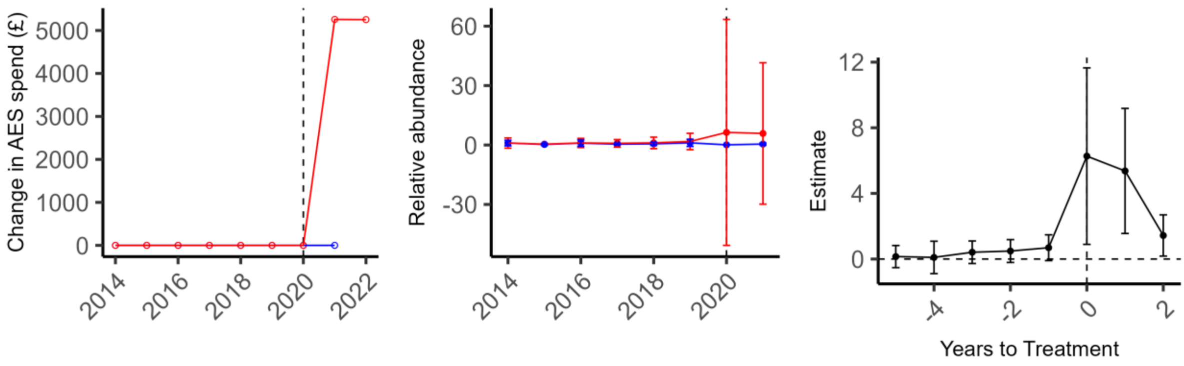
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.0380	0.31	-0.12	0.9000
-3	0.2300	0.28	0.82	0.4200
-2	0.0700	0.26	0.27	0.7900
-1	0.0970	0.26	0.37	0.7100
0	-0.1600	0.27	-0.58	0.5600
1	-0.0083	0.28	-0.03	0.9800
2	-0.1700	0.26	-0.63	0.5300
3	-0.7800	0.72	-1.10	0.2800

SI Figure A9. Pair 27, including Chenies 88 (treatment) and Chenies 43 (control).



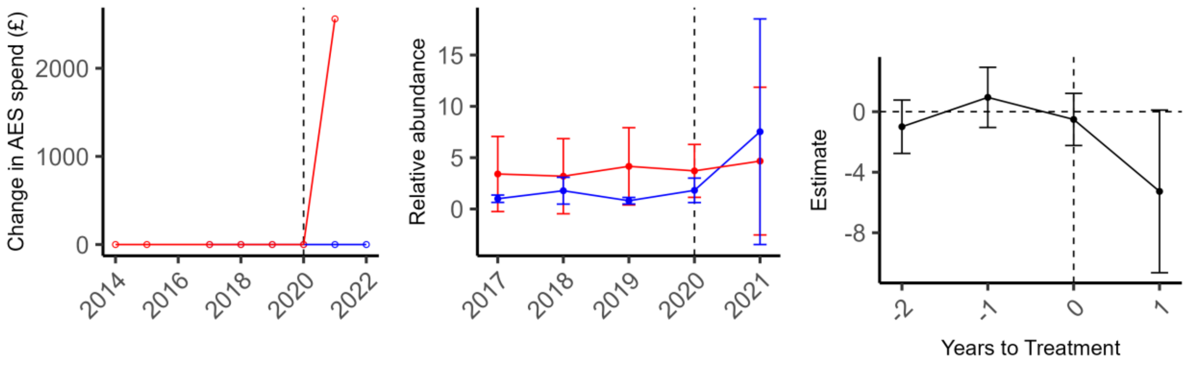
Years to Treatment	estimate	std.error	statistic	p.value
-4	0.5000	0.53	0.940	0.3500
-3	-0.2100	0.45	-0.470	0.6400
-2	0.2800	0.46	0.600	0.5500
-1	0.0095	0.45	0.021	0.9800
0	-0.0940	0.46	-0.200	0.8400
1	0.0220	0.47	0.047	0.9600
2	0.3100	0.51	0.610	0.5400
3	-0.6800	0.81	-0.850	0.4000

SI Figure A10. Pair 32, including Chenies 94 (treatment) and Chenies 43 (control).



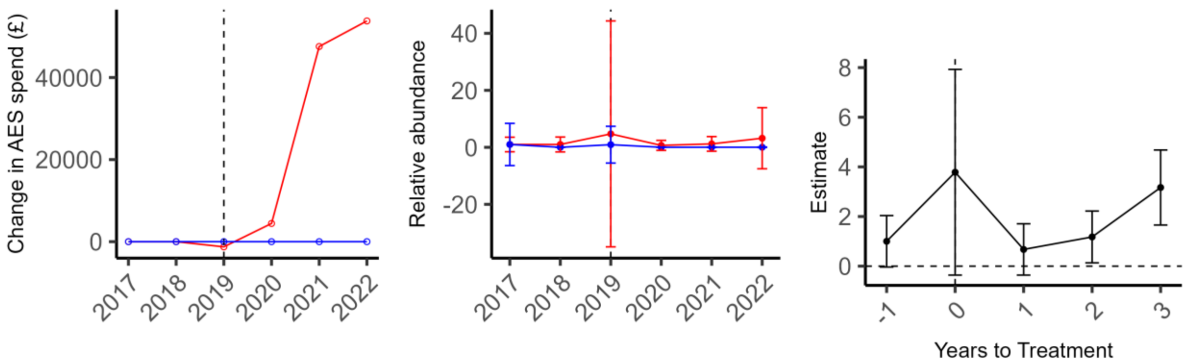
Years to Treatment	estimate	std.error	statistic	p.value
-5	0.150	0.67	0.22	0.8200
-4	0.099	0.99	0.10	0.9200
-3	0.410	0.69	0.60	0.5500
-2	0.490	0.70	0.70	0.4800
-1	0.690	0.79	0.88	0.3800
0	6.300	5.40	1.20	0.2400
1	5.400	3.80	1.40	0.1600
2	1.400	1.30	1.10	0.2500

SI Figure A11. Pair 41, including Chenies 105 (treatment) and Chenies 39 (control).



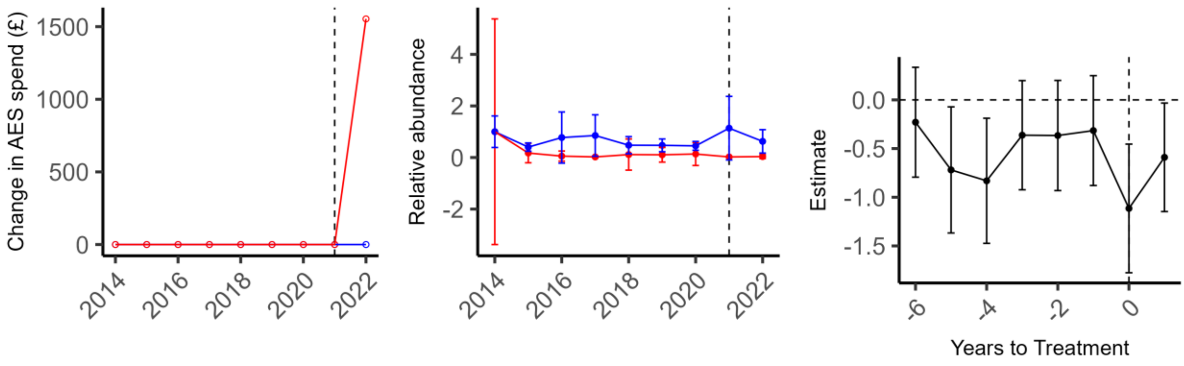
Years to Treatment	estimate	std.error	statistic	p.value
-2	-1.00	1.8	-0.56	0.5700
-1	0.94	2.0	0.47	0.6400
0	-0.51	1.7	-0.30	0.7700
1	-5.30	5.4	-0.98	0.3300

SI Figure A12. Pair 42, including Chenies 107 (treatment) and Chenies 59 (control).



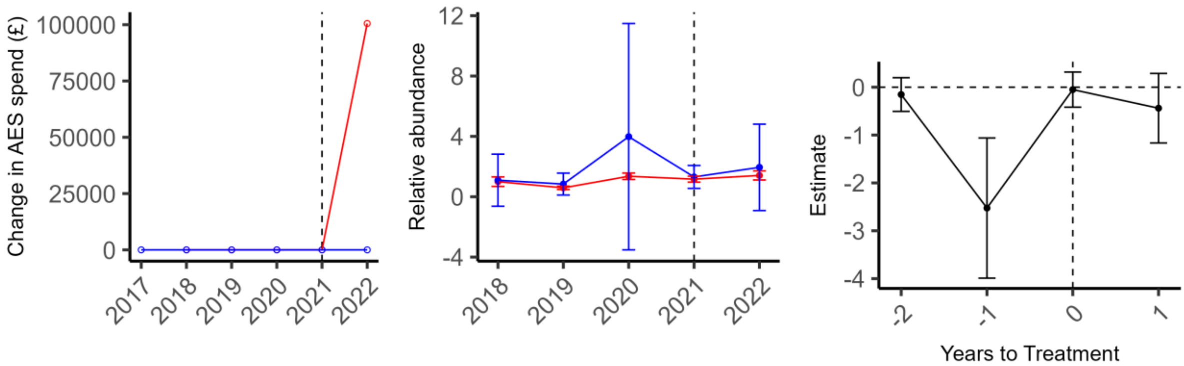
Years to Treatment	estimate	std.error	statistic	p.value	
-1	1.00	1.0	0.97	0.3300	
0	3.80	4.1	0.91	0.3600	
1	0.67	1.0	0.65	0.5100	
2	1.20	1.0	1.10	0.2600	
3	3.20	1.5	2.10	0.0360	*

SI Figure A13. Pair 95, including High Moorsley 57 (treatment) and High Moorsley 69 (control).



Years to Treatment	estimate	std.error	statistic	p.value
-6	-0.23	0.56	-0.41	0.6800
-5	-0.72	0.65	-1.10	0.2700
-4	-0.83	0.64	-1.30	0.2000
-3	-0.36	0.56	-0.65	0.5200
-2	-0.37	0.57	-0.65	0.5200
-1	-0.32	0.56	-0.56	0.5800
0	-1.10	0.66	-1.70	0.0920
1	-0.59	0.56	-1.10	0.2900

SI Figure A14. Pair 124, including Predannack 105 (treatment) and Predannack 68 (control).

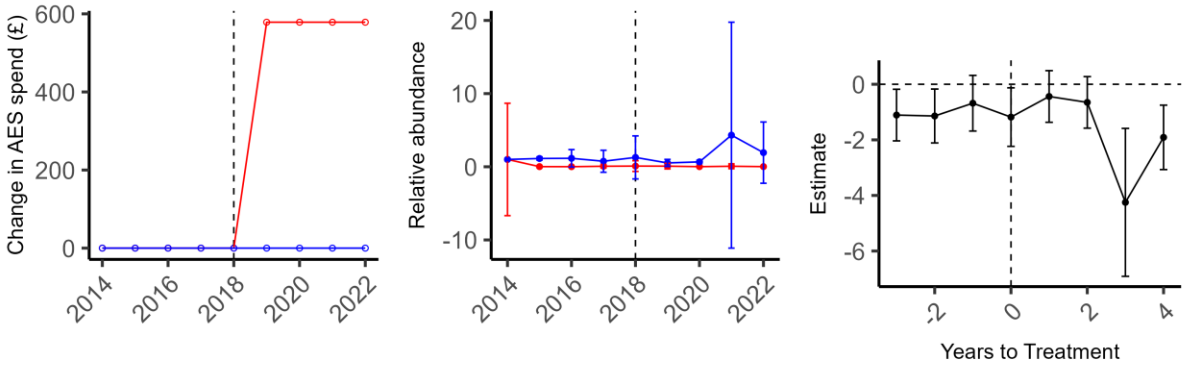


Years to Treatment	estimate	std.error	statistic	p.value
-2	-0.15	0.35	-0.44	0.6600
-1	-2.50	1.50	-1.70	0.0860
0	-0.05	0.37	-0.14	0.8900
1	-0.44	0.73	-0.60	0.5500

SI Figure A15. Pair 145, including Thurnham 68 (treatment) and Thurnham 87 (control).

