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A Targeting Bonus for More Effective Agri-Environmental Policy

Matteo Zavalloni¹  | Katherine Simpson²  | Nick Hanley² 

¹University of Urbino Carlo Bo, Urbino, Italy | ²University of Glasgow, Glasgow, UK

Correspondence: Matteo Zavalloni (matteo.zavalloni@uniurb.it)

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ABSTRACT

Despite significant policy interventions and conservation initiatives, incentives for the conservation of biodiversity have been criticised for being ecologically ineffective and economically inefficient. This paper examines a novel approach to improve the ecological and economic performance of such incentives. Specifically, we analyse the ecological and economic effectiveness of a targeting bonus which establishes a two-part subsidy for changes to land management when the ecological benefits of such changes vary spatially. Using a spatially explicit mathematical programming model applied to an empirical case study in the UK, we show that a targeting bonus has the potential to enhance efficiency, with the magnitude of gains depending on the strength of the spatial correlation between opportunity costs and ecological benefits, as well as the size of the budget and the definition of the targeting zone. We find that the targeting bonus offers major advantages when the most ecologically beneficial land parcels are positively correlated with highest opportunity costs for farmers; and that the additional benefits of the targeting bonus relative to a no-bonus subsidy scheme eventually decline as the share of the bonus is increased.

1 | Introduction

In the last decade (2014–2020) agri-environment scheme (AES) payments accounted for almost 20 billion euros of Common Agricultural Policy funds in the European Union, with the specific purpose of “greening” European agriculture (Pagliacci and Zavalloni 2024; Pe'er et al. 2019). AESs are typically shaped as a voluntary scheme with a homogeneous payment that is linked to the implementation of a given practice—for example, the establishment of woodland, or the reduction of chemical inputs (Hanley 2026). This payment level supposedly covers the (average) opportunity cost of the pro-environmental practice that it is incentivising. Despite this effort, AESs have been criticised for being ineffective, economically inefficient, and not capable of reversing biodiversity decline (Pe'er et al. 2022).

A major criticism of AES is that they provide homogeneous payments that do not address the importance of *location*, both

in terms of the location of the production unit which accepts an AES contract, and land use in the wider landscape surrounding this unit (Bradfer-Lawrence et al. 2025). The ecological benefits of a given action (such as reducing grazing levels) can be expected to vary with both locational aspects (Börner et al. 2017). Thus, knowing how to provide higher incentives to farmers in locations where potential ecological benefits are highest becomes important to policy design, since, *ceteris paribus*, an improvement in the spatial allocation of payments is consistent with an increase in overall scheme efficiency.

A large literature has investigated ways to improve the design of AES by addressing this issue. For example, papers have suggested the design of spatially heterogeneous payments (Harzer and Quaas 2026; Wätzold and Drechsler 2005) and of spatial targeting (Fooks et al. 2016; Wünscher et al. 2008) to address the heterogeneity in the ecological benefits of conservation efforts. Instruments such as the agglomeration bonus, collective

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incentives (Nguyen et al. 2022) and threshold bonuses (Limbach and Rozan 2023) have been suggested to incentivise the spatial coordination and connectivity of habitat implementation. Conservation auctions would provide a means to tailor the rewards for conservation to the local opportunity costs (Nguyen et al. 2024), hence reducing the farmers' surplus and reducing the costs of the policy implementations. Result-based and hybrid payment schemes condition the rewards to environmental outcomes and thus implicitly embed the importance of location (Simpson et al. 2023).

The objective of this paper is to analyse the ecological effectiveness of a *targeting bonus* and how it is affected by the definition of the targeting area. The underlying idea, similarly to Wätzold and Drechsler (2005), is that a regulator has information on the heterogeneity of the ecological productivity across a landscape. Addressing this heterogeneity, they provide a bonus, on top of a regular homogeneous payment, to ensure additional monetary benefits for conversion of agricultural land to conservation habitats in areas recognised as having higher potential ecological benefits. Farmers outside these areas receive a baseline payment for participation, while those within the target area receive a bonus plus the baseline payment.

We examine how the performance of such a scheme depends on the way targeting areas are defined. In particular, we analyse how the ecological outcomes of the targeting bonus vary with the spatial resolution of the ecological data used to delineate targeting areas, as well as with the overall budget available for conservation payments. Intuitively, lower data resolution may lead to less precise targeting, increasing the likelihood that land parcels with relatively low ecological value are included in the targeting area. Potential trade-offs then emerge between larger targeting areas and more tailored ones. We therefore investigate the ecological value of improving data resolution in the definition of targeting areas.

To address these questions, we develop a spatially-explicit mathematical programming model to simulate farmers' responses to the targeting bonus. The model is applied to a case study using economic and ecological data from a real UK landscape, building upon the work by Simpson et al. (2023). While there is a growing literature on impact assessment of existing AES (e.g. Bertoni et al. 2020; Palmer et al. 2026; Schaub et al. 2025), in silico experiments such as ours have been extensively used to simulate novel designs of policy instruments that, given the lack of real implementation, cannot otherwise be evaluated empirically (see, for example, De Petris et al. 2025; Gerling et al. 2025; Reidsma et al. 2018; Zavalloni and Bareille 2026).

Our results show: (i) how the use of a novel *targeting bonus* can improve the efficiency with which biodiversity targets are reached, where there is spatial variation in both opportunity costs and ecological benefits—defined as the potential increase in a target species population from a change in land use—and (ii) how the efficiency gains of the targeting bonus depend on the spatial correlation of opportunity costs with ecological benefits, and on the budget size. Moreover, our results show that an improvement in the resolution of the data used to define the targeting area highly improves the ecological effectiveness of the targeting bonus when the budget size is relatively low. For

larger budget sizes, the opposite is true as larger areas enrolled provide ecological benefits that overcompensate a better selection of targeting parcels.

Our paper provides several contributions to the literature on novel agri-environmental schemes. Our paper contributes primarily to the literature on spatial targeting (e.g. Fooks et al. 2016; Wünscher et al. 2008) and spatially differentiated payments (Babcock et al. 1997; Ferraro 2003; Harzer and Quaas 2026; Wätzold and Drechsler 2005). These studies show the benefits of accounting for location heterogeneity, typically under the assumption of perfect knowledge regarding the ecological productivity of different sites. We complement this literature by providing insights on the effectiveness of spatially differentiated rewards across varying data resolutions used to define the targeting area. In this respect, our paper is parallel to the increasing literature on the value of information for the definition of agri-environmental schemes (Polasky and Solow 2001), especially in the context of result-based schemes (Zabel and Roe 2009; Zavalloni et al. 2025). Moreover, while there is extensive research on defining spatial targeting (De Mendonça et al. 2025; Deng et al. 2022; Guo et al. 2020; López-Cubillos et al. 2022; Mingie and Cho 2020; Van Der Horst 2007), evaluations of incentive design that explicitly account for actual species and ecological dynamics remain scarce (Armsworth et al. 2012). For example, Wünscher et al. (2008) analyse different methods to define spatial targeting but only use habitat types as proxies of biodiversity. Our work addresses this gap by incorporating a species-specific abundance model to determine the effectiveness of the schemes.

2 | The Model

2.1 | Model Description

The main intuition underlying the formulation of a targeting bonus is the heterogeneity in the ecological *productivity* of parcels of land (Armsworth et al. 2012; Nguyen et al. 2024). In such a situation, setting heterogeneous payment levels that depend on the location of conservation efforts could improve the ecological effectiveness of an AES. Here we model a simple situation in which a regulator provides a targeting bonus on top of a regular baseline payment if habitat improvement (a switch from land farmed only for farming profit to land managed at least partly for conservation) is implemented in an area that has been identified as more *ecological* productive. The targeting bonus might be interpreted as a simplification of a result-based scheme, since the policy designer sets a differentiated reward which varies with the expected ecological outcome, but only over two levels (the baseline subsidy and the bonus payment), rather than continuously as in a payment for results (or modelled results) scheme. The targeted scheme may offer benefits in terms of transaction costs compared to modelled results, by avoiding the need for highly granular, site-specific payments, making it more practical for policymakers to implement at scale. Finally, it may offer lower administration costs than a spatially-differentiated payment scheme as discussed in Armsworth et al. (2012).

The mathematical description of the model is as follows. Imagine a landscape composed of a number of farmers, each owning one parcel of land. Each farmer i^1 can either allocate land

to conservation habitat ($X_i = 1$) or to productive agricultural activities ($X_i = 0$). Assume for simplicity that this decision is binary. Allocating land to habitat entails a farm-specific cost k_i , representing the opportunity costs of foregoing agricultural profits plus any direct costs associated with establishing the habitat (e.g. tree planting costs). With no additional (private) benefits from habitat, farmers would allocate land to conservation habitat only if an external reward is granted (Schulze et al. 2024). A regulator provides a homogeneous payment p per area of agricultural land that is converted to habitat. The regulator has some knowledge on the ecological productivity of each parcel of land. Using this knowledge, they define a targeting area T , which is a subset of the parcels composing the landscape. Farmers that are located within this targeting area obtain, in addition to p , a bonus b . Assuming profit maximising behaviour, the response of the farmers to such a scheme is described by the following maximisation problem:

$$\max_{X_i} \Pi = \sum_i [X_i \cdot p + (1 - X_i) \cdot k_i] + \sum_{i \in T} X_i \cdot b \quad (1)$$

$$\sum_i X_i \cdot p + \sum_{i \in T} X_i \cdot b \leq B \quad (2)$$

Equations (1) and (2) represent respectively the profit of the farmers when facing our conservation scheme and a budget constraint. In Equation (1), the first term represents the reward that is obtained by allocating land to habitat in any part of the landscape; the second term represents the agricultural profits that are obtained if land is kept under farming; the third term represents the bonus that is attributed to those parcels located within the targeting area T that are converted to habitat. Note that by setting $b = 0$, Equation (1) would describe a regular/homogeneous agri-environmental payment for action scheme. Equation (2) represents a budget constraint that limits the expenses of the regulator to a maximum budget amount (B). If Equation (2) does not apply, and as X_i is a binary variable, farmers within the targeting area will implement habitat if $p + b \geq k_i$, farmers outside the targeting area will implement habitat if $p \geq k_i$. In other words, the parcels that will be enrolled are those for which the subsidy is greater than the opportunity costs. The inclusion of the budget constraints adds a ranking to the enrolment of the parcels in the scheme, up to the level that satisfies the constraint. Only a subset of the parcels for which the subsidy is greater than the opportunity costs are enrolled, that is, those that ensure the highest profits at the aggregate. To evaluate the biodiversity outcome, we rely on the function: $V = \sum_i X_i \cdot v_i$, where v is the ecological productivity (or benefit) of the given parcel. This can be interpreted as measuring the outcome of some biodiversity metric (e.g., species richness or abundance).

2.2 | Application

2.2.1 | Case Study and Spatial Data

Our model is applied to the Tees Valley, Pennine Uplands, and North York Moors in northern England, covering approximately 5,400 km². The landscape is represented using the Ordnance Survey British National Grid, with each 1 km × 1 km parcel treated

as an individual decision-making unit (“farmer”) in the model ($n = 5,280$).

The model is underpinned by multiple spatial datasets describing land cover, crop distribution, soil quality, livestock distribution, and the ecological indicator of interest. These datasets are spatially aligned and combined to construct the variables required for the different model components, including agricultural opportunity costs and ecological outcomes. Land cover information is derived primarily from the CEH Land Cover Map and CEH Land Cover Plus: Crops datasets, which provide spatially explicit classifications of arable land (by crop type), grassland (by grassland type), forest, coastal, and urban classes. Soil quality information is derived from the Soil scapes dataset, which provides a simplified classification of soil characteristics relevant to agricultural productivity. Additional Ordnance Survey Open Data layers are used within the ecological model. A summary of all spatial data sources is provided in Appendix A.

2.2.2 | Opportunity Costs

In the model, participation in the AES involves the conversion of agricultural land to low-intensity grassland, which is defined as the sole conservation land use. Low-intensity grassland represents non-productive land management for biodiversity purposes and does not include arable production or livestock farming. As such, participation in the AES implies a complete cessation of agricultural production on the converted parcel. We assume that conversion to low-intensity grassland does not incur additional restoration or management costs for farmers, such that opportunity costs arise solely from foregone agricultural profits. Farmers’ opportunity costs were calculated as the foregone agricultural profits (gross margins) associated with switching from current agricultural production to conservation land management.

2.2.3 | Crop Production

For crop production, crop coverage at the 1 km × 1 km resolution was combined with crop-specific gross margin values available from SRUC Farm Management Handbook (Beattie, 2019) expressed on a per-hectare basis and categorised by productivity level (low, medium, and high yield). Spatial variation in crop yields was captured using soil information from the Soilscales dataset, which defines 27 soil map units with associated productivity-related attributes. Soilscales data were processed in a GIS to derive a soil quality classification at the 1 km × 1 km resolution and linked to the spatial distribution of crops. Soil quality classes were mapped to the corresponding low, medium, or high yield categories used in the crop gross margin data, allowing broad spatial variation in crop productivity to be represented consistently across the study area.

2.2.4 | Livestock Production

Agricultural profits also included the value of livestock production. Livestock numbers by type (cattle and sheep) were obtained from the England Agricultural Census at a 5 km × 5 km spatial resolution. Gross margin values for each livestock type were sourced from the SRUC Farm Management Handbook (Beattie, 2019) and

applied to calculate total livestock gross margins within each 5 km × 5 km grid. To allocate livestock production and associated gross margins to the 1 km × 1 km parcels used in the model, a spatial disaggregation procedure was implemented in ArcGIS. Livestock were assumed to occur only on land cover classes suitable for grazing, namely acid grassland, improved grassland, calcareous grassland, neutral grassland, and heather grassland. Within each 5 km × 5 km grid, livestock numbers and corresponding gross margins were proportionally allocated to constituent 1 km × 1 km parcels according to each parcel's share of the total area of eligible grassland. This area-weighted allocation ensured that livestock and associated economic values were assigned only to suitable land cover types, while preserving total livestock numbers and gross margins at the 5 km × 5 km resolution.

2.2.5 | Eligibility and Land Conversion Assumptions

Within the modelled AES, improved grassland was the only grassland type considered eligible under the bonus scheme. Acid, neutral, calcareous, and heather grasslands were not treated as agriculturally productive land within the model. When improved grassland is converted to low-intensity grassland, we assume that all agricultural production (crop and livestock) on that parcel ceases. Transitions to alternative livestock management systems (e.g. extensive grazing) are not modelled. Consequently, changes in livestock-related costs reflect foregone gross margins rather than adjustments in stocking density, productivity, or management intensity. Finally, we assume that the currently observed land management practice for each farmer is privately optimal and that switching to a new land management practice, such as conservation, results in a net loss in agricultural profits.

2.2.6 | Ecological Modelling of Benefits

In this study, we modelled two bird populations as ecological benefit indicators: the Eurasian oystercatcher (*Haematopus ostralegus*) and the Northern lapwing (*Vanellus vanellus*). Both species are classified as 'Near Threatened' on the International IUCN Red List of Threatened Species (BirdLife International, 2020). This listing is due to population declines primarily attributed to the loss and degradation of breeding habitats, driven by changing agricultural practices such as the conversion of traditional meadows into intensive grassland monocultures (Franks et al. 2017). This allows us to model two alternative targeting scenarios, one for each species (that is, one for each ecological benefit type).

To estimate the current abundance of each species and the change in abundance of each focus species under changing agricultural land use (as a consequence of farmers enrolling into the AES scheme), we undertook species abundance modelling. Species abundance models are routinely used in ecology to generate predictions of species abundance for unsampled locations in a study area using existing data from sampled areas, extrapolating this to new areas based on their ecological characteristics (Barker et al. 2014). The first stage of the modelling process² was to produce a regression model to identify which parameters (land use and ecological characteristics) predict current distributions

for each species. This allowed us to identify which land management practices are most beneficial to the species (related to the parameters used in the modelling process) and thus serve as our incentivised conservation land management practice within the AES. The species abundance model was then used to predict how the distribution and abundance of the target species could alter as a result of a change in land use to low-intensity grassland, which we define as the sole "conservation land use" in the model³. We used data on lapwing and oystercatcher species distribution and abundance collected by the British Breeding Survey for the eastern region of the UK. These data have been widely used in ecological modelling to predict species distribution and abundance and for landscape-scale studies (e.g., Balmer et al. 2013). Explanatory variables were selected based on literature on bird habitat suitability (e.g., Tattoni et al. 2012). Habitat data was sourced from the CEH Land Cover Map 2015 (LCM2015), classifying land into 21 categories based on UK Biodiversity Action Plan Broad Habitats. Arable and horticulture land was further divided into 11 crop types using the CEH Land Cover Plus: Crops map, yielding 30 classifications in total. Additional environmental variables were derived using OS Open Map including average altitude of the land parcel, distances to features such as roads, railways, pylons, watercourses, and tidal boundaries. A detailed description of the ecological model and associated results is available in Appendix A.

2.2.7 | Targeting Bonus Implementation

Combining the ecological modelling approaches outlined above and spatial data analyses in ArcGIS we identified priority conservation areas for each species which gives us two distinct scenarios for implementing the targeting bonus. This allows us to evaluate the potential benefits of the targeting bonuses based on opportunity costs and land characteristics. Both species (oystercatcher and lapwing) respond positively to agricultural land being restored to low-intensity grassland. However, the location of the greatest gains differs between the two species. For both species-based scenarios, the base AES payment level p was derived as the average opportunity cost per hectare of restoring agricultural land to low-intensity grassland across the case study region, giving a payment rate of £585 per hectare. All farms within the priority conservation area in any simulation are eligible for the targeting bonus if they decide to participate in the scheme; all farms outside the area receive only the basic subsidy but no bonus.

Scenario 1: Oystercatcher Conservation on Coastal Land

Our ecological modelling results indicate that increases in oystercatcher abundance due to AES enrolment are significantly greater on land parcels located closest to the tidal boundary of the case study area. As such, this scenario targets the conservation of oystercatchers on agricultural land located near the coastline. Using spatial boundary line measurements, we delineated the optimal conservation area for oystercatchers. Farmers operating in these coastal areas are likely to have relatively low opportunity costs per hectare due to the limited agricultural profitability of coastal land. Consequently, their likelihood of participating in the conservation scheme is expected to be high, even in the absence of

a targeting bonus (which we test below). To assess the sensitivity of our findings, we expanded the analysis to include parcels within 1 and 2 km of the coastline.