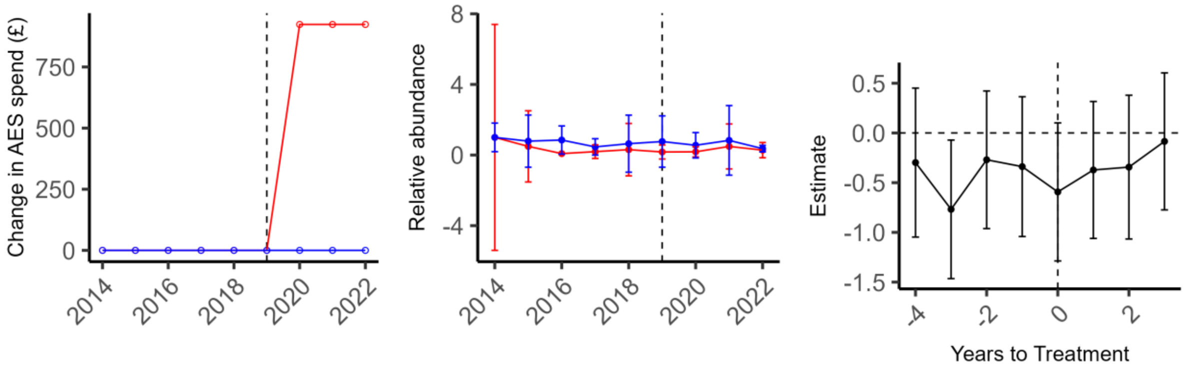
7.5.2 Measure B

Dynamic BACI model results for each comparison included for AES measure B. From left to right, plots show (1) AES spend per year in the CVP; (2) the second plot shows the normalized trend in insect abundance in the control and treated CVP and (3) dynamic BACI model results. Red lines correspond to the treated CVP and blue lines correspond to the control CVP in each plot



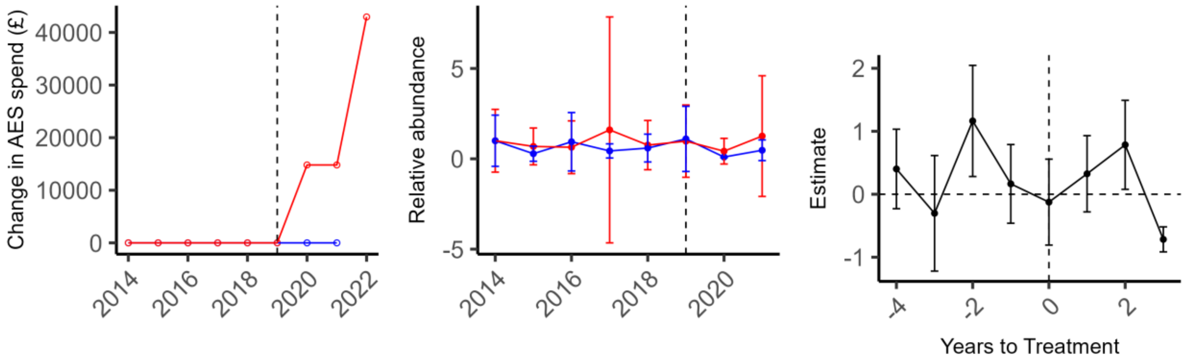
Years to Treatment	estimate	std.error	statistic	p.value
-3	-1.10	0.93	-1.20	0.2300
-2	-1.10	0.97	-1.20	0.2400
-1	-0.68	1.00	-0.68	0.5000
0	-1.20	1.10	-1.10	0.2600
1	-0.44	0.93	-0.47	0.6400
2	-0.65	0.93	-0.70	0.4800
3	-4.20	2.70	-1.60	0.1100
4	-1.90	1.20	-1.60	0.1000

SI Figure B1. Pair 4, including Chenies 29 (treatment) and Chenies 32 (control).



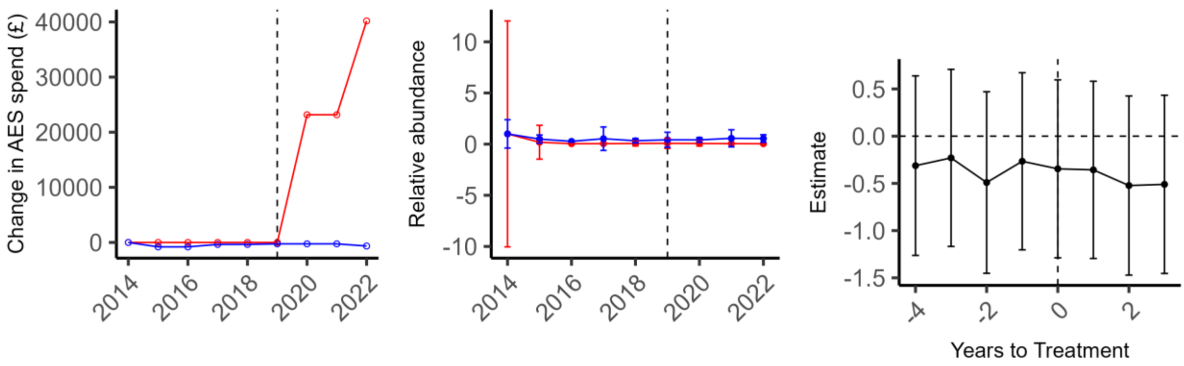
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.300	0.75	-0.40	0.6900
-3	-0.770	0.70	-1.10	0.2700
-2	-0.270	0.69	-0.39	0.7000
-1	-0.340	0.70	-0.48	0.6300
0	-0.590	0.69	-0.85	0.3900
1	-0.370	0.69	-0.54	0.5900
2	-0.340	0.72	-0.48	0.6300
3	-0.085	0.69	-0.12	0.9000

SI Figure B2. Pair 5, including Chenies 31 (treatment) and Chenies 42 (control).



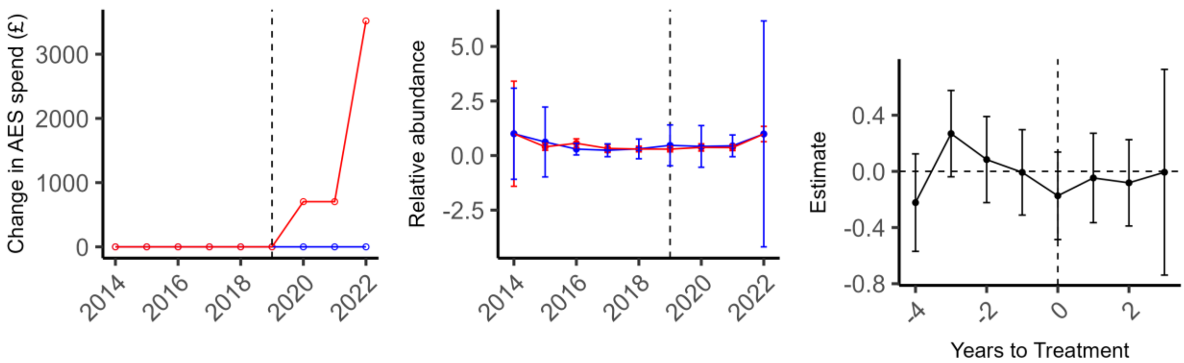
Years to Treatment	estimate	std.error	statistic	p.value	
-4	0.40	0.63	0.64	0.5200	
-3	-0.30	0.92	-0.33	0.7400	
-2	1.20	0.88	1.30	0.1900	
-1	0.16	0.62	0.26	0.7900	
0	-0.13	0.68	-0.18	0.8500	
1	0.32	0.61	0.54	0.5900	
2	0.78	0.71	1.10	0.2700	
3	-0.72	0.20	-3.60	0.0003	*

SI Figure B3. Pair 7, including Chenies 40 (treatment) and Chenies 39 (control).



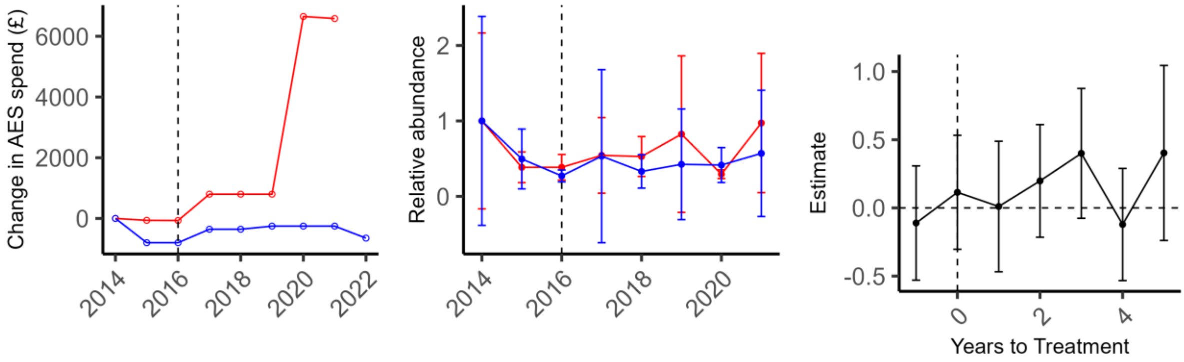
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.31	0.95	-0.33	0.7400
-3	-0.23	0.94	-0.25	0.8100
-2	-0.49	0.96	-0.51	0.6100
-1	-0.27	0.94	-0.28	0.7800
0	-0.35	0.94	-0.37	0.7100
1	-0.36	0.94	-0.38	0.7000
2	-0.52	0.95	-0.55	0.5800
3	-0.51	0.94	-0.54	0.5900

SI Figure B4. Pair 8, including Chenies 41 (treatment) and Chenies 75 (control).



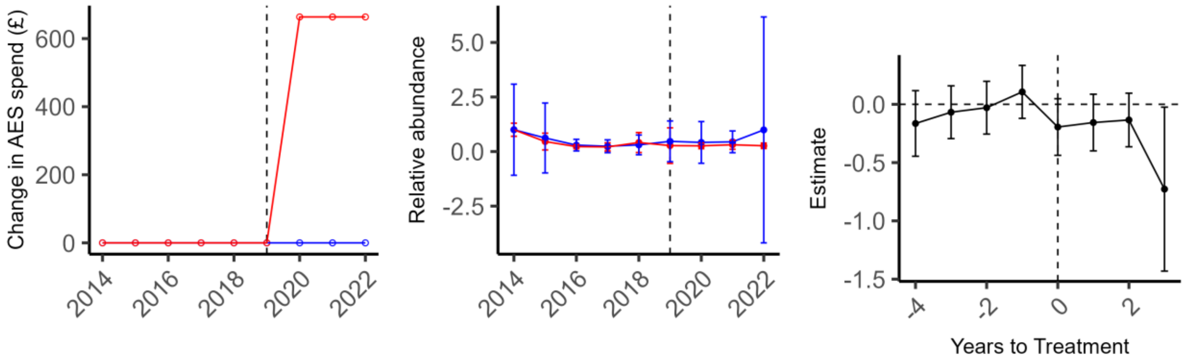
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.2200	0.35	-0.6400	0.5200
-3	0.2700	0.31	0.8700	0.3800
-2	0.0840	0.31	0.2700	0.7800
-1	-0.0071	0.30	-0.0230	0.9800
0	-0.1700	0.31	-0.5600	0.5800
1	-0.0470	0.32	-0.1500	0.8800
2	-0.0820	0.31	-0.2700	0.7900
3	-0.0062	0.73	-0.0084	0.9900

SI Figure B5. Pair 11, including Chenies 53 (treatment) and Chenies 43 (control).



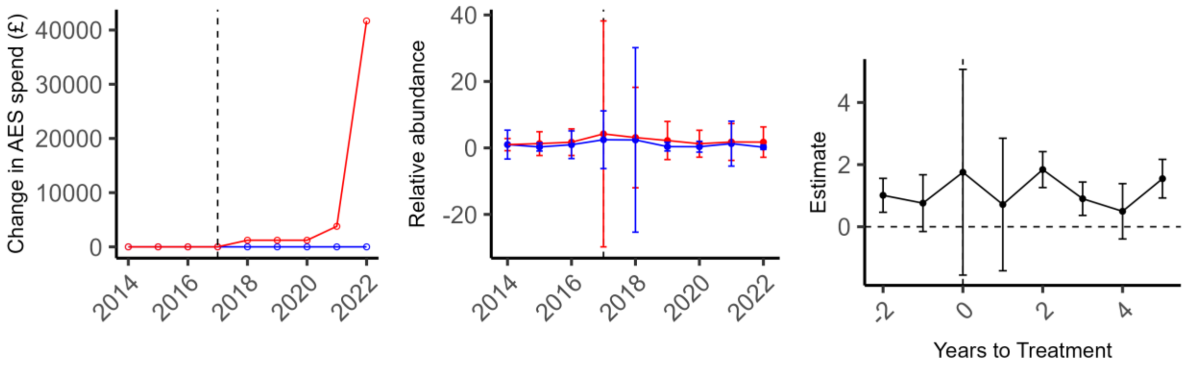
Years to Treatment	estimate	std.error	statistic	p.value
-1	-0.11	0.42	-0.260	0.7900
0	0.11	0.42	0.270	0.7800
1	0.01	0.48	0.022	0.9800
2	0.20	0.41	0.480	0.6300
3	0.40	0.48	0.840	0.4000
4	-0.12	0.41	-0.300	0.7700
5	0.40	0.64	0.630	0.5300

SI Figure B6. Pair 13, including Chenies 63 (treatment) and Chenies 75 (control).