Scenario 2: Lapwing Conservation on Low-Lying Agricultural Land

Our ecological modelling results indicate that increases in lapwing abundance due to AES enrolment are likely to be significantly greater on agricultural land parcels in areas where there is a mosaic of grassland habitats, which for this case study is found in low-lying agricultural landscapes away from the coast. These agricultural areas are currently characterised by intensive livestock production, which poses challenges for conservation due to the associated high opportunity costs of land-use change. The targeting bonus is therefore hypothesized to play a critical role in offsetting these financial impacts and increasing farmer participation in an AES for increasing lapwing abundance. That is, we predict that the relative advantage of the targeting bonus will be greater in Scenario 2 than in Scenario 1.

2.3 | Numerical Implementation

We numerically solve the model described in section 2.1, with simulations that are based on the case study data. As indicated, we identify for each parcel of land, the area (a_i) that is eligible for a habitat conservation bonus. For comparison purposes, we fix the maximum amount of payment that is rewardable to P and define the targeting bonus as a share (β) of it. Using the notation of the previous section, $p = (1 - \beta) \cdot P$ and $b = \beta \cdot P$. To interpret the results, note that if $\beta = 0$, then there is no effective targeting (no bonus), that is, any parcel that is converted to habitat would obtain the same payment, irrespectively on the location. If $\beta = 1$, farmers within the targeting area become the exclusive recipients of the AES subsidy, and no payments are offered to farmers outside the targeting area. Alternatively, if, for example, $\beta = 0.3$ and $P = 1000\text{£/ha}$, then a parcel outside the targeting area would obtain a payment of 700£, while inside the targeting area would obtain the payment of 700£ plus the targeting bonus of 300£. Given these elements, Equations (1) and (2) are adjusted as follows:

$$\max_{X_i} \Pi = \sum_i X_i \cdot a_i \cdot P \cdot (1 - \beta) + (1 - X_i) \cdot k_i + \sum_{i \in T} X_i \cdot a_i \cdot P \cdot \beta \quad (3)$$

s.t.

$$\sum_i X_i \cdot a_i \cdot P \cdot (1 - \beta) + \sum_{i \in T} X_i \cdot a_i \cdot P \cdot \beta \leq B \quad (4)$$

The results are based on simulations that are implemented using the parameter levels that are summarized in Table 1.

Spatial targeting areas were defined at three nested spatial resolutions (1 km, 5 km, and 10 km) consistent with the UK National Grid. Targeting was first identified at the native 1 km $\times$ 1 km parcel resolution used throughout the model. Coarser targeting resolutions were then constructed by aggregating (dissolving) contiguous 1 km parcels into 5 km $\times$ 5 and 10 km $\times$ 10 km grid cells, such that any grid cell intersecting the original 1 km targeting area was classified as eligible for the targeting bonus. This aggregation

procedure results in progressively larger and less spatially precise targeting areas at coarser resolutions, while ecological outcomes continue to be calculated at the original 1 km resolution.

3 | Results

3.1 | Base Case

3.1.1 | Effectiveness of the Targeting Bonus

Figure 1 depicts the results for both species scenarios, taking into account a base payment level of 585£/ha and a budget of $B = 10M\text{£}$. The effect of introducing (and the subsequent increase in) the targeting bonus has a similar effect on the total number of parcels enrolled into the AES for both species. However, the conservation outcomes of these land use changes differ considerably, as the ecological benefit of spatial targeting is significantly different between the two species. Panel (A) shows that the budget is a binding constraint up to relatively large bonus share levels ($\beta = 0.6$ for oystercatcher, $\beta = 0.7$ for lapwing). In other words, for bonus levels higher than those thresholds, the budget is no longer limiting the enrolment into the AES, whereas the payment level is. As it is clear from panel (B), further increases in the bonus share entail a reduction in the baseline payment that causes a substantial reduction in the parcels outside the targeting area that enrol into the scheme. At the same time, the baseline payment plus the bonus (i.e., $P = 585\text{£/ha}$) is not high enough to cause any additional allocation of parcels to habitat within the targeting area. The ultimate result is that the maximum conservation habitat within the targeting area is reached at $\beta = 0.6$ for oystercatcher and $\beta = 0.7$ for lapwing.

Panel (C) further substantiates such results. The panel depicts the biodiversity outcome in terms of percentage change with respect to the scenario where there are no targeting area and no targeting bonus (i.e., $\beta = 0$). For both species, introducing a targeting bonus increases the biodiversity score. As expected, the change is however substantially higher for lapwing (Scenario 2) than for the oystercatcher (Scenario 1), since opportunity costs and ecological benefits are only weakly positively correlated for oystercatchers, but strongly positively correlated for lapwings. The parcels that are best suited to conserve oystercatcher are characterized by relatively lower opportunity costs than those that are best suited for the lapwing. As such, a relatively high conservation of the oystercatcher level is reached even in the absence of a targeting bonus. Indeed at $\beta = 0$, the biodiversity score for the oystercatcher is $V = 38.2$, while at $\beta = 1$ the score is $V = 260$; the targeting causes a 5-fold increase in the biodiversity score. For the lapwing, we have $V = 2.3$ in the case of no targeting, and $V = 253$ for the case of pure targeting (i.e. roughly a 100-fold increase in the score). Thus, our main result is that the targeting bonus offers the highest potential efficiency gains when potential ecological benefits and opportunity costs are positively spatially correlated.

3.1.2 | Spatial Correlation and Heterogeneity in Costs and Ecological Impacts of Grassland Restoration

To further interpret the species-specific differences in the effectiveness of spatial targeting, we examine the spatial relationship

TABLE 1 | Description of the parameters used in the numerical example.

Parameter	Description	Values
a_i	Size of parcels	From the data (ha)
P	Maximum payment level	585£/ha
β	Bonus level share	From 0 to 1 with 0.1 step
k_i	Opportunity costs	From the data (£)
B	Budget	2 M £, 2.5 M £, 5 M £, 10 M £, 40 M £

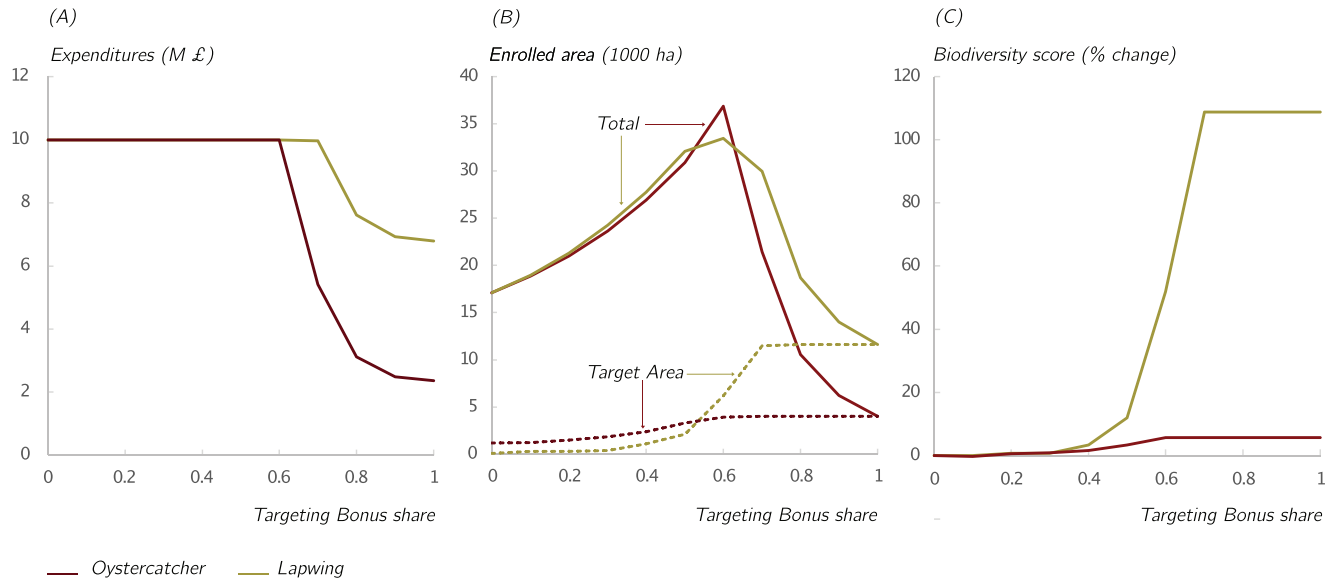


FIGURE 1 | Results for oystercatcher (red) and lapwing (yellow) for different levels of the Targeting Bonus share, at $P = 585\text{£/ha}$. Panel (A) shows the overall expenditures; Panel (B) depicts the implementation of the total habitat (full line) and the habitat in the target area (dotted line); Panel (C) depicts the biodiversity score as the percentage change with respect to no targeting bonus share.

TABLE 2 | Pairwise correlation between opportunity costs of forgone agricultural production (opportunity costs) under current land use and predicted increases in abundance oystercatcher and lapwing.