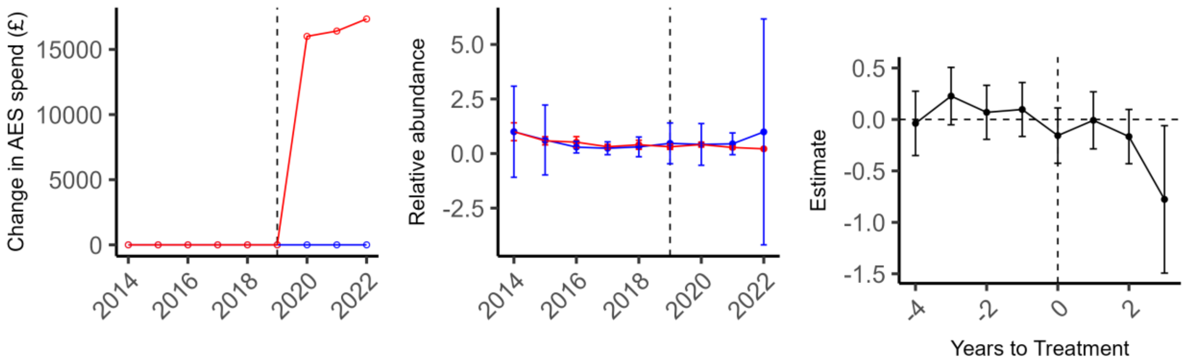
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.160	0.28	-0.58	0.5600
-3	-0.068	0.23	-0.30	0.7600
-2	-0.029	0.23	-0.13	0.9000
-1	0.110	0.23	0.47	0.6400
0	-0.190	0.24	-0.80	0.4200
1	-0.160	0.24	-0.64	0.5200
2	-0.130	0.23	-0.58	0.5600
3	-0.730	0.70	-1.00	0.3000

SI Figure B7. Pair 14, including Chenies 64 (treatment) and Chenies 43 (control).



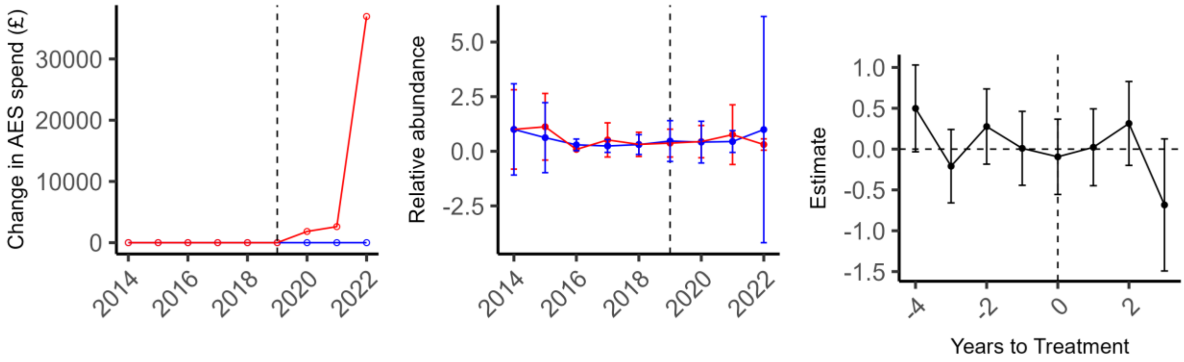
Years to Treatment	estimate	std.error	statistic	p.value	
-2	1.00	0.55	1.90	0.0640	
-1	0.76	0.91	0.83	0.4100	
0	1.80	3.30	0.53	0.6000	
1	0.72	2.10	0.34	0.7400	
2	1.80	0.58	3.20	0.0015	*
3	0.90	0.54	1.70	0.0930	
4	0.50	0.89	0.56	0.5800	
5	1.50	0.62	2.50	0.0130	*

SI Figure B8. Pair 22, including Chenies 81 (treatment) and Chenies 30 (control).



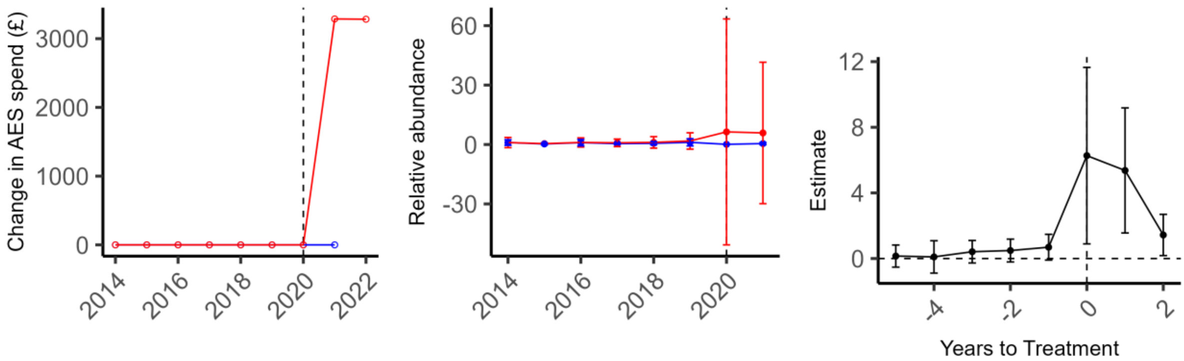
Years to Treatment	estimate	std.error	statistic	p.value
-4	-0.0380	0.31	-0.12	0.9000
-3	0.2300	0.28	0.82	0.4200
-2	0.0700	0.26	0.27	0.7900
-1	0.0970	0.26	0.37	0.7100
0	-0.1600	0.27	-0.58	0.5600
1	-0.0083	0.28	-0.03	0.9800
2	-0.1700	0.26	-0.63	0.5300
3	-0.7800	0.72	-1.10	0.2800

SI Figure B9. Pair 27, including Chenies 88 (treatment) and Chenies 43 (control).



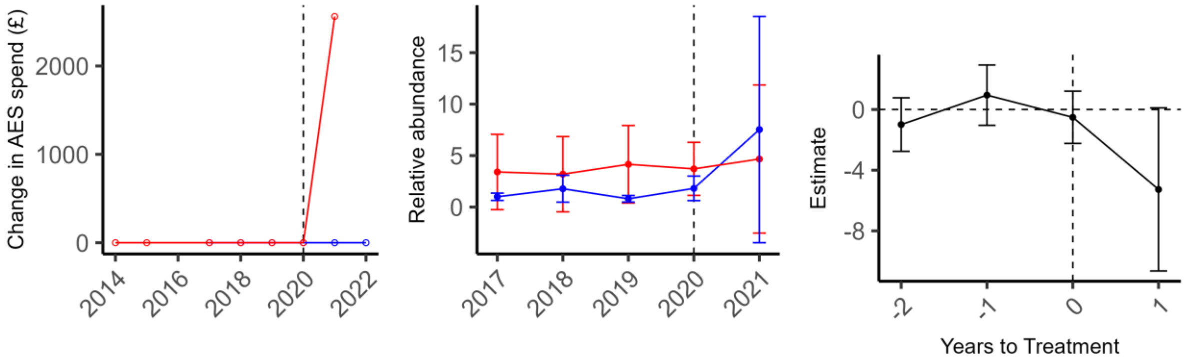
Years to Treatment	estimate	std.error	statistic	p.value
-4	0.5000	0.53	0.940	0.3500
-3	-0.2100	0.45	-0.470	0.6400
-2	0.2800	0.46	0.600	0.5500
-1	0.0095	0.45	0.021	0.9800
0	-0.0940	0.46	-0.200	0.8400
1	0.0220	0.47	0.047	0.9600
2	0.3100	0.51	0.610	0.5400
3	-0.6800	0.81	-0.850	0.4000

SI Figure B10. Pair 32, including Chenies 94 (treatment) and Chenies 43 (control).



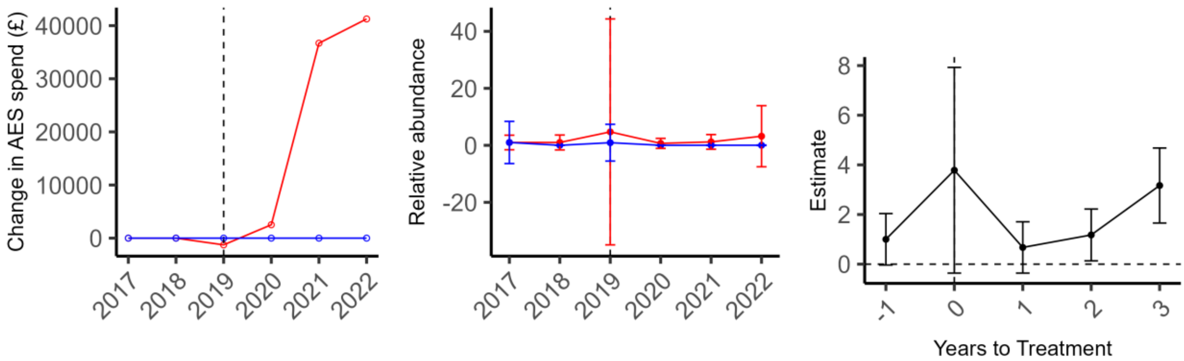
Years to Treatment	estimate	std.error	statistic	p.value
-5	0.150	0.67	0.22	0.8200
-4	0.099	0.99	0.10	0.9200
-3	0.410	0.69	0.60	0.5500
-2	0.490	0.70	0.70	0.4800
-1	0.690	0.79	0.88	0.3800
0	6.300	5.40	1.20	0.2400
1	5.400	3.80	1.40	0.1600
2	1.400	1.30	1.10	0.2500

SI Figure B11. Pair 41, including Chenies 105 (treatment) and Chenies 39 (control).



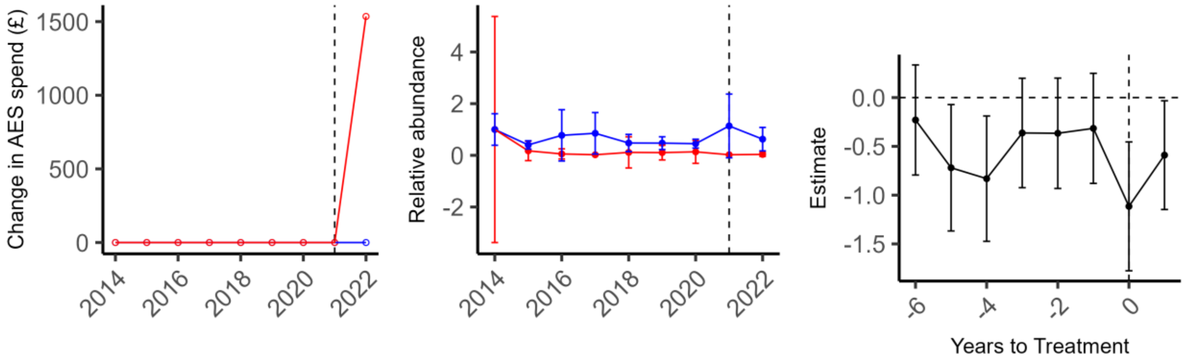
Years to Treatment	estimate	std.error	statistic	p.value
-2	-1.00	1.8	-0.56	0.5700
-1	0.94	2.0	0.47	0.6400
0	-0.51	1.7	-0.30	0.7700
1	-5.30	5.4	-0.98	0.3300

SI Figure B12. Pair 42, including Chenies 107 (treatment) and Chenies 59 (control).



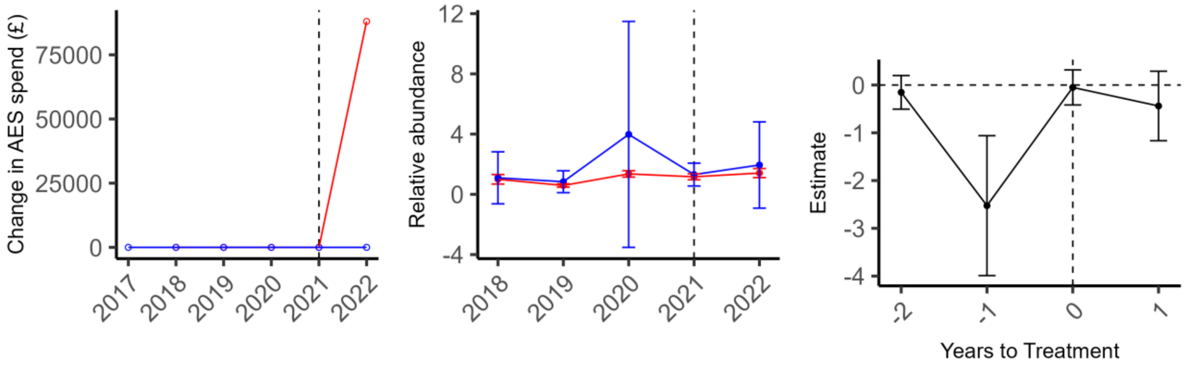
Years to Treatment	estimate	std.error	statistic	p.value	
-1	1.00	1.0	0.97	0.3300	
0	3.80	4.1	0.91	0.3600	
1	0.67	1.0	0.65	0.5100	
2	1.20	1.0	1.10	0.2600	
3	3.20	1.5	2.10	0.0360	*

SI Figure B13. Pair 95, including High Moorsley 57 (treatment) and High Moorsley 69 (control).