	Opportunity costs	Increase in oystercatcher abundance	Increase in lapwing abundance
Opportunity costs	1		
Increase in oystercatcher abundance	0.2913***	1	
Increase in lapwing abundance	0.6776***	0.2798***	1

*** $p < 0.01$. Pairwise Pearson correlations computed across all eligible land parcels.

between opportunity costs and the ecological productivity of grassland restoration across all eligible land parcels in the case-study area. Consistent with earlier applications of this modelling framework (Simpson et al. 2022), we use a pairwise correlation analysis to explore these spatial relationships. Opportunity costs are positively correlated with ecological productivity for both species, although the strength of the relationship differs markedly (Table 2). The correlation is moderate for oystercatcher ($r = 0.29$, $n = 5236$, $p < 0.001$), indicating that higher ecological gains are only weakly associated with higher opportunity cost parcels. In contrast, the correlation is substantially stronger for

lapwing ($r = 0.68$, $n = 5236$, $p < 0.001$), implying that parcels delivering the largest gains in lapwing abundance are more strongly associated with high opportunity costs. The ecological productivity measures for the two species are themselves only weakly correlated ($r = 0.27$, $n = 5236$, $p < 0.001$), suggesting limited spatial overlap in high-benefit parcels.

These differences in the strength of spatial correlation help explain the species-specific efficiency gains observed in Figure 1. For oystercatcher, a large share of ecological gains can be realised even without spatial targeting, as high-benefit parcels

TABLE 3 | Description of the landscape variables.

Variable	Mean	Median	Standard deviation	Coefficient of variation
Opportunity cost per ha	318.2	246.72	244.01	0.77
Lapwing gain (all possible parcels enrol)	0.61	0.00	1.15	1.87
Oystercatcher gain (all possible parcels enrol)	0.29	0.00	0.99	3.42

are not strongly concentrated among the highest-cost sites. For lapwing, by contrast, the strong positive correlation implies that substantial ecological gains are concentrated in high-cost parcels, such that spatial targeting yields significantly larger efficiency gains. More generally, the results indicate that both the sign and magnitude of spatial correlation, together with the underlying spatial variation in costs and ecological productivity, play a key role in determining the effectiveness of targeted agri-environment schemes.

To further interpret the results, Table 3 presents summary statistics of the opportunity costs of habitat conservation and of potential lapwing and oystercatcher gains. The distributions of costs and ecological benefits also differ in their dispersion: opportunity costs show lower variation relative to the mean ($CV = 0.77$) than lapwing gains ($CV = 1.87$) or oystercatcher gains ($CV = 3.42$). The greater dispersion of oystercatcher gains does not, however, translate into larger efficiency gains from targeting: the weak spatial correlation between oystercatcher gains and opportunity costs ($r = 0.29$) means that high-benefit parcels are not concentrated among high-cost sites, limiting the additional gains that targeting can deliver. For lapwing, the combination of spatially concentrated gains and strong positive correlation with opportunity costs drives the substantially larger efficiency gains observed in Figure 1.

3.1.3 | Changing Budget

Having described results in the base case, we now proceed to a sensitivity analysis. We explore the effects of changes in the policy budget (Figure 2). We vary the level from $B = 10M£$ (full line) to $B = 40M£$ (dashed line) and $B = 2.5M£$ (dotted line), holding constant a maximum level of payment to $P = 585£/ha$. Decreasing the budget does not affect the main results. However, the budget is always limiting enrolment—for any level of the targeting bonus share—for the lapwing for $B = 2.5M£$. Unsurprisingly, the reduction in the budget entails a reduction in the biodiversity score for both species at low levels of targeting share. The reduction is greater for the lapwing than for the oystercatcher, as for the latter the budget levels are still not limiting enrolment for relatively high targeting bonus shares. Increasing the budget, instead, greatly affects the results for both species, even though the targeting increases the biodiversity score. At $B = 40M£$, there is a peak in the biodiversity score at respectively $\beta = 0.3$ for oystercatcher and $\beta = 0.4$ for lapwing. Further increases in the targeting bonus share lead to a reduction in biodiversity. In other words, if the budget is relatively large, there are trade-offs between incentivising habitat implementation in the entire landscape and

restricting the subsidy to where it is more ecologically productive. Spatial targeting becomes the most effective option when the budget is tight.

3.2 | Lowering Spatial Resolutions

Now we compare the previous results, generated by defining the targeting area with ecological data at a spatial resolution of 1 km^2 , to those generated by defining the targeting area with ecological data at a spatial resolution of 10 km^2 . Intuitively, lowering the spatial resolution of the ecological model would enlarge the targeting area, and hence would select less ecologically productive parcels. The ultimate outcome in terms of effectiveness however depends on the trade-off between having a larger area that is converted to habitat or a smaller one that is more ecologically productive.

In Figure 3 we display the results regarding the effect of using lower resolution data for defining the targeting area. First look at the expenditures (panel A1 and A2 for respectively lapwing and oystercatcher). For both cases, lowering the spatial resolution increases the public expenditures. For the oystercatcher, in the case of 10 km^2 resolution, the budget becomes binding for the entire range of targeting bonus share. The reason behind this is that the reduction in the spatial resolution generates targeting areas that are larger, and hence more farmers are eligible for the bonus. This is reflected in the size of the enrolled area. Panels B1 and B2 (for respectively lapwing and oystercatcher) show that when the targeting bonus is beyond a threshold, lowering the spatial resolution actually increases the amount of enrolled land. Indeed, as we have seen in the previous section, targeting bonus shares that go beyond a threshold entail a reduction in the baseline payment and hence a reduction in the parcels outside the targeting area that enrol into the scheme. This pattern is milder if the spatial resolution is lower, as the targeting area is larger.

The ultimate outcome in terms of ecological effectiveness is however differentiated by the targeted species. For oystercatcher, an improvement in the resolution of the ecological data used to define the targeting area increases the biodiversity score for any level of the targeting bonus share (panel C2). When the scheme only incentivises the enrolment of land within the targeting area, that is, if $\beta = 1$, improving the data resolution causes an increase in the biodiversity score of 55% as improved targeting allows high-productivity parcels to be selected more precisely, outweighing any loss in total targeted area.

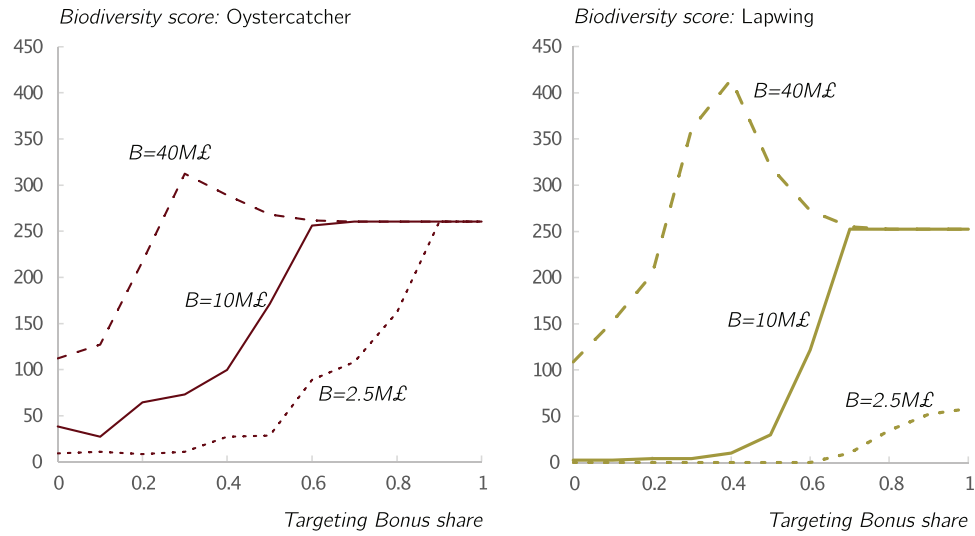


FIGURE 2 | Biodiversity score for oystercatcher (left, red) and lapwing (right, yellow) under different policy budget (10M£, full line; 40M£, dashed line; 2.5M£, dotted line). $P = 585\text{£/ha}$.