Years to Treatment	estimate	std.error	statistic	p.value
-6	-0.23	0.56	-0.41	0.6800
-5	-0.72	0.65	-1.10	0.2700
-4	-0.83	0.64	-1.30	0.2000
-3	-0.36	0.56	-0.65	0.5200
-2	-0.37	0.57	-0.65	0.5200
-1	-0.32	0.56	-0.56	0.5800
0	-1.10	0.66	-1.70	0.0920
1	-0.59	0.56	-1.10	0.2900

SI Figure B14. Pair 124, including Predannack 105 (treatment) and Predannack 068 (control).

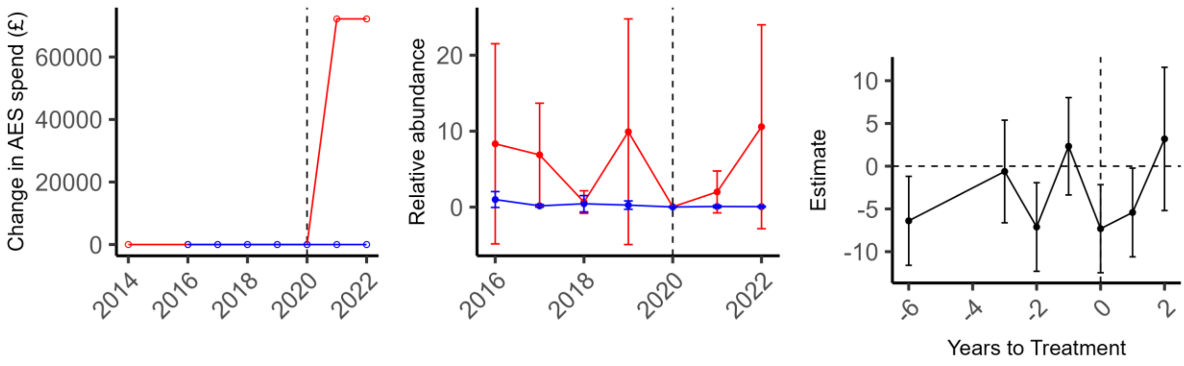


Years to Treatment	estimate	std.error	statistic	p.value
-2	-0.15	0.35	-0.44	0.6600
-1	-2.50	1.50	-1.70	0.0860
0	-0.05	0.37	-0.14	0.8900
1	-0.44	0.73	-0.60	0.5500

SI Figure B15. Pair 145, including Thurnham 068 (treatment) and Thurnham 087 (control).

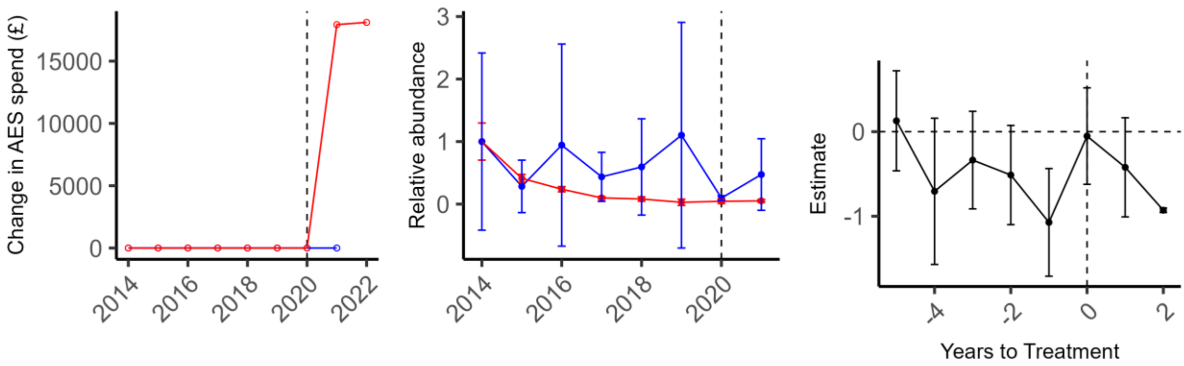
7.5.3 Excluded matches

We exclude the following comparisons based on visual inspection of trend. For these 2 and 30 (C1 and C2), the trends markedly diverge. For pair 31 (C3), there was error in estimation leading caused by extremely high variance in 1 year of data, leading to BACI model failure.



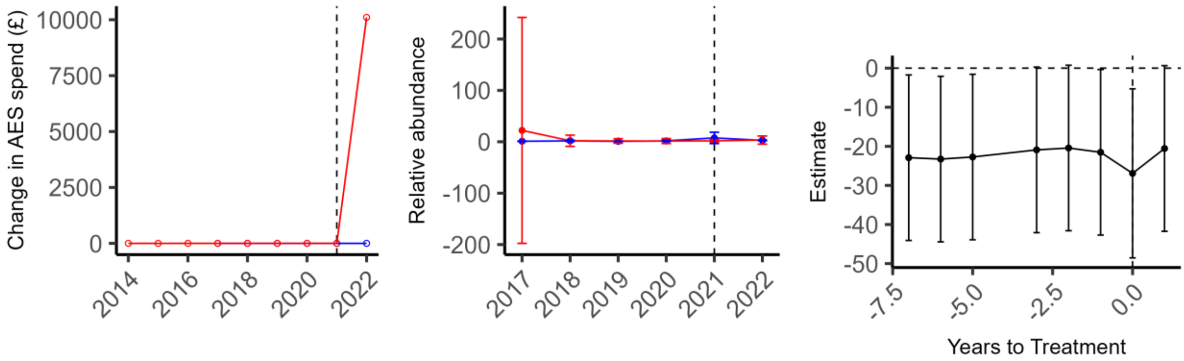
Years to Treatment	estimate	std.error	statistic	p.value
-6	-6.40	5.2	-1.20	0.2200
-3	-0.62	6.0	-0.10	0.9200
-2	-7.10	5.2	-1.40	0.1700
-1	2.30	5.7	0.41	0.6800
0	-7.30	5.2	-1.40	0.1600
1	-5.40	5.2	-1.00	0.3000
2	3.20	8.4	0.38	0.7000

SI Figure C1 Pair 2, including Chenies 18 (treatment) and Chenies 19 (control). Reasoning for exclusion: the control unit shows a relatively static trend compared to the highly variable trend in the control unit.



Years to Treatment	estimate	std.error	statistic	p.value	
-5	0.130	0.590	0.220	0.8300	
-4	-0.710	0.860	-0.820	0.4100	
-3	-0.340	0.580	-0.580	0.5600	
-2	-0.510	0.590	-0.870	0.3800	
-1	-1.100	0.640	-1.700	0.0920	
0	-0.052	0.570	-0.091	0.9300	
1	-0.420	0.590	-0.720	0.4700	
2	-0.930	0.026	-35.000	0.0000	*

SI Figure C2 Pair 30, including Chenies 92 (treatment) and Chenies 39 (control). Reasoning for exclusion: the treated unit shows a clear declining insect abundance trend, while the control unit is relatively more static and variable.



Years to Treatment	estimate	std.error	statistic	p.value
-7	-23	21	-1.10	0.2800
-6	-23	21	-1.10	0.2700
-5	-23	21	-1.10	0.2800
-3	-21	21	-0.99	0.3200
-2	-20	21	-0.96	0.3300
-1	-22	21	-1.00	0.3100
0	-27	22	-1.20	0.2100
1	-21	21	-0.97	0.3300

SI Figure C2 Pair 31, including Chenies 59 (treatment) and Chenies 39 (control). Reasoning for exclusion: Estimation error in calculation of heteroskedasticity-robust standard errors, likely due to highly uneven variance between years; 2017 in the treated CVP had a much larger error than other included years (ca. -200 – 200).

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7.6 AES option tables

SI Table 1. Countryside Stewardship option codes and descriptions, detailing which options are excluded from AES measure A and AES measure B.

Option Code	Option description	Measure A exclude	Measure B exclude	Staley et al. (2021) category
SW4	12-24m watercourse buffer strip on cultivated land	FALSE	FALSE	Grass buffer strips or margins
SW1	4-6m buffer strip on cultivated land	FALSE	FALSE	Grass buffer strips or margins
SW2	4-6m buffer strip on intensive grassland	FALSE	FALSE	Grass buffer strips or margins
RP18	Above ground tanks	FALSE	TRUE	None
AC1	Access Capital Items	TRUE	TRUE	None
APO	Additional Parcel Option	FALSE	TRUE	None
SP10	Administration of group managed agreements supplement	TRUE	TRUE	None
FG7	Anti-predator combination fencing for vulnerable ground-nesting birds.	FALSE	TRUE	None
FG8	Anti-predator temporary electric fencing	FALSE	TRUE	None
SW7	Arable reversion to grassland with low fertiliser inputs	FALSE	FALSE	Arable reversion
AQ1	Automatic slurry scraper	FALSE	TRUE	None
AB16	Autumn Sown BumbleBird Mix	FALSE	FALSE	Pollinator flower and nectar sources

FG14	Badger Gates	FALSE	TRUE	None
AB2	Basic Overwinter stubble	FALSE	FALSE	Winter stubble including following sileage or fodder crops
AB3	Beetle banks	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
RP26	Biofilters	FALSE	TRUE	None
WN1	Blocking Grips or Drainage Channels	FALSE	TRUE	None
SP3	Bracken control supplement	FALSE	TRUE	None
AB13	Brassica fodder crop	FALSE	TRUE	Winter bird food sources
WN9	Brick, Stone or Concrete Sluice	FALSE	TRUE	None
WT1	Buffering in field ponds and ditches in improved grassland	FALSE	FALSE	Grass buffer strips or margins
WT2	Buffering in-field ponds and ditches on arable land	FALSE	FALSE	Grass buffer strips or margins
FY2	Capital investments to improve access infrastructure to woodlands.	FALSE	TRUE	None
FY2A	Capital investments to improve access infrastructure to woodlands.	FALSE	TRUE	None
LV1	Cattle Grid	TRUE	TRUE	None
SP6	Cattle grazing supplement	TRUE	TRUE	None
RP12	Check dams and woody debris dams	FALSE	TRUE	None
SB4	Chemical Bracken Control	FALSE	TRUE	None
CT6	Coastal vegetation management supplement	FALSE	TRUE	None
RP15	Concrete yard renewal	FALSE	TRUE	None
RP8	Constructed wetlands for the treatment of pollution	FALSE	TRUE	None
WN10	Construction of water penning structures	FALSE	FALSE	Wet grassland
SP4	Control of invasive plant species supplement	FALSE	TRUE	None
TE10	Coppicing Bank-side Trees	FALSE	TRUE	None
AC2	Countryside Educational Visits Accreditation Scheme (CEVAS)	TRUE	TRUE	None
CT2	Creation of coastal sand dunes and vegetated shingle on arable land improved grassland	FALSE	FALSE	Sand dune management
TE13	Creation of dead wood habitat on trees	FALSE	FALSE	Woodland management and creation
WT9	Creation of fen	FALSE	FALSE	Fen management
GS14	Creation of grassland for target features	FALSE	FALSE	Grassland management
LH3	Creation of heathland from arable or improved grassland	FALSE	FALSE	Lowland heathland management
CT5	Creation of inter-tidal and saline habitat by non-intervention	FALSE	TRUE	None
CT7	Creation of inter-tidal and saline habitat on intensive grassland	FALSE	TRUE	None
WT7	Creation of reedbed	FALSE	FALSE	Wet grassland
WN2	Creation of scrapes and gutters	FALSE	TRUE	None
GS8	Creation of species-rich grassland	FALSE	FALSE	Species rich grassland creation
WD8	Creation of successional areas and scrub	FALSE	FALSE	Scrub management
BE5	Creation of traditional orchards	FALSE	TRUE	None
WD12	Creation of upland wood pasture	FALSE	FALSE	Woodland management and creation
GS11	Creation of wet grassland for breeding waders	FALSE	FALSE	Wet grassland
GS12	Creation of wet grassland for wintering waders and wildfowl	FALSE	FALSE	Wet grassland
WD6	Creation of wood pasture	FALSE	FALSE	Woodland management and creation

RP5	Cross drains/unit	FALSE	TRUE	None
AB11	Cultivated areas for arable plants	FALSE	FALSE	Uncropped cultivated margins/plots
WS1	Deer Control and Management	FALSE	TRUE	None
FG16	Deer Pedestrain Gate	FALSE	TRUE	None
FG17	Deer Vehicle Gate	FALSE	TRUE	None
FG11	Deer exclosure plot/unit	FALSE	TRUE	None
FY1	Deer high seat / unit	FALSE	TRUE	None
SP1	Difficult sites supplement	FALSE	TRUE	None
WN4	Ditch, Dyke and Rhine Creation	FALSE	TRUE	Ditch management
WN3	Ditch, Dyke and Rhine Restoration	FALSE	TRUE	Ditch management
BN4	Earth Bank Restoration	FALSE	TRUE	None
BN3	Earth bank creation	FALSE	TRUE	None
RP9	Earth banks and soil bunds/unit	FALSE	TRUE	None
ED1	Educational Access	TRUE	TRUE	None
WS4	Enable permissive access (by foot) across the whole woodland	TRUE	TRUE	None
UP1	Enclosed rough grazing	FALSE	TRUE	None
SW5	Enhanced management of maize crops	FALSE	TRUE	Undersown spring cereal
AB6	Enhanced overwinter stubble	FALSE	FALSE	Winter bird food sources
RP31	Equipment to disrupt tramlines in arable areas	FALSE	TRUE	None
PA2	Feasibility Study	TRUE	TRUE	None
FG1	Fencing	FALSE	TRUE	None
FG5	Fencing supplement - difficult sites	FALSE	TRUE	None
RP19	First-flush rainwater diverters/downpipe filters	FALSE	TRUE	None
RP30	Floating covers for slurry stores and lagoons	FALSE	TRUE	None
SW15	Flood mitigation on arable reversion to grassland	FALSE	FALSE	Arable reversion
SW16	Flood mitigation on permanent grassland	FALSE	TRUE	None
AB8	Flower rich margins and plots	FALSE	FALSE	Flower rich margins and plots
RP2	Gateway relocation	FALSE	TRUE	None
LV3	Hard bases for livestock drinkers	TRUE	TRUE	None
LV4	Hard bases for livestock feeders	TRUE	TRUE	None
AB14	Harvested low input cereal	FALSE	TRUE	Low input cereals
GS15	Haymaking supplement	FALSE	FALSE	Grassland management
BN6	Hedgerow Coppicing	FALSE	FALSE	Hedgerow management
BN7	Hedgerow Gapping	FALSE	FALSE	Hedgerow management
BN8	Hedgerow Supplement - Casting Up	FALSE	FALSE	Hedgerow management
BN10	Hedgerow Supplement - Top Binding and Staking	FALSE	FALSE	Hedgerow management
BN9	Hedgerow Supplement - substantial Pre-Work	FALSE	FALSE	Hedgerow management
BN5	Hedgerow laying	FALSE	FALSE	Hedgerow management
HE1	Historic and archaeological feature protection.	TRUE	TRUE	None
TE14	Identification of orchard fruit tree varieties	FALSE	TRUE	None
PA1	Implementation Plan/Unit	TRUE	TRUE	None
SW3	In-field grass strips	FALSE	FALSE	Grass buffer strips or margins
RP23	Installation of livestock drinking troughs (in draining pens for freshly dipped sheep)	FALSE	TRUE	None
RP6	Installation of piped culverts and ditches	FALSE	TRUE	Ditch management

SP7	Introduction of cattle grazing on the Scilly Isles	FALSE	FALSE	Grassland management
FG6	Invisible fencing system	FALSE	TRUE	None
RP33	Large Leaky Woody Dam	FALSE	TRUE	None
WB3	Large Wildlife Box	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
GS4	Legume and herb-rich swards	FALSE	FALSE	Flower rich margins and plots
GS17	Lenient Grazing Supplement	FALSE	FALSE	Grassland management
RP24	Lined biobed plus pesticide loading and washdown area	FALSE	TRUE	None
RP25	Lined biobed with existing washdown area	FALSE	TRUE	None
RP4	Livestock and machinery hardcore tracks	TRUE	TRUE	None
WD9	Livestock exclusion supplement - scrub and successional areas	FALSE	FALSE	Grassland management
LV2	Livestock handling facilities	TRUE	TRUE	None
LV7	Livestock troughs	FALSE	TRUE	None
AQ2	Low ammonia emission flooring for livestock buildings	FALSE	TRUE	None
HS1	Maintenance of Weatherproof Traditional Farm Buildings	TRUE	TRUE	None
HS8	Maintenance of Weatherproof Traditional Farm Buildings in Remote Areas	TRUE	TRUE	None
HS6	Maintenance of designed/engineered water-bodies	TRUE	TRUE	None
FM2	Major preparatory work for Priority Habitats (creation and restoration) and Priority Species	FALSE	FALSE	Threatened and priority species and habitats
SW12	Making space for water	FALSE	FALSE	Wet grassland
UP3	Management of Moorland	FALSE	FALSE	Moor and heath management
CT3	Management of coastal saltmarsh	FALSE	TRUE	None
CT1	Management of coastal sand dunes and vegetated shingle	FALSE	FALSE	Sand dune management
WT3	Management of ditches of high environmental value	FALSE	TRUE	Ditch management
WT8	Management of fen	FALSE	FALSE	Fen management
FM1	Management of geodiversity features	FALSE	TRUE	None
GS13	Management of grassland for target features	FALSE	FALSE	Grassland management
BE3	Management of hedgerows	FALSE	FALSE	Hedgerow management
HS5	Management of historic and archaeological features on grassland	TRUE	TRUE	None
HS7	Management of historic water meadows through traditional irrigation	TRUE	FALSE	Wet grassland
SW8	Management of intensive grassland adjacent to a watercourse	FALSE	TRUE	Grassland erosion management
LH1	Management of lowland heathland	FALSE	FALSE	Lowland heathland management
WT10	Management of lowland raised bog	FALSE	FALSE	Lowland raised bog
UP4	Management of moorland vegetation supplement	FALSE	FALSE	Moor and heath management
WT4	Management of ponds of High Wildlife value (100 sq m or less)	FALSE	TRUE	None
WT5	Management of ponds of High Wildlife value (more than 100 sq m)	FALSE	TRUE	None
WT6	Management of reedbed	FALSE	FALSE	Wet grassland
UP2	Management of rough grazing for birds	FALSE	FALSE	Wet grassland
GS6	Management of species-rich grassland	FALSE	FALSE	Species rich grassland creation
WD7	Management of successional areas and scrub	FALSE	FALSE	Scrub management
BE4	Management of traditional orchards	FALSE	TRUE	None

WD10	Management of upland wood pasture and parkland	FALSE	TRUE	Upland grassland and moorland management
GS9	Management of wet grassland for breeding waders	FALSE	FALSE	Wet grassland
GS10	Management of wet grassland for wintering waders and wildfowl	FALSE	FALSE	Wet grassland
WD4	Management of wood pasture and parkland	FALSE	FALSE	Woodland management and creation
SB5	Mechanical bracken control	FALSE	TRUE	None
WB2	Medium Wildlife Box	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
UP5	Moorland re-wetting supplement	FALSE	FALSE	Moor and heath management
OP4	Multi species ley	FALSE	FALSE	Flower rich margins and plots
SP8	Native breeds at risk supplement	FALSE	FALSE	Rare breeds grazing
AB1	Nectar Flower Mix	FALSE	FALSE	Pollinator flower and nectar sources
AB5	Nesting Plots for Lapwing	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
SW14	Nil fertiliser supplement	FALSE	FALSE	Low input grassland
OR4	Organic Conversion - Horticulture	FALSE	FALSE	Organic management
OR5	Organic Conversion - Top Fruit	FALSE	FALSE	Organic management
OT6	Organic Land Management - Enclosed Rough Grazing	FALSE	FALSE	Organic management
OT4	Organic Land Management - Horticulture	FALSE	FALSE	Organic management
OT5	Organic Land Management - Top Fruit	FALSE	FALSE	Organic management
OT3	Organic Land Management - rotational land	FALSE	FALSE	Organic management
OT2	Organic Land Management - unimproved permanent grassland	FALSE	FALSE	Organic management
OR1	Organic conversion - improved permanent grassland	FALSE	FALSE	Organic management
OR3	Organic conversion - rotational land	FALSE	FALSE	Organic management
OR2	Organic conversion - unimproved permanent grassland	FALSE	FALSE	Organic management
OT1	Organic land management - improved permanent grassland	FALSE	FALSE	Organic management
OP1	Overwintered stubble	FALSE	TRUE	Winter bird food sources
TE9	Parkland Tree Guard - welded steel	FALSE	TRUE	None
LV5	Pasture pumps and associated pipework/unit	FALSE	TRUE	Grassland erosion management
FG3	Permanent electric fencing	FALSE	TRUE	None
GS2	Permanent grassland with very low inputs (outside SDAs)	FALSE	FALSE	Low input grassland
GS5	Permanent grassland with very low inputs in SDA	FALSE	FALSE	Low input grassland
LV8	Pipework for livestock troughs	FALSE	TRUE	Grassland erosion management
TE3	Planting Fruit Trees	FALSE	TRUE	None
TE1	Planting Standard Hedgerow Tree	FALSE	FALSE	Hedgerow management
TE2	Planting Standard Parkland Tree	FALSE	TRUE	None
BN11	Planting new hedges	FALSE	FALSE	Hedgerow management
WN6A	Pond Management - creation - (areas more than 100 sq m)	FALSE	TRUE	None
WN5A	Pond Management - creation (first 100 sq m)	FALSE	TRUE	None
WN6B	Pond Management - restoration - (areas more than 100 sq m)	FALSE	TRUE	None
WN5B	Pond Management - restoration - first 100 sq m	FALSE	TRUE	None
BE1	Protection of in-field trees on arable land	FALSE	TRUE	None

BE2	Protection of in-field trees on intensive grassland	FALSE	TRUE	None
FG4	Rabbit fencing supplement	FALSE	TRUE	None
RP16	Rainwater goods	FALSE	TRUE	None
SP2	Raised water level supplement	FALSE	TRUE	None
SW18	Raised water levels on grassland on peat soils	FALSE	FALSE	Wet grassland
LV6	Ram pumps and pipework/unit	FALSE	TRUE	Grassland erosion management
HS3	Reduced depth, non-inversion cultivation on historic and archaeological features	TRUE	TRUE	None
RP20	Relocation of sheep dips and pens	FALSE	TRUE	None
RP21	Relocation of sheep pens only	FALSE	TRUE	None
HE3	Removal of eyesore	TRUE	TRUE	None
LH2	Restoration of forestry and woodland to lowland heathland	FALSE	FALSE	Woodland management and creation
WN7	Restoration of large water bodies	FALSE	TRUE	None
WD11	Restoration of upland wood pasture and parkland	FALSE	FALSE	Upland management
WD5	Restoration of wood pasture and parkland	FALSE	FALSE	Woodland management and creation
GS7	Restoration towards species-rich grassland	FALSE	FALSE	Species rich grassland management
WS2	Restore and maintain plantations on ancient woodlands sites	FALSE	FALSE	Woodland management and creation
HS9	Restricted depth crop establishment to protect archaeology under and arable rotation	TRUE	TRUE	None
RP1	Resurfacing of gateways	TRUE	TRUE	None
SB6A	Rhododendron control	FALSE	TRUE	None
SB6B	Rhododendron control	FALSE	TRUE	None
SB6C	Rhododendron control	FALSE	TRUE	None
SW11	Riparian management strip	FALSE	FALSE	Grass buffer strips or margins
RP28	Roofing (sprayer washdown area, manure storage area, ...)	FALSE	TRUE	None
GS16	Rush infestation control supplement	FALSE	TRUE	None
GS3	Ryegrass seed-set as winter food for birds	FALSE	TRUE	Winter bird food sources
SB1A	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB1B	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB1C	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB1D	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB1E	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB1F	Scrub Control and Felling Diseased Trees	FALSE	TRUE	Scrub management
SB2	Scrub control - difficult sites	FALSE	TRUE	Scrub management
HS4	Scrub control on historic and archaeological features	TRUE	TRUE	Scrub management
SW10	Seasonal livestock removal on intensive grassland	FALSE	FALSE	Grassland management
SW9	Seasonal livestock removal on intensive grassland	FALSE	FALSE	Grassland management
RP7	Sediment ponds and traps/sq m	FALSE	TRUE	None
RP29	Self supporting covers for slurry stores/sq m	FALSE	TRUE	None
RP22	Sheep dip drainage aprons and sumps	FALSE	TRUE	None
FG2	Sheep netting	FALSE	TRUE	None
SP5	Shepherding supplement	TRUE	TRUE	None
RP10	Silt filtration dams or seepage barriers	FALSE	TRUE	None
AB4	Skylark Plots	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites