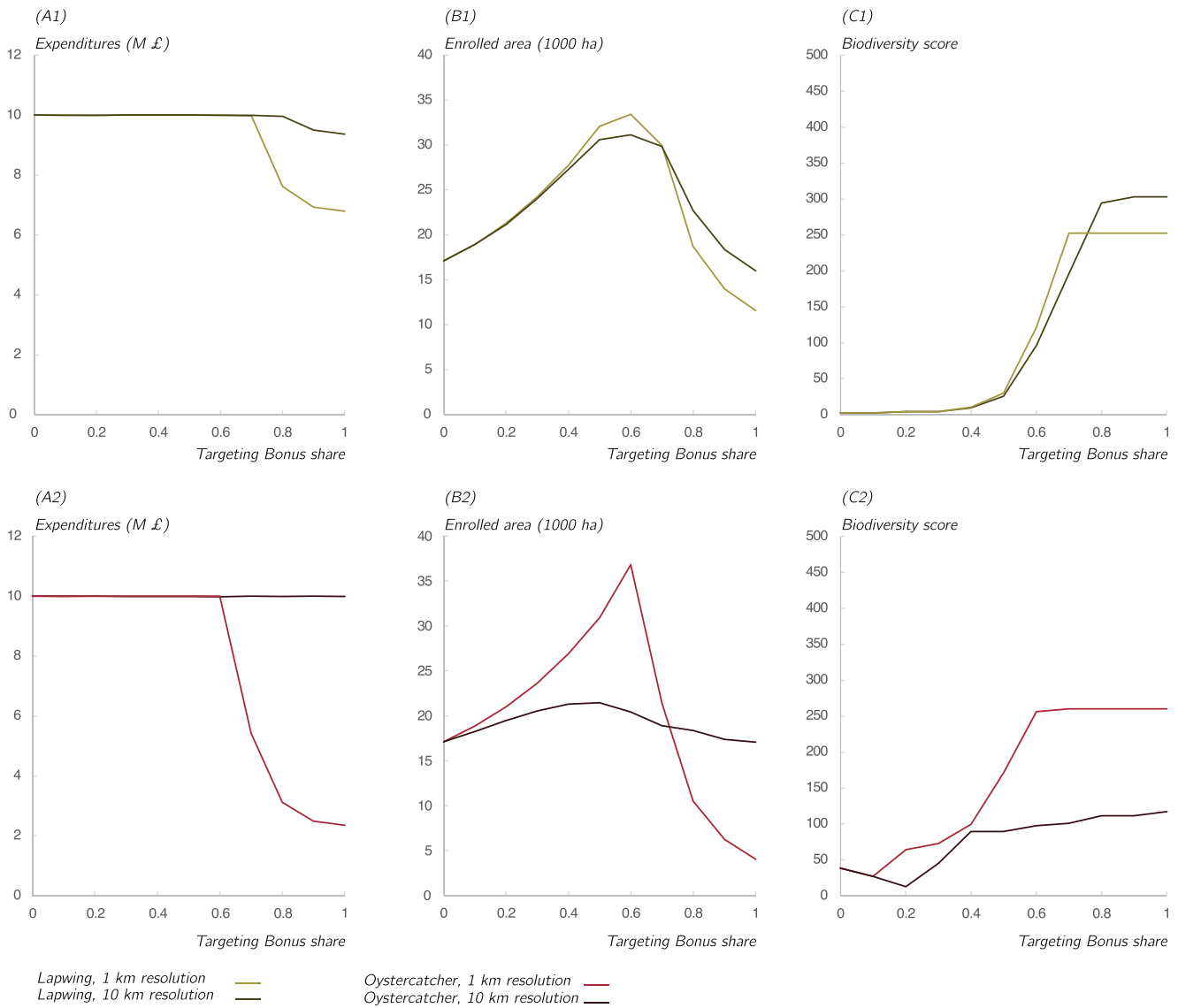


FIGURE 3 | Expenditures (first column), enrolled area (second column) and biodiversity (third column) score for lapwing (first line) and oystercatcher (second line) under a spatial resolution of 1 km^2 and 10 km^2 . $P = 585\text{£/ha}$; $B = 10\text{M£}$.

In contrast, outcomes for lapwing are much less sensitive to data resolution. Beyond a targeting bonus share of $\beta = 0.7$, improving the data resolution does not increase, and may actually reduce biodiversity value. This reflects the strong positive spatial correlation between lapwing gains and opportunity costs ($r = 0.68$, Table 2): even under coarser targeting, the bonus preferentially attracts farmers on high-cost parcels, which are also those delivering the greatest lapwing gains. In addition, these high-cost, high-benefit parcels are spatially concentrated within the case study area, so that enlarging the targeting area does not substantially dilute average ecological productivity. As a result, conservation outcomes are relatively insensitive to the spatial resolution of the targeting data.

3.2.1 | Effect of Budget Changes

We further explore the potential trade-offs between better parcel selections and larger targeting area by varying the available budget under different spatial resolutions. The results of this analysis are presented in Figure 4, which depicts the biodiversity scores for the lapwing and the oystercatcher under three budget scenarios: 2.5M€, 10M€, and 40M€ for the two alternative spatial resolutions analysed above.

When the budget is relatively low ($B = 2.5\text{M€}$), and the targeting area is defined by using the 10 km² spatial resolution, the advantages of implementing a targeting bonus are rather low. Compared to a situation where there is no targeting, exclusively incentivising the enrolment in the targeting area would entail an increase of about 27 and 1 points in the biodiversity score, for respectively lapwing and oystercatcher. In such a setting, improving the spatial resolution would cause a substantial increase in the effectiveness of the targeting bonus, from a score of $V = 11$ to $V = 260$ for oystercatcher and from $V = 26$ to $V = 58$ for lapwing.

The results show an opposite outcome when the budget is of 40M€. Beyond a level $\beta = 0.3$ for lapwing and $\beta = 0.4$ for oystercatcher, increasing the spatial resolution causes a decrease in the effectiveness of the scheme. As we have seen in the previous section, increasing the budget provides funds for additional parcels to be converted. The targeting scheme however constrains the enrollable parcels. Hence the lower resolution targeting area entails larger enrollable area in the case of pure targeting. The ultimate outcome is that the additional benefits due to the larger enrolled area overcome the better selection due to the higher spatial resolution data.

3.2.2 | Enlarging the Targeting Area

Finally, we further explore the effect of the definition of the targeting areas on the ecological effectiveness of the targeting bonus. In particular, we run the simulations for larger targeting areas, that is, 1 and 2 km wider buffers. From a policy perspective, decision-makers may face pressure to expand the targeting area, as farmers located just outside the eligibility boundary may question their exclusion or lobby for inclusion in the higher potential payment zone. Additionally, some degree of uncertainty

in the predictive power of the ecological model may warrant a more flexible definition of the targeting area. We run such analyses with an effectively limiting budget of $B = 2\text{M€}$, and $P = 585\text{€}/\text{ha}$. The results, depicted in Figure 5, underpin the effectiveness of a (properly designed) targeting bonus. Indeed, for both oystercatcher and lapwing, enlarging the targeting area as a fraction of the total landscape (while holding constant the budget) reduces the biodiversity score when the targeting bonus share is above about 0.6. Enlarging the area entails an increase in potential recipients of the bonus. However, the new potential recipients have lower opportunity costs and lower ecological productivity than those defined by the stricter targeting area. The result is that enlarging the targeting bonus area causes a relocation of the conserved habitat away from the most ecologically productive parcels and an ultimate reduction in the biodiversity score.

4 | Discussion and Conclusions

Wätzold and Drechsler (2005) were the first to discuss the idea that the policy designer faces a choice between a spatially variable subsidy which reflects spatial variation in both opportunity costs and ecological benefit, and a uniform payment which ignores this spatial variation but is administratively simpler and perhaps perceived as fairer. They present a model which shows the consequences of this choice, but this model is not parameterised with real data or for an actual landscape. Indeed, spatial targeting has been extensively studied within the literature focussing on how to improve the economic effectiveness of AES design (Kuhfuss et al. 2016; Simpson et al. 2023). However, empirical evaluations of incentive designs that explicitly account for actual species and ecological dynamics remain scarce. Moreover, the importance of data resolution in defining the targeting areas, and hence their effect on the ecological effectiveness of the scheme, has been overlooked. Using a spatially explicit mathematical programming model we investigated the economic efficiency and ecological effectiveness of a novel spatially-explicit targeting bonus within a payment for actions AES. The ecological benefits of a targeting bonus were simulated for two species, oystercatcher and lapwing, which both respond positively to the same change in land management practice (switching of agricultural land to low intensive grassland). For both species, the marginal benefits (in terms of increased abundance) differ in terms of spatial location across the landscape, and where spatial correlations between ecological benefit (potential gain) and opportunity costs differ from weakly positive (oystercatcher) to strongly positive (lapwing). This importance of the spatial correlation between opportunity costs and potential ecological benefits in the context of the performance of AES-type incentives has been found by other researchers, for example Nthambi et al. (2024). Finally, the ecological benefits of the targeting bonus have been assessed under different definitions of the targeting areas.

Results indicate that introducing bonuses for creating conserved land in a targeting area always increases the ecological and economic effectiveness of the AES scheme. This result is in line with previous studies considering spatial targeting (e.g. Simpson et al. 2023; Wünscher et al. 2008). However, we show that the magnitude of the advantages is species dependent: they are greater in the case of the lapwing compared to the oystercatcher.