RP32	Small Leaky Woody Dam	FALSE	TRUE	None
WB1	Small Wildlife Box	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
RP27	Sprayer or applicator load and washdown area/sq m	FALSE	TRUE	None
FY3	Squirrel Traps and Maintenance	FALSE	TRUE	None
WS3	Squirrel control and management	FALSE	TRUE	None
FG13	Stone Gate Post	FALSE	TRUE	None
BN13	Stone Wall - Top Wiring	TRUE	TRUE	None
BN12	Stone Wall Restoration	TRUE	TRUE	None
BN2	Stone faced bank restoration	FALSE	TRUE	None
BN14	Stone wall supplement - Stone from quarry	TRUE	TRUE	None
BN15	Stone wall supplement - difficult sites	TRUE	TRUE	None
BN1	Stone-faced bank repair	FALSE	TRUE	None
RP17	Storage tanks underground	FALSE	TRUE	None
TE12	Stump Grinding	FALSE	TRUE	None
BE7	Supplement for restorative pruning of fruit trees	FALSE	TRUE	None
OP3	Supplementary feeding for farmland birds	FALSE	TRUE	Winter bird food sources
AB12	Supplementary winter feeding for farmland birds	FALSE	TRUE	Winter bird food sources
RP11	Swales	FALSE	TRUE	None
GS1	Take field corners and small areas out of management	FALSE	TRUE	Field corners
HS2	Take historic and archaeological features currently on cultivated land out of cultivation.	TRUE	TRUE	None
FG10	Temporary deer fencing / m	FALSE	TRUE	None
SP9	Threatened species supplement	FALSE	FALSE	Threatened and priority species and habitats
WN8	Timber sluice/unit	FALSE	TRUE	None
TE8	Tree Guard (wood post and wire)	FALSE	TRUE	None
TE7	Tree guard (Wood post and rail)	FALSE	TRUE	None
TE6	Tree guard (tube and mesh)	FALSE	TRUE	None
BC4	Tree guard (wood post and wire)	FALSE	TRUE	None
SB3	Tree removal	FALSE	TRUE	None
TE11A	Tree surgery	FALSE	TRUE	None
TE11B	Tree surgery	FALSE	TRUE	None
AB15	Two year sown legume fallow	FALSE	FALSE	Fallow plots for ground-nesting birds
OP5	Undersown cereal	FALSE	TRUE	Undersown spring cereal
AB10	Unharvested cereal headland	FALSE	TRUE	Conservation headlands
UP6	Upland livestock exclusion supplement	FALSE	TRUE	Upland grassland and moorland management
SW13	Very low nitrogen inputs to groundwaters	FALSE	FALSE	Low input grassland
BE6	Veteran Tree Surgery	FALSE	TRUE	None
FG15	Water Gates	FALSE	TRUE	None
RP3	Watercourse crossing/unit	FALSE	TRUE	None
WT11	Wetland cutting supplement	FALSE	FALSE	Wet grassland
WT12	Wetland grazing supplement	FALSE	FALSE	Wet grassland
AB7	Wholecrop cereals	FALSE	TRUE	None
OP2	Wild bird seed mixture	FALSE	FALSE	Flower rich margins and plots
AB9	Winter bird food	FALSE	TRUE	Winter bird food sources

SW6	Winter cover crops	FALSE	TRUE	None
FG12	Wooden Field Gate	FALSE	TRUE	None
FG9	Woodland Fencing - Deer	FALSE	TRUE	None
PA3	Woodland Management plan/per ha	TRUE	FALSE	Woodland management and creation
TE4A	Woodland Tree Planting - Biodiversity	FALSE	FALSE	Woodland management and creation
TE4D	Woodland Tree Planting - Hedges and clumps	FALSE	FALSE	Woodland management and creation
TE4B	Woodland Tree Planting - Improving water quality or reducing flood risk	FALSE	FALSE	Woodland management and creation
TE4C	Woodland Tree Planting - Restock after a tree health issue	FALSE	FALSE	Woodland management and creation
TE5	Woodland Tree Planting - Treeshelter Supplement	FALSE	FALSE	Woodland management and creation
WD1	Woodland creation - maintenance payments	FALSE	FALSE	Woodland management and creation
WD3	Woodland edges on arable land	FALSE	FALSE	Woodland management and creation
WD2	Woodland improvement	FALSE	FALSE	Woodland management and creation
RP13	Yard - underground drainage pipework	FALSE	TRUE	None
RP14	Yard inspection pit	FALSE	TRUE	None

SI Table 2 Environmental Stewardship option codes and descriptions, detailing which options excluded from AES Measure A and Measure B.

Option title	Option code	Measure A exclude	Measure B exclude	Staley et al. (2021) category
12 m buffer strips for watercourses on cultivated land	HJ9	FALSE	FALSE	Grass buffer strips or margins
12m buffer strips for watercourses on cultivated land	EJ9	FALSE	FALSE	Grass buffer strips or margins
12m buffer strips for watercourses on cultivated land	OJ9	FALSE	FALSE	Grass buffer strips or margins
2 m buffer strips on cultivated land	HE1	FALSE	FALSE	Grass buffer strips or margins
2 m buffer strips on intensive grassland	HE4	FALSE	FALSE	Grass buffer strips or margins
2m buffer strip on organic grassland	OE4	FALSE	FALSE	Grass buffer strips or margins
2m buffer strips on cultivated land	EE1	FALSE	FALSE	Grass buffer strips or margins
2m buffer strips on intensive grassland	EE4	FALSE	FALSE	Grass buffer strips or margins
2m buffer strips on rotational land	OE1	FALSE	FALSE	Grass buffer strips or margins
4 m buffer strips on cultivated land	HE2	FALSE	FALSE	Grass buffer strips or margins
4 m buffer strips on intensive grassland	HE5	FALSE	FALSE	Grass buffer strips or margins
4 m buffer strips on organic grassland	OHE5	FALSE	FALSE	Grass buffer strips or margins
4m buffer strip on organic grassland	OE5	FALSE	FALSE	Grass buffer strips or margins
4m buffer strips on cultivated land	EE2	FALSE	FALSE	Grass buffer strips or margins

4m buffer strips on intensive grassland	EE5	FALSE	FALSE	Grass buffer strips or margins
4m buffer strips on rotational land	OE2	FALSE	FALSE	Grass buffer strips or margins
6 m buffer strips on cultivated land	HE3	FALSE	FALSE	Grass buffer strips or margins
6 m buffer strips on intensive grassland	HE6	FALSE	FALSE	Grass buffer strips or margins
6 m buffer strips on organic grassland	OHE6	FALSE	FALSE	Grass buffer strips or margins
6 m buffer strips on rotational land	OHE3	FALSE	FALSE	Grass buffer strips or margins
6m buffer strip on organic grassland	OE6	FALSE	FALSE	Grass buffer strips or margins
6m buffer strip on organic grassland next to a watercourse	OE10	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on cultivated land	EE3	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on cultivated land next to a watercourse	EE9	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on intensive grassland	EE6	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on intensive grassland next to a watercourse	EE10	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on rotational land	OE3	FALSE	FALSE	Grass buffer strips or margins
6m buffer strips on rotational land next to a watercourse	OE9	FALSE	FALSE	Grass buffer strips or margins
ASD to Jan 2010 Nectar flower mixture in grassland areas	HG3	FALSE	FALSE	Flower rich margins and plots
ASD to Jan 2010 Wild bird seed mixture	HG2NR	FALSE	FALSE	Flower rich margins and plots
ASD to Jan 2010 Wild bird seed mixture	HG2	FALSE	FALSE	Flower rich margins and plots
ASD to Jan 2010 Wild bird seed mixture in grassland areas	EG2	FALSE	FALSE	Flower rich margins and plots
ASD to Nov 2010 Access for people with reduced mobility	HN5	TRUE	TRUE	None
ASD to Nov 2010 Linear and open access base payment	HN1	TRUE	TRUE	None
ASD to Nov 2010 Permissive bridleway / cycle path access	HN4	TRUE	TRUE	None
ASD to Nov 2010 Permissive footpath access	HN3	TRUE	TRUE	None
ASD to Nov 2010 Permissive open access	HN2	TRUE	TRUE	None
ASD to Nov 2010 Upgrading access - people with reduced mobility	HN7	TRUE	TRUE	None
ASD to Nov 2010 Upgrading access for cyclists/horses	HN6	TRUE	TRUE	None
Ancient trees in arable fields	HC5	FALSE	TRUE	None
Ancient trees in intensively-managed grass fields	HC6	FALSE	TRUE	None
Arable reversion by natural regeneration	HD7	FALSE	FALSE	Arable reversion
Beetle banks	HF7	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
Beetle banks	EF7	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
Beetle banks	OF7	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
Beetle banks	OHF7	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites

Bracken control supplement	HR5	FALSE	TRUE	None
Brassica fodder crops followed by over-wintered stubbles	HG5	FALSE	TRUE	Winter stubble including following sileage or fodder crops
Buffering in-field ponds in arable land	EE8	FALSE	FALSE	Grass buffer strips or margins
Buffering in-field ponds in arable land	HE8	FALSE	FALSE	Wet grassland
Buffering in-field ponds in arable land	HE8	FALSE	FALSE	Grass buffer strips or margins
Buffering in-field ponds in improved grassland	EE7	FALSE	FALSE	Grass buffer strips or margins
Buffering in-field ponds in improved permanent grassland	HE7	FALSE	FALSE	Grass buffer strips or margins
Buffering in-field ponds in rotational land	OE8	FALSE	FALSE	Grass buffer strips or margins
Cattle grazing on upland grassland and moorland	UL18	FALSE	FALSE	Upland management
Cattle grazing on upland grassland and moorland	UHL18	FALSE	FALSE	Upland management
Cattle grazing on upland grassland and moorland	UOL18	FALSE	FALSE	Upland management
Cereal headlands for birds	HF9NR	FALSE	FALSE	Conservation headlands
Cereal headlands for birds	EF9	FALSE	FALSE	Conservation headlands
Cereals for whole crop silage followed by over-wintered stubbles	EG4	FALSE	TRUE	Winter stubble including following sileage or fodder crops
Cereals for whole crop silage followed by over-wintered stubbles	OG4	FALSE	TRUE	Winter stubble including following sileage or fodder crops
Cereals for whole-crop silage followed by overwintered stubble	HG4	FALSE	TRUE	Winter stubble including following sileage or fodder crops
Cereals for whole-crop silage followed by overwintered stubble	OHG4	FALSE	TRUE	Winter stubble including following sileage or fodder crops
Combined hedge and ditch management (incorporating EB1)	EB8	FALSE	TRUE	Hedge and ditch management
Combined hedge and ditch management (incorporating EB2)	EB9	FALSE	TRUE	Hedge and ditch management
Combined hedge and ditch management (incorporating EB3)	EB10	FALSE	TRUE	Hedge and ditch management
Combined hedge and ditch management (incorporating OB1)	OB8	FALSE	TRUE	Hedge and ditch management
Combined hedge and ditch management (incorporating OB2)	OB9	FALSE	TRUE	Hedge and ditch management
Combined hedge and ditch management (incorporating OB3)	OB10	FALSE	TRUE	Hedge and ditch management
Commons and shared grazing	UX1	TRUE	TRUE	None
Creation of fen	HQ8	FALSE	FALSE	Fen management
Creation of grassland for target features	HK17	FALSE	FALSE	Grassland management
Creation of inter-tidal and saline habitat by non-intervention	HP9	FALSE	TRUE	None
Creation of inter-tidal and saline habitat on arable land	HP7	FALSE	TRUE	None
Creation of inter-tidal and saline habitat on grassland	HP8	FALSE	TRUE	None

Creation of lowland heathland from arable or improved grassland	HO4	FALSE	FALSE	Lowland heathland management
Creation of lowland heathland on worked mineral sites	HO5	FALSE	FALSE	Lowland heathland management
Creation of reedbeds	HQ5	FALSE	FALSE	Wet grassland
Creation of species-rich, semi-natural grassland	HK8	FALSE	FALSE	Species rich grassland management
Creation of successional areas and scrub	HC17	FALSE	FALSE	Scrub management
Creation of traditional orchards	HC21	FALSE	TRUE	None
Creation of upland heathland	HL11	FALSE	FALSE	Upland management
Creation of vegetated shingle and sand dune on grassland	HP4	FALSE	FALSE	Sand dune management
Creation of wet grassland for breeding waders	HK13	FALSE	FALSE	Wet grassland
Creation of wet grassland for wintering waders and wildfowl	HK14	FALSE	FALSE	Wet grassland
Creation of wood pasture	HC14	FALSE	FALSE	Woodland management and creation
Creation of woodland in the SDA	HC9	FALSE	FALSE	Woodland management and creation
Creation of woodland outside of the SDA & ML	HC10	FALSE	FALSE	Woodland management and creation
Crop establishment by direct drilling (non-rotational)	HD6	FALSE	TRUE	None
Crop protection management plan (pre-RDPE)	EM4	FALSE	TRUE	None
Cultivated fallow plots or margins for arable plants	HF20NR	FALSE	FALSE	Threatened and priority species and habitats
Cultivated fallow plots or margins for arable plants	HF20	FALSE	FALSE	Threatened and priority species and habitats
Ditch management	EB6	FALSE	TRUE	Ditch management
Ditch management	OB6	FALSE	TRUE	Ditch management
Earth bank management (both sides) on/above the moorland line	UB12	FALSE	TRUE	None
Earth bank management (on both sides)	EB12	FALSE	TRUE	None
Earth bank management (on both sides)	OB12	FALSE	TRUE	None
Earth bank management (on one side)	EB13	FALSE	TRUE	None
Earth bank management (on one side)	OB13	FALSE	TRUE	None
Earth bank management (one side) on/above the moorland line	UB13	FALSE	TRUE	None
Earth bank restoration	UB16	FALSE	TRUE	None
Educational access - base payment	HN8	TRUE	TRUE	None
Educational access - base payment	HN8CW	TRUE	TRUE	None
Educational access - payment per visit	HN9	TRUE	TRUE	None
Educational access - payment per visit	HN9CW	TRUE	TRUE	None
Enclosed rough grazing	HL5	FALSE	FALSE	Grassland management
Enclosed rough grazing	OHL5	FALSE	FALSE	Grassland management
Enclosed rough grazing: SDA land & ML parcels under 15ha	EL5	FALSE	FALSE	Grassland management
Enclosed rough grazing:SDA land & ML parcels under 15ha(organic)	OL5	FALSE	FALSE	Grassland management
Enhanced management of maize crops to reduce erosion and run-off	EJ10	FALSE	TRUE	Undersown spring cereal

Enhanced strips for target species on intensive grassland	HE11	FALSE	FALSE	Grass buffer strips or margins
Enhanced wild bird seed mix plots	HF12NR	FALSE	FALSE	Flower rich margins and plots
Enhanced wild bird seed mix plots	HF12	FALSE	FALSE	Flower rich margins and plots
Establishment of hedgerow trees by tagging	EC23	FALSE	FALSE	Hedgerow management
Extended overwintered stubbles	EF22	FALSE	TRUE	Winter bird food sources
FEP Payment to Party	FEP	TRUE	TRUE	None
Farm Environment Record (FER)	EA1	TRUE	TRUE	None
Farm Environment Record (FER)	OA1	TRUE	TRUE	None
Field corner management	EF1	FALSE	TRUE	Field corners
Field corner management	OF1	FALSE	TRUE	Field corners
Field corner management: SDA land	EL1	FALSE	TRUE	Field corners
Floristically enhanced grass margin	HE10	FALSE	FALSE	Flower rich margins and plots
Fodder crop management to retain or re-create an arable mosaic	HG6NR	FALSE	TRUE	None
Fodder crop management to retain or re-create an arable mosaic	HG6	FALSE	TRUE	None
Grassland and arable	UX2	FALSE	FALSE	Upland management
Grassland and arable	UOX2	FALSE	FALSE	Upland management
Grazing supplement for cattle	HR1	FALSE	TRUE	None
Grazing supplement for native breeds at risk	HR2	FALSE	FALSE	Rare breeds grazing
Half ditch management	EB7	FALSE	TRUE	Ditch management
Half ditch management	OB7	FALSE	TRUE	Ditch management
Haymaking	UL20	FALSE	FALSE	Low input grassland
Haymaking	UHL20	FALSE	FALSE	Low input grassland
Haymaking	UOL20	FALSE	FALSE	Low input grassland
Haymaking	UOL20	FALSE	FALSE	Low input grassland
Haymaking	UOHL20	FALSE	FALSE	Low input grassland
Hedgerow management for landscape (on both sides of a hedge)	EB1	FALSE	FALSE	Hedgerow management
Hedgerow management for landscape (on both sides of a hedge)	OB1	FALSE	FALSE	Hedgerow management
Hedgerow management for landscape (on one side of a hedge)	EB2	FALSE	FALSE	Hedgerow management
Hedgerow management for landscape (on one side of a hedge)	OB2	FALSE	FALSE	Hedgerow management
Hedgerow management for landscape and wildlife	EB3	FALSE	FALSE	Hedgerow management
Hedgerow management for landscape and wildlife	OB3	FALSE	FALSE	Hedgerow management
Hedgerow restoration	UB14	FALSE	FALSE	Hedgerow management
Hedgerow restoration	EB14	FALSE	FALSE	Hedgerow management
Hedgerow restoration	UOB14	FALSE	FALSE	Hedgerow management
Hedgerow restoration	OB14	FALSE	FALSE	Hedgerow management
Hedgerow tree buffer strips on cultivated land	EC24	FALSE	FALSE	Hedgerow management
Hedgerow tree buffer strips on cultivated land	HC24	FALSE	FALSE	Hedgerow management

Hedgerow tree buffer strips on grassland	EC25	FALSE	FALSE	Hedgerow management
Hedgerow tree buffer strips on grassland	HC25	FALSE	FALSE	Hedgerow management
Hedgerow tree buffer strips on organic grassland	OC25	FALSE	FALSE	Hedgerow management
Hedgerow tree buffer strips on rotational land	OC24	FALSE	FALSE	Hedgerow management
Improved land conversion payment	ILC	FALSE	FALSE	Grassland management
In-bye pasture & meadows with very low inputs: SDA land	EL3	FALSE	FALSE	Low input grassland
In-bye pasture & meadows with very low inputs: SDA land(organic)	OL3	FALSE	FALSE	Low input grassland
In-field grass areas	EJ5	FALSE	TRUE	Grassland erosion management
In-field grass areas to prevent erosion and run-off	OHJ5	FALSE	TRUE	Grassland erosion management
In-field grass areas to prevent erosion or run-off	HJ5	FALSE	TRUE	Grassland erosion management
In-field grass areas to prevent erosion or run-off	OJ5	FALSE	TRUE	Grassland erosion management
Inundation grassland supplement	HQ13	FALSE	FALSE	Wet grassland
Landscape management	HIOS1	FALSE	TRUE	None
Legume- and herb-rich swards	HK21	FALSE	FALSE	Flower rich margins and plots
Legume- and herb-rich swards	EK21	FALSE	FALSE	Flower rich margins and plots
Legume- and herb-rich swards	OK21	FALSE	FALSE	Flower rich margins and plots
Legume- and herb-rich swards	OHK21	FALSE	FALSE	Flower rich margins and plots
Low depth, non-inversion cultivation on archaeological features	HD3	TRUE	TRUE	None
Low depth, non-inversion cultivation on archaeological features	ED3	TRUE	TRUE	None
Low depth, non-inversion cultivation on archaeological features	OD3	TRUE	TRUE	None
Low depth, non-inversion cultivation on archaeological features	OHD3	TRUE	TRUE	None
Low input spring cereal to retain or re-create an arable mosaic	HG7NR	FALSE	TRUE	Low input cereals
Low input spring cereal to retain or re-create an arable mosaic	HG7	FALSE	TRUE	Low input cereals
Maintaining high water levels to protect archaeology	HD8	TRUE	TRUE	None
Maintaining visibility of archaeological features on moorland	UD13	TRUE	TRUE	None
Maintaining visibility of archaeological features on moorland	UHD13	TRUE	TRUE	None
Maintaining visibility of archaeological features on moorland	UOD13	TRUE	TRUE	None
Maintenance of coastal saltmarsh	HP5	FALSE	TRUE	None
Maintenance of designed/engineered water bodies	HD9	TRUE	TRUE	None
Maintenance of fen	HQ6	FALSE	FALSE	Fen management
Maintenance of grassland for target features	HK15	FALSE	FALSE	Grassland management
Maintenance of hedges of very high environmental value (1 side)	HB12	FALSE	FALSE	Hedgerow management
Maintenance of hedges of very high environmental value (2 sides)	HB11	FALSE	FALSE	Hedgerow management
Maintenance of high value traditional orchards	HC18	FALSE	TRUE	None

Maintenance of lowland heathland	HO1	FALSE	FALSE	Lowland heathland management
Maintenance of lowland raised bog	HQ9	FALSE	FALSE	Lowland raised bog
Maintenance of moorland	HL9	FALSE	FALSE	Moor and heath management
Maintenance of ponds of high wildlife value < 100 sq m	HQ1	FALSE	FALSE	Wet grassland
Maintenance of ponds of high wildlife value > 100 sq m	HQ2	FALSE	FALSE	Wet grassland
Maintenance of reedbeds	HQ3	FALSE	FALSE	Wet grassland
Maintenance of remote weatherproof traditional farm buildings	UD12	TRUE	TRUE	None
Maintenance of remote weatherproof traditional farm buildings	UHD12	TRUE	TRUE	None
Maintenance of rough grazing for birds	HL7	FALSE	FALSE	Grassland management
Maintenance of sand dunes	HP1	FALSE	FALSE	Sand dune management
Maintenance of species-rich, semi-natural grassland	HK6	FALSE	FALSE	Grassland management
Maintenance of successional areas and scrub	HC15	FALSE	FALSE	Scrub management
Maintenance of traditional farm buildings	ED1	TRUE	TRUE	None
Maintenance of traditional farm buildings	OD1	TRUE	TRUE	None
Maintenance of traditional orchards in production	HC19	FALSE	TRUE	None
Maintenance of traditional water meadows	HD10	FALSE	FALSE	Wet grassland
Maintenance of watercourse fencing	HJ11	FALSE	TRUE	None
Maintenance of watercourse fencing	EJ11	FALSE	TRUE	None
Maintenance of watercourse fencing	EJ11	FALSE	TRUE	None
Maintenance of watercourse fencing	OJ11	FALSE	TRUE	None
Maintenance of weatherproof traditional farm buildings	HD1	TRUE	TRUE	None
Maintenance of weatherproof traditional farm buildings	OHD1	TRUE	TRUE	None
Maintenance of wet grassland for breeding waders	HK9	FALSE	FALSE	Wet grassland
Maintenance of wet grassland for wintering waders and wildfowl	HK10	FALSE	FALSE	Wet grassland
Maintenance of wood pasture and parkland	HC12	FALSE	FALSE	Woodland management and creation
Maintenance of woodland	HC7	FALSE	FALSE	Woodland management and creation
Maintenance of woodland fences	EC3	FALSE	FALSE	Woodland management and creation
Maintenance of woodland fences	OC3	FALSE	FALSE	Woodland management and creation
Manage rush pastures: SDA land & ML parcels under 15ha	EL4	FALSE	FALSE	Wet grassland management / Species rich grassland
Manage rush pastures: SDA land & ML parcels under 15ha(organic)	OL4	FALSE	FALSE	Wet grassland management / Species rich grassland
Manage rush pastures: outside SDA & ML	EK4	FALSE	FALSE	Wet grassland management /

				Species rich grassland
Manage rush pastures: outside SDA & ML(organic)	OK4	FALSE	FALSE	Wet grassland management / Species rich grassland
Management of archaeological features on grassland	HD5	TRUE	TRUE	None
Management of archaeological features on grassland	ED5	TRUE	TRUE	None
Management of archaeological features on grassland	OHD5	TRUE	TRUE	None
Management of archaeological features on grassland	OD5	TRUE	TRUE	None
Management of ditches of very high environmental value	HB14	FALSE	TRUE	Ditch management
Management of enclosed rough grazing for birds	UL22	FALSE	TRUE	None
Management of enclosed rough grazing for birds	UOL22	FALSE	TRUE	None
Management of field corners	HF1	FALSE	TRUE	Field corners
Management of field corners	OHF1	FALSE	TRUE	Field corners
Management of heather, gorse and grass	HL12	FALSE	FALSE	Grassland management
Management of maize crops to reduce soil erosion	EJ2	FALSE	TRUE	Undersown spring cereal
Management of rare arable bulb/flora	HIOS2	FALSE	FALSE	Threatened and priority species and habitats
Management of rush pastures	HK4	FALSE	FALSE	Wet grassland
Management of rush pastures	OHK4	FALSE	FALSE	Wet grassland
Management of rush pastures in SDAs	HL4	FALSE	FALSE	Wet grassland
Management of scrub on archaeological features	HD4	TRUE	TRUE	None
Management of scrub on archaeological features	ED4	TRUE	TRUE	None
Management of scrub on archaeological features	OD4	FALSE	TRUE	None
Management of scrub on archaeological features	OHD4	FALSE	TRUE	None
Management of upland grassland for birds	UL23	FALSE	FALSE	Grassland management
Management of upland grassland for birds	UHL23	FALSE	FALSE	Grassland management
Management of upland grassland for birds	UOL23	FALSE	FALSE	Grassland management
Management of wood edges	OC4	FALSE	FALSE	Grassland management
Management of woodland edges	EC4	FALSE	FALSE	Woodland management and creation
Management of woodland edges	HC4	FALSE	FALSE	Woodland management and creation
Management of woodland edges	OHC4	FALSE	FALSE	Woodland management and creation
Manure management plan (pre-RDPE)	EM3	FALSE	TRUE	None
Mixed stocking	HK5	FALSE	FALSE	Grassland management
Mixed stocking	EK5	TRUE	FALSE	Grassland management