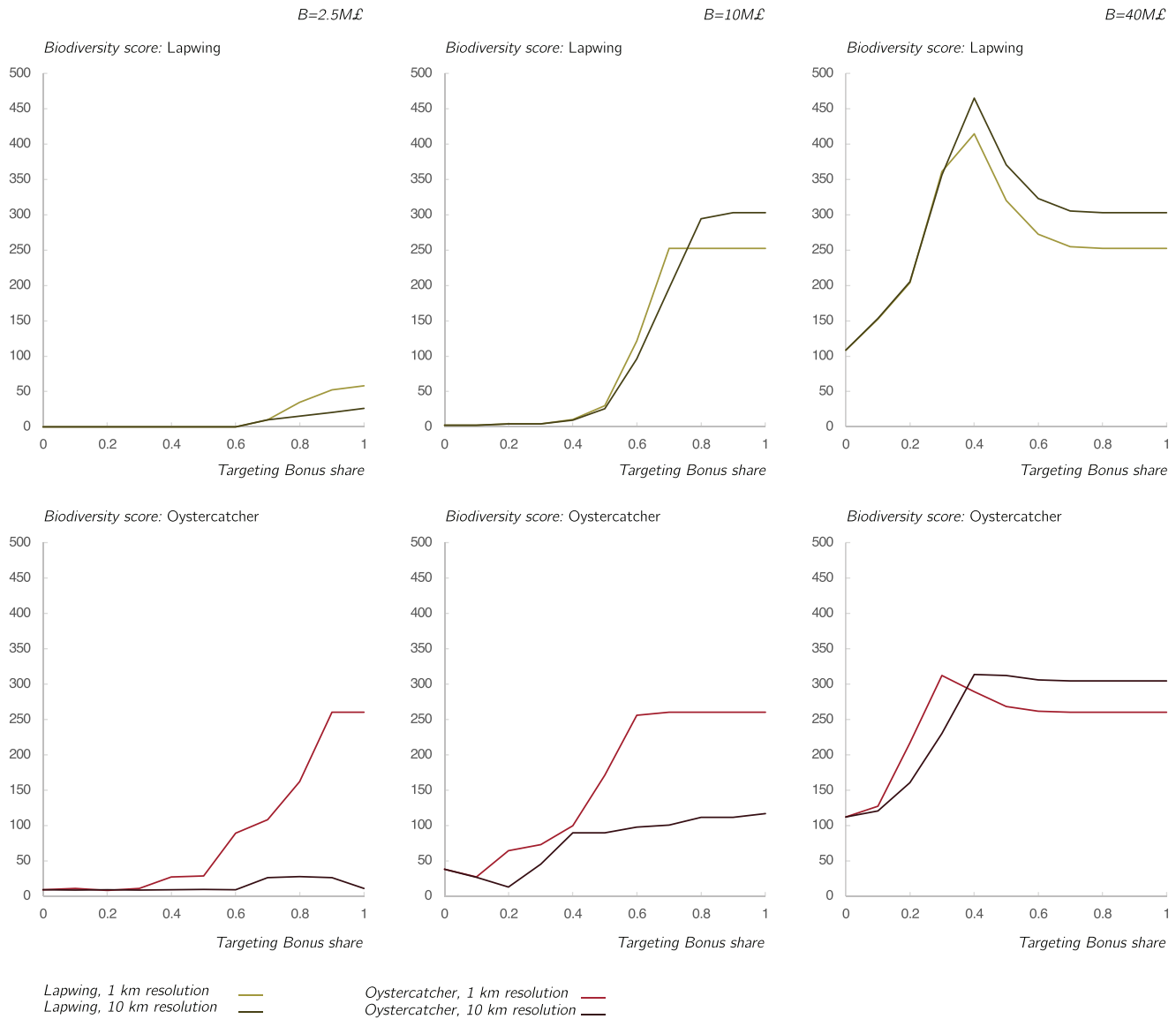


FIGURE 4 | Biodiversity score for lapwing (first line) and oystercatcher (second line) for different budget levels— $B = 2.5\text{M}\text{£}$ (first column), $B = 10\text{M}\text{£}$ (second column), $B = 40\text{M}\text{£}$ (third column)—under a spatial resolution of 1 km^2 and 10 km^2 . $P = 585\text{£/ha}$.

This was also a finding in a spatially-explicit optimisation model for AES in the Peak District, England, which compared uniform payments with spatially-differentiated payments using actual data on ecological responses and simulated data on opportunity costs (Armsworth et al. 2012).

Our results indicate that for a given payment rate, increasing the proportion of the payment allocated to the targeting bonus eventually reaches a tipping point in terms of overall expenditure on the AES. For oystercatcher, under a starting budget of $10\text{ M}\text{£}$ and a payment rate of 585£/ha , once 60% of the expenditure is allocated to the targeting bonus, fewer land parcels enrol in the scheme, resulting in an overall decrease in budget expenditure (to $5\text{ M}\text{£}$). Despite the decline in spending, the ecological effectiveness improves slightly, as a greater share of the enrolled land is now located in the higher priority areas, as evidenced by the increases in the biodiversity score on the enrolled parcels.

The benefits of the targeting bonus are even stronger for the lapwing scenario, with the bonus improving the economic efficiency and the ecological effectiveness of the AES. With a fixed payment rate of 585£/ha and a total budget of $10\text{ M}\text{£}$, allocating 70% of the AES payment to the targeting bonus marks a tipping point. At this level, fewer land parcels enrol in the AES, particularly those outside of the targeted areas, leading to a modest reduction in overall budget expenditure (to $8\text{ M}\text{£}$). However, this shift is accompanied by a substantial improvement in ecological effectiveness. Specifically, the biodiversity score, measured by the change in lapwing numbers more than doubles, a 110% increase compared to a scheme with no targeting bonus. This indicates that spatial targeting increases the economic efficiency of the scheme: we achieve better conservation outcomes per pound spent, even though overall enrolment and expenditure decrease. In short, the targeting bonus helps concentrate effort where it matters most, but it also reduces the scheme's reach beyond those targeted zones.

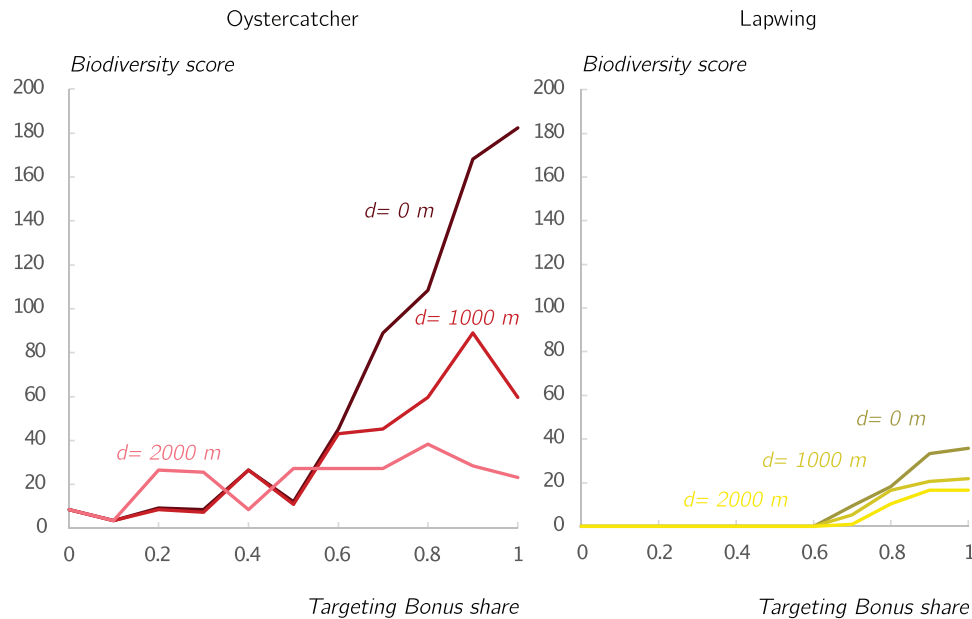


FIGURE 5 | Biodiversity score for different definition of the targeting area, depending on the distance of the coast ($d = 0$, dark red; $d = 1000$ m, red; $d = 2000$ m, light red). The simulations are run at $B = 2\text{M}\text{€}$ and $P = 585\text{€}/\text{ha}$.

Our results support the initial hypothesis that a targeting bonus will play a critical role in offsetting the financial impacts and increasing farmer participation in an AES where the most ecologically beneficial land parcels are positively correlated with highest opportunity costs for farmers. This confirms the theoretical result of Wätzold and Drechsler (2005) in the case of concave benefit functions. Similarly to their results, we find that the magnitude of these gains depends on the strength of this spatial relationship, as illustrated by the contrast between our oystercatcher and lapwing scenarios. For oystercatcher, we find only a moderate positive correlation ($+0.29$) between the opportunity costs and ecological productivity, implying that parcels delivering high ecological gains are not strongly concentrated among the highest-cost sites. These are primarily located along the coastal margin. As a result, a substantial share of potential oystercatcher gains can be realised even in the absence of a targeting bonus, as farmers managing relatively low-cost, high-benefit parcels are likely to enrol under a uniform payment scheme.

In contrast, for lapwing, ecological productivity is strongly positively correlated ($+0.68$) with opportunity costs, such that the largest increases in lapwing abundance are concentrated on high-cost parcels. Farmers managing these parcels are unlikely to participate in an agri-environment scheme without additional financial incentives. In this case, the targeting bonus plays a crucial role in offsetting high opportunity costs and inducing participation in locations where ecological gains are greatest. These findings highlight the importance of accounting not only for the presence but also for the strength of spatial correlation between opportunity costs and ecological benefits when designing targeted incentive schemes, and illustrate how targeting bonuses can substantially improve conservation outcomes in contexts where high ecological value is closely associated with high economic trade-offs. Unfortunately, we cannot investigate the effects of changing the sign of the spatial correlation between opportunity costs and environmental benefits in the present data, since unlike in the data

analysed by Nthambi et al. (2024), we do not observe a negative pattern of spatial correlation for any of our environmental targets.

This paper builds on our earlier work reported in Simpson et al. (2023), where the authors use the same modelling structure to evaluate differences between paying for actions to increase populations of lapwing, curlew and oystercatcher with paying for modelled (predicted) outcomes in the same landscape. However, paying for modelled outcomes is essentially the same as having a potentially perfectly-varying payment for action across farmers, with the variation emerging from the spatial variation in the ecological productivity of the conservation action on the desired biodiversity outcome. Such a spatially-differentiated incentive which is different, at the limit, for each farmer, risks a high administration cost and accusations of unfairness, since farmers are being offered different payments for undertaking the same action (here, create low intensity grassland), as Wätzold and Drechsler (2005) first pointed out. In contrast, the targeting bonus offers a very simple structure with just two payment levels, where the bonus is only paid within a clearly-defined spatial area where ecological productivity is “high” rather than “low”. This, we claim, is a major advantage IF such a targeting bonus still has high levels of cost-effectiveness compared to a uniform subsidy. That is the question which the present paper addresses, thus adding to the results presented in Simpson et al. (2023).

The benefits of a targeting bonus are likely to be context specific, strongly related to the relationship between the opportunity cost of farmers enrolling in the AES and distribution of the specie(s) of interest across the landscape. Interestingly, in our case, despite both species responding positively to the restoration of low intensity grassland on agricultural land, the location of the most beneficial parcels was substantially different. This highlights the complexities in the design of AES schemes intending to deliver multiple biodiversity outcomes. As Wätzold and Drechsler (2005) noted, “... the specific assumptions behind the shape of the bene-

fit functions need to be borne in mind.”. We have not been able to consider the implications of negatively-correlated environmental benefits and opportunity costs, but the nature of the distributions of benefits and costs may also matter. We find in our data that opportunity costs are less widely dispersed around the mean than environmental benefits, whilst the environmental benefits of improving oystercatcher habitat are more widely dispersed than is the case for lapwing habitat (the coefficient of variation is 3.42 and 1.87, respectively). Moreover, the effectiveness of the spatial targeting is highly dependent on the size of the budget. In the case of a relatively large budget, while some small levels of targeting bonus are beneficial, solely restricting subsidies to targeting areas is detrimental. Indeed, in such cases, there appears to be trade-offs between allowing the incentivisation of habitat in the entire landscape and tailoring the instrument to where it is more ecologically productive. From another perspective, when the budget is effectively constraining enrolment, enlarging the targeting area reduces the effectiveness of the scheme. This is further confirmed by the analysis related to the different definition of the targeting areas. Lowering the resolution of data used to define the targeting area causes a reduction in the ecological effectiveness of the scheme. The opposite is true in case the budget is large. In such a situation, targeting is relatively less effective, and larger (and less specific) areas are to be preferred.

A limitation of our approach is that the ecological effectiveness tested within our targeting bonus depends heavily on the accuracy of ecological models used to predict expected outcomes from changes in land management. In our species abundance model, predictions are less reliable for land parcels located in areas with sparse data and for the small number of parcels that support exceptionally high bird abundances. Additionally, our ecological model does not account for temporal dynamics—unlike, for example, the land use change examples in Bradfer-Lawrence et al. (2025) and Dobson et al. (2025). Furthermore, our optimisation model assumes that farmers' motivations to participate are based purely on the financial incentive offered. Research on AES participation has shown that farmers' decisions to participate in agri-environmental schemes are influenced by a range of factors beyond financial incentives. These include contract length, monitoring responsibilities, individual farmer characteristics, and the perceived behaviour of peers (Baumgart-Getz et al. 2012; Dessart et al. 2019; Murphy et al. 2014). Furthermore, we do not incorporate any transaction costs at the level of the individual farmer.

Further analysis is needed to refine our understanding of the targeting bonus and its effectiveness. First, we compare the outcome of the targeting bonus with that of a homogeneous payment. However, as mentioned, a targeting bonus could be interpreted as a simplification of a result-based scheme, and a comparison with such a scheme would be interesting. With result-based schemes, our targeting bonus shares the idea of setting heterogeneous incentive levels according to varying ecological benefit (Gars et al. 2024). Intuitively, our targeting bonus has the advantage of being action-based, and hence not plagued by the uncertainty that characterizes result-based payment schemes in a way which depresses sign-up rates (Derissen and Quaas 2013). On the other hand, by reducing incentives to two levels, the targeting bonus misses the capacity of result-based schemes to fully tailor the payment to variations in ecological benefit. Second, we do not take

into account spatial spillovers, temporal spillovers or threshold effects in the conservation of biodiversity (Drechsler et al. 2010). Additional analyses could extend the current ones by evaluating the effectiveness of a targeting bonus when threshold effects exist. In such cases, the targeting bonus could lead to agglomeration effects (Fooks et al. 2016; Rudolf et al. 2022) but without the complexity of the agglomeration bonus scheme (Bareille et al. 2023).

In conclusion, our findings highlight the value of incorporating spatial targeting mechanisms into the design of AES. By linking payments more closely to ecological priorities, targeting bonuses can substantially improve biodiversity outcomes. These gains are particularly pronounced when high-priority conservation areas overlap with parcels that would otherwise be too costly to enrol. Importantly, spatial targeting also increases economic efficiency by concentrating spending on land that delivers the greatest ecological return, often reducing overall scheme enrolment and expenditure. Our findings offer broadly-applicable insights for the design of AES worldwide, as they are driven by observable spatial relationships—such as agricultural profitability, land use, and predicted bird abundance. In terms of current AES design in the UK (our case study country), we note that most payments under Environmental Land Management schemes are still payments for action which ignore the spatial location of the farmer, with the exception of the collective action contracts offered under the Landscape Recovery scheme. However, though spatial criteria are part of the decision over what contracts to offer here, there is no use of a targeting bonus to focus actions within the collective once a contract is awarded. Our results underscore the importance of tailoring incentive structures to spatial ecological realities in order to maximise both the impact and cost-effectiveness of conservation policy.

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EDINA Agricultural Census

England and Wales Agricultural census data supplied by EDINA at the University of Edinburgh and the Department of Environment, Food and Rural Affairs (DEFRA) for England, The Welsh Assembly Government, or The Scottish Government (formerly SEERAD).

CEH Land Cover

Rowland, C.S., Morton, R.D., Carrasco, L., McShane, G., O'Neil, A.W., Wood, C.M. (2017).

Land Cover Map 2015 (vector, GB). NERC Environmental Information Data Centre

<https://doi.org/10.5285/6c6c9203-7333-4d96-88ab-78925e7a4e73>

CEH Land Cover plus Crops

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Soil Quality—LandIS

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Ordnance Survey Open Data

Contains OS data Crown Copyright OS Open Roads, OS Open Rivers, OS Terrain 50, Boundary-Line™, Code-Points Open and 1:250 000 Scale Colour Raster, 2018.

Endnotes

¹As there is a one-to-one correspondence between farmers and parcels, *i* indicates also the parcels.

²The model is described in detail in Simpson et al. (2023), whilst brief details are provided in Appendix to this paper.

³In practice, the optimal conservation land use may vary by location, but to simplify we specify a single practice, namely conversion to low-intensity grassland. In a payment for action scheme, this would be the single management action farmers would have to undertake to qualify for payment.

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Appendix A

Ecological Modelling Methods and Results

The ecological species abundance model presented in this Appendix is the same as that used in previous publications (Simpson et al. 2021a, 2021b, 2022, 2023). It is included here to provide a complete description of the underlying ecological component required to implement the spatially-explicit mathematical programming model used in the main analysis. No methodological changes have been made to the ecological model for the present study.

A1 Overview of the Ecological Modelling Approach

To quantify ecological benefits associated with land-use change under AES, we developed species abundance models (SAMs) for two focal bird species: the Eurasian oystercatcher (*Haematopus ostralegus*) and the Northern lapwing (*Vanellus vanellus*). Species abundance models are widely used to predict species abundance across landscapes by relating observed counts to environmental and land-use characteristics and then extrapolating these relationships to unsampled locations (Barker et al. 2014). In this study, SAMs were used to: (i) estimate current species abundance under existing land use, and (ii) predict changes in abundance resulting from conversion of agricultural land to low-intensity grassland under AES participation.

A2 Species Data

Species count data were obtained from the British Trust for Ornithology's Breeding Bird Survey (BBS). BBS data have been extensively used for modelling bird distributions and abundance at national and regional scales (e.g. Balmer et al. 2013; Renwick et al. 2012). The BBS is based on a stratified random sample of 1 km × 1 km grid squares across the UK National Grid, designed to provide representative coverage of habitats and regions while accounting for volunteer availability (Risely et al. 2010). Within each sampled square, trained volunteers conduct two standardised bird counts during the breeding season, following a reconnaissance visit. Surveys are conducted along predefined transects, with all birds seen or heard recorded. For this analysis, the maximum count across the two visits was used, consistent with standard BBS methodology (Harris et al. 2019). Squares where a species was not recorded were assigned a count of zero. To ensure consistency with the geographical context of the case study region, we restricted the modelling dataset to BBS squares located within the eastern region of the UK. This resulted in 1,798 sampled squares for 2016 and 1,835 squares for 2017.

A3 Explanatory Variables

Explanatory variables were selected based on the literature on farmland bird habitat associations and to ensure consistency with the economic components of the model (Brotons et al. 2004; Tattoni et al. 2012). All variables were derived at the 1 km × 1 km resolution to match the model's decision-making units.

Land Cover and Crop Variables

Land cover data were derived from the CEH Land Cover Map 2015 (LCM2015), which classifies land into 21 UK Biodiversity Action Plan Broad Habitat categories. Arable and horticultural land was further disaggregated into 11 crop types using the CEH Land Cover Plus: Crops dataset. For modelling purposes, "improved grassland" from LCM2015 and "grassland" from the crops dataset were combined, resulting in 30 land-use categories in total. The area (hectares) of each land cover and crop type within each 1 km × 1 km parcel was calculated using spatial overlay analysis in ArcGIS.