Mixed stocking	OK5	FALSE	FALSE	Grassland management
Mixed stocking	OHK5	FALSE	FALSE	Grassland management
Moorland	UX3	FALSE	FALSE	Moor and heath management
Moorland	UOX3	FALSE	FALSE	Moor and heath management
Moorland and rough grazing: ML land only	EL6	FALSE	FALSE	Moor and heath management
Moorland re-wetting supplement	HL13	FALSE	FALSE	Wet grassland
Nectar Flower mixture	EF4NR	FALSE	FALSE	Pollinator flower and nectar sources
Nectar Flower mixture	OF4NR	FALSE	FALSE	Pollinator flower and nectar sources
Nectar Flower mixture	EF4	FALSE	FALSE	Pollinator flower and nectar sources
Nectar Flower mixture	OF4	FALSE	FALSE	Pollinator flower and nectar sources
Nectar flower mixture	HF4NR	FALSE	FALSE	Pollinator flower and nectar sources
Nectar flower mixture	OHF4NR	FALSE	FALSE	Pollinator flower and nectar sources
Nectar flower mixture	HF4	FALSE	FALSE	Pollinator flower and nectar sources
Nectar flower mixture	OHF4	FALSE	FALSE	Pollinator flower and nectar sources
Nil fertiliser supplement	HJ8	FALSE	TRUE	(Supplement to) Grassland erosion management
No cutting strip within meadows	UL21	FALSE	FALSE	Flower rich margins and plots
No cutting strip within meadows	UHL21	FALSE	FALSE	Flower rich margins and plots
No cutting strip within meadows	UOL21	FALSE	FALSE	Flower rich margins and plots
No supplementary feeding on moorland	UL17	FALSE	FALSE	Moor and heath management
No supplementary feeding on moorland	UHL17	FALSE	FALSE	Moor and heath management
Non payment option - permanent grassland for Article 13	A13	FALSE	FALSE	Grassland management
Non-Organic threshold payment option	OPTELSTHR	FALSE	TRUE	None
Non-displayable Organic threshold options	OPTOELSTHR	FALSE	FALSE	Organic management
Organic Management	OU1	FALSE	FALSE	Organic management
Over-wintered stubbles	EF6	FALSE	TRUE	Winter bird food sources
Over-wintered stubbles	OF6	FALSE	TRUE	Winter bird food sources
Overwintered stubble	HF6	FALSE	TRUE	Winter bird food sources
Overwintered stubble	OHF6	FALSE	TRUE	Winter bird food sources
Permanent grassland with low inputs	HK2	FALSE	FALSE	Low input grassland
Permanent grassland with low inputs	OHK2	FALSE	FALSE	Low input grassland
Permanent grassland with low inputs in SDAs	HL2	FALSE	FALSE	Low input grassland
Permanent grassland with low inputs: outside SDA & ML	EK2	FALSE	FALSE	Low input grassland
Permanent grassland with low inputs: outside SDA & ML(organic)	OK2	FALSE	FALSE	Low input grassland
Permanent grassland with very low inputs	HK3	FALSE	FALSE	Low input grassland
Permanent grassland with very low inputs	OHK3	FALSE	FALSE	Low input grassland

Permanent grassland with very low inputs in SDAs	HL3	FALSE	FALSE	Low input grassland
Permanent grassland with very low inputs in SDAs	OHL3	FALSE	FALSE	Low input grassland
Permanent grassland with very low inputs: outside SDA & ML	EK3	FALSE	FALSE	Low input grassland
Permanent grassland with very low inputs:outside SDA&ML(organic)	OK3	FALSE	FALSE	Low input grassland
Permanent in-bye grassland with low inputs: SDA land	EL2	FALSE	FALSE	Low input grassland
Permanent in-bye grassland with low inputs: SDA land(organic)	OL2	FALSE	FALSE	Low input grassland
Post and wire fencing along watercourses	UJ3	FALSE	TRUE	None
Preventing erosion or run-off from intensively managed grassland	HJ6	FALSE	TRUE	Grassland erosion management
Protection of in field trees - grassland	OC2	FALSE	TRUE	None
Protection of in field trees - rotational land	OC1	FALSE	TRUE	None
Protection of in-field trees (arable)	EC1	FALSE	TRUE	None
Protection of in-field trees (grassland)	EC2	FALSE	TRUE	None
Protection of in-field trees on arable land	HC1	FALSE	TRUE	None
Protection of in-field trees on grassland	HC2	FALSE	TRUE	None
Raised water levels supplement	HK19	FALSE	FALSE	Wet grassland
Reduced herbicide cereal crop preceding over-wintered stubble	EF15	FALSE	TRUE	Winter bird food sources
Reduced herbicide cereal crops followed by overwintered stubble	HF15	FALSE	TRUE	Winter bird food sources
Reintroduction of conservation grazing other than St Mary's	HIOS4	FALSE	FALSE	Grassland management
Reintroduction of conservation grazing to St Mary's	HIOS3	FALSE	FALSE	Grassland management
Restoration of coastal saltmarsh	HP6	FALSE	TRUE	None
Restoration of fen	HQ7	FALSE	FALSE	Fen management
Restoration of forestry areas to lowland heathland	HO3	FALSE	FALSE	Woodland management and creation
Restoration of grassland for target features	HK16	FALSE	FALSE	Grassland management
Restoration of lowland heath	HO2	FALSE	FALSE	Lowland heathland management
Restoration of lowland raised bog	HQ10	FALSE	FALSE	Lowland raised bog
Restoration of moorland	HL10	FALSE	FALSE	Moor and heath management
Restoration of reedbeds	HQ4	FALSE	FALSE	Wet grassland
Restoration of rough grazing for birds	HL8	FALSE	TRUE	None
Restoration of sand dune systems	HP2	FALSE	FALSE	Sand dune management
Restoration of species-rich, semi-natural grassland	HK7	FALSE	FALSE	Species rich grassland management
Restoration of successional areas and scrub	HC16	FALSE	FALSE	Scrub management
Restoration of traditional orchards	HC20	FALSE	TRUE	None
Restoration of wet grassland for breeding waders.	HK11	FALSE	FALSE	Wet grassland
Restoration of wet grassland for wintering waders and wildfowl	HK12	FALSE	FALSE	Wet grassland
Restoration of wood pasture and parkland	HC13	FALSE	FALSE	Woodland management and creation

Restoration of woodland	HC8	FALSE	FALSE	Woodland management and creation
Reversion to low input grassland to prevent erosion/run-off	HJ4	FALSE	TRUE	Grassland erosion management
Reversion to unfertilised grassland to prevent erosion/run-off	HJ3	FALSE	FALSE	Low input grassland
Ryegrass seed-set as winter/spring food for birds	HK20	FALSE	TRUE	Winter bird food sources
Saltmarsh livestock exclusion supplement	HP11	FALSE	TRUE	None
Seasonal livestock exclusion supplement	HL15	FALSE	FALSE	Grassland management
Seasonal livestock removal from intensively managed grassland	HJ7	FALSE	FALSE	Grassland management
Sheep fencing around small woodlands	UC5	FALSE	FALSE	Woodland management and creation
Sheep fencing around small woodlands	UOC5	FALSE	FALSE	Woodland management and creation
Shepherding supplement	HL16	TRUE	FALSE	None
Skylark plots	EF8	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
Skylark plots	HF8	FALSE	TRUE	Beetle bank, invertebrate and bird nesting sites
Soil management plan (pre-RDPE)	EM1	FALSE	TRUE	None
Stone faced Hedge bank management on both sides	OB4	FALSE	TRUE	None
Stone faced Hedge bank management on one side	OB5	FALSE	TRUE	None
Stone faced hedge bank management on both sides	EB4	FALSE	TRUE	None
Stone faced hedge bank management on one side	EB5	FALSE	TRUE	None
Stone wall protection and maintenance	EB11	TRUE	TRUE	None
Stone wall protection and maintenance on/above the moorland line	UB11	TRUE	TRUE	None
Stone wall protection and maintenance on/above the moorland line	UOB11	TRUE	TRUE	None
Stone wall restoration	UB17	TRUE	TRUE	None
Stone wall restoration	UOB17	TRUE	TRUE	None
Stone-faced hedgebank management (both sides) on/above ML	UB4	FALSE	TRUE	None
Stone-faced hedgebank management (both sides) on/above ML	UOB4	FALSE	TRUE	None
Stone-faced hedgebank management (one side) on/above ML	UB5	FALSE	TRUE	None
Stone-faced hedgebank restoration	UB15	FALSE	TRUE	None
Stonewall protection and maintenance	OB11	TRUE	TRUE	None
Supplement for control of invasive plant species	HR4	FALSE	TRUE	None
Supplement for difficult sites	HR7	FALSE	TRUE	None
Supplement for extensive grazing on saltmarsh	HP10	FALSE	FALSE	Wet grassland management
Supplement for group applications	HR8	TRUE	TRUE	None
Supplement for group applications	HR8WF	FALSE	TRUE	None
Supplement for haymaking	HK18	FALSE	FALSE	Low input grassland
Supplement for small fields	HR6	FALSE	TRUE	None

Supplement to add wildflowers to buffer strips and field corners	EE12	FALSE	FALSE	Pollinator flower and nectar sources
Supplement to add wildflowers to buffer strips and field corners	HE12	FALSE	FALSE	Pollinator flower and nectar sources
Supplement to add wildflowers to buffer strips and field corners	OHE12	FALSE	FALSE	Pollinator flower and nectar sources
Supplementary feeding in winter for farmland birds	HF24	FALSE	TRUE	Winter bird food sources
Supplementary feeding in winter for farmland birds	EF23	FALSE	TRUE	Winter bird food sources
Supplementary feeding in winter for farmland birds	OF23	FALSE	TRUE	Winter bird food sources
Take archaeological features out of cultivation	HD2	TRUE	TRUE	None
Take archaeological features out of cultivation	ED2	TRUE	TRUE	None
Take archaeological features out of cultivation	OD2	FALSE	TRUE	None
Take archaeological features out of cultivation (Org)	OHD2	TRUE	TRUE	None
Take field corners out of management	HK1	FALSE	TRUE	Field corners
Take field corners out of management	OHK1	FALSE	TRUE	Field corners
Take field corners out of management in SDAs	HL1	FALSE	TRUE	Field corners
Take field corners out of management: outside SDA & ML	EK1	FALSE	TRUE	Field corners
Take field corners out of management: outside SDA & ML(organic)	OK1	FALSE	TRUE	Field corners
Top fruit orchards conversion payment	TFC	FALSE	TRUE	None
Uncropped cultivated areas for ground-nesting birds - arable	HF13NR	FALSE	FALSE	Fallow plots for ground-nesting birds
Uncropped cultivated areas for ground-nesting birds - arable	HF13	FALSE	FALSE	Fallow plots for ground-nesting birds
Uncropped cultivated areas for ground-nesting birds - arable	EF13	FALSE	FALSE	Fallow plots for ground-nesting birds
Uncropped cultivated areas for ground-nesting birds - rotational	OF13	FALSE	FALSE	Fallow plots for ground-nesting birds
Uncropped, cultivated areas for ground-nesting birds	OHF13	FALSE	FALSE	Fallow plots for ground-nesting birds
Uncropped, cultivated margins for rare plants	HF11	FALSE	FALSE	Threatened and priority species and habitats
Uncropped, cultivated margins for rare plants	OHF11	FALSE	FALSE	Threatened and priority species and habitats
Uncropped, cultivated margins for rare plants on arable land	EF11	FALSE	FALSE	Threatened and priority species and habitats
Under sown spring cereals	EG1	FALSE	TRUE	Undersown spring cereal
Under sown spring cereals	OG1	FALSE	TRUE	Undersown spring cereal
Undersown spring cereals	HG1	FALSE	TRUE	Undersown spring cereal
Undersown spring cereals	OHG1	FALSE	TRUE	Undersown spring cereal
Unenclosed moorland rough grazing	HL6	FALSE	TRUE	Undersown spring cereal
Unharvested cereal headlands for birds and rare arable plants	HF10NR	FALSE	TRUE	Winter bird food sources
Unharvested cereal headlands for birds and rare arable plants	HF10	FALSE	TRUE	Winter bird food sources
Unharvested cereal headlands for birds and rare arable plants	EF10	FALSE	TRUE	Winter bird food sources
Unharvested, fertiliser-free conservation headland	HF14NR	FALSE	FALSE	Conservation headlands

Unharvested, fertiliser-free conservation headland	HF14	FALSE	FALSE	Conservation headlands
Wetland cutting supplement	HQ11	FALSE	FALSE	Wet grassland
Wetland grazing supplement	HQ12	FALSE	FALSE	Wet grassland
Wild bird seed mixture	HF2NR	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	EF2NR	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	OF2NR	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	EF2	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	HF2	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	OF2	FALSE	FALSE	Flower rich margins and plots
Wild bird seed mixture	OHF2	FALSE	FALSE	Flower rich margins and plots
Winter cover crops	EJ13	FALSE	TRUE	None
Winter cover crops	HJ13	FALSE	TRUE	None
Winter cover crops	OJ13	FALSE	TRUE	None
Winter livestock removal next to streams, rivers and lakes	UJ12	FALSE	TRUE	None
Winter livestock removal next to streams, rivers and lakes	UHJ12	FALSE	TRUE	None
Woodland livestock exclusion	UC22	FALSE	FALSE	Woodland management and creation
Woodland livestock exclusion	UHC22	FALSE	FALSE	Woodland management and creation
Woodland livestock exclusion supplement	HC11	FALSE	FALSE	Woodland management and creation