Additional Environmental Variables

Additional environmental covariates were derived from Ordnance Survey Open Data products. These included mean elevation (derived from OS

Terrain digital elevation data), distances to linear infrastructure (roads, railways, electricity pylons, watercourses, and tidal boundaries), and infrastructure density measures where appropriate. These variables capture landscape features known to influence bird abundance and habitat suitability. Summary statistics for all explanatory variables are provided in Table A1.

A4 Modelling Framework

Species abundance was modelled using generalized linear models with a negative binomial error structure to account for overdispersion in count data (Potts and Elith 2006). Let us denote as a random variable the single species count, Y_{ij} , from the i th site and the j th count. We assume:

$$E(Y_{ij}) = \mu_{ij}$$

We Allow the Mean to be a Positive Function of Covariates

$$\mu_{ij} = \exp(\mathbf{x}'_{ij}\boldsymbol{\beta}),$$

where $\mathbf{x}_{ij}$ is a vector of measured covariates for the j th count of the i th site, and $\boldsymbol{\beta}$ a vector of parameters. We fit the following model for each regression method:

$$\mathbf{x}'_{ij}\boldsymbol{\beta} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_n x_{in} + \varepsilon_i$$

Data from 2016 and 2017 were pooled, with a year dummy included to control for inter-annual variation. All models were estimated using maximum likelihood methods in R.

A5 Ecological Modelling Results

Regression results for the preferred models for each species are presented in Table A2. Across both species, crop cover was consistently negatively associated with abundance, particularly for cereals and oilseed rape. In contrast, grassland-related land cover types were generally less negative or neutral, depending on species and context. Infrastructure variables such as road density, proximity to pylons, and distance to watercourses also exhibited statistically significant effects, highlighting the importance of landscape context alongside land management. These results indicate that conversion of arable land to grassland has the potential to increase local abundance for both focal species, conditional on other environmental characteristics of the parcel.

A6 Linking Land-use Change to Species Abundance

Once species–environment relationships were established, the estimated models were used to generate predictions for all 1 km × 1 km parcels within the case study region under alternative land-use scenarios.

First, baseline abundance was predicted for each parcel using observed land use. Second, a counterfactual land-use scenario was constructed in which parcels classified as arable land were converted to grassland, while all other environmental variables were held constant. The species abundance models were then re-applied to this modified landscape.

For each parcel, the ecological benefit of land conversion was calculated as the difference between predicted abundance under the counterfactual and baseline scenarios. Aggregating these parcel-level differences yields estimates of total species abundance change across the region (Tables A3 and A4).

This approach provides a spatially explicit measure of ecological gains attributable to agricultural land conversion, which is directly linked to the economic decision-making framework used in the AES model.

TABLE A1 | Descriptive statistics for the environmental variables derived from the open data products for model years 2016 and 2017.

Variables		2016: <i>n</i> = 1798			2017: <i>n</i> = 1835		
		Mean	Min	Max	Mean	Min	Max
UK Broad Habitat Classifications	Acid Grassland (area hectares)	5.38	0	100	4.82	0	100
	Bog (area hectares)	2.43	0	100	2.19	0	100
	Broadleaf Woodland (area hectares)	7.48	0	92.66	7.67	0	92.66
	Calcareous Grassland (area hectares)	0.28	0	59.22	0.28	0	59.22
	Coniferous Woodland (area hectares)	4.22	0	100	4.34	0	100
	Fen, Marsh and Swamp (area hectares)	0.07	0	57.54	0.07	0	57.54
	Freshwater (area hectares)	0.91	0	90.47	0.96	0	90.47
	Low Intensity Grassland (area hectares)	28.7	0	99.48	28.79	0	99.41
	Heather (area hectares)	2.86	0	100	3.13	0	100
	Heather Grassland (area hectares)	1.73	0	100	1.79	0	100
	Inland Rock (area hectares)	0.3	0	100	0.39	0	100
	Littoral Rock (area hectares)	0.04	0	10.76	0.03	0	10.76
	Littoral Sediment (area hectares)	0.22	0	69.65	0.2	0	69.65
	Neutral Grassland (area hectares)	0.1	0	20.01	0.1	0	20.01
	Saltmarsh (area hectares)	0.21	0	65.7	0.21	0	65.7
	Saltwater (area hectares)	0.31	0	66.19	0.3	0	66.19
	Suburban (area hectares)	9.33	0	97.76	9.76	0	97.76
	Supralittoral Rock (area hectares)	0	0	2.46	0	0	2.46
	Supralittoral Sediment (area hectares)	0.17	0	93.23	0.19	0	93.23
	Urban (area hectares)	3.62	0	100	3.89	0	100
Crop classifications	Beets (area hectares)	0.47	0	60.5	1.05	0	57.52
	Field Beans (area hectares)	1.79	0	61.06	1.54	0	69.93
	Maize (area hectares)	0.6	0	39.59	0.99	0	44.52
	Oil Seed Rape (area hectares)	3.45	0	89.29	3.09	0	72.12
	Other crop type (area hectares)	6.9	0	71.28	4.86	0	64.22
	Potato (area hectares)	0.63	0	35.63	0.92	0	43.37
	Spring Barley (area hectares)	1.76	0	54.69	2.49	0	63.18
	Spring Wheat (area hectares)	2.48	0	60.27	2.16	0	56.07
	Winter Barley (area hectares)	2.92	0	61.56	2.97	0	60.21
	Winter Wheat (area hectares)	10.28	0	96.41	10.41	0	88.44
Other environmental variables	Distance from nearest A road (km)	2.68	0.00	67.85	2.57	0	66.87
	Distance from nearest Motorway (km)	31.96	0.02	278.25	31.88	0.02	278.25
	Distance from nearest B Road (km)	3.1	0.00	70.64	3.04	0	69.11
	Distance from nearest Any road (km)	0.66	0.00	66.43	0.54	0	66.04
	Distance from nearest overhead electricity pylons (km)	5.05	0.00	48.68	5	0	48.68
	Distance from nearest railway line (km)	5.13	0.00	59.83	5.02	0	55.32
	Road Density within the land parcel (weighted)	4.24	0.00	30.68	4.32	0	27.24
	Road Density within the land parcel (unweighted)	3.33	0.00	24.47	3.4	0	24.47
	Density of railway lines within the land parcel	0.14	0.00	2.97	0.14	0	4.47

(Continues)

TABLE A1 | (Continued)

Variables		2016: <i>n</i> = 1798			2017: <i>n</i> = 1835		
		Mean	Min	Max	Mean	Min	Max
Density of overhead pylons within the land parcel	0.16	0.00	2.79	0.17	0	2.79	
Contour (mean elevation m)	120.86	−1.24	996.09	122.11	−1.24	1,052.58	
Distance from tidal boundary (km)	19.09	0.00	89.33	19.17	0	89.33	
Distance from nearest watercourse (km)	0.8	0.00	8.15	0.79	0	7.16	

TABLE A2 | Results of the negative binomial model for predicting individual species abundance.

Variables		Curlew model		Lapwing model		Oystercatcher model	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
UK Broad Habitat Classifications	Acid Grassland (area ha)	0.003	−0.011	−0.036***	−0.009	−0.023***	−0.009
	Bog (area ha)	0.001	−0.011	−0.043***	−0.01	−0.024***	−0.009
	Broadleaf woodland (area ha)	−0.053***	−0.012	−0.081***	−0.011	−0.041***	−0.01
	Calcareous grassland (area ha)	0.023	−0.017	−0.036**	−0.016	0.002	−0.017
	Coniferous woodland (area ha)	−0.021**	−0.011	−0.074***	−0.01	−0.033***	−0.009
	Fen, marsh and swamp (area ha)	−0.037	−0.034	−0.005	−0.013	−0.022	−0.014
	Freshwater (area ha)	−0.025*	−0.014	−0.048***	−0.013	0.011	−0.011
	Heather (area ha)	0.004	−0.011	−0.038***	−0.01	−0.023**	−0.009
	Improved Grassland (area ha)	0.002	−0.011	0.028	−0.009	−0.01	−0.009
	Heather grassland (area ha)	0.008	−0.011	−0.035***	−0.01	−0.011	−0.009
	Inland rock (area ha)	−0.097***	−0.027	−0.130***	−0.038	−0.053***	−0.016
	Littoral rock (area ha)	0.088	−0.149	−0.646***	−0.177	0.283***	−0.093
	Littoral sediment (area ha)	0.023	−0.024	−0.168***	−0.05	0.076***	−0.022
	Neutral grassland (area ha)	0.048	−0.043	0.036	−0.035	−0.037	−0.048
	Saltmarsh (area ha)	0.063***	−0.023	0.029*	−0.017	0.047***	−0.016
	Saltwater (area ha)	0.013	−0.015	−0.086***	−0.019	0.004	−0.013
	Suburban (area ha)	−0.079***	−0.014	−0.100***	−0.012	−0.031***	−0.009
	Supralittoral rock (area ha)	−0.543*	−0.321	0.082	−0.159	−0.118	−0.152
	Supralittoral sediment (area ha)	−0.044**	−0.022	−0.048***	−0.015	0.003	−0.011
	Urban (area ha)	−0.068***	−0.019	−0.078***	−0.015	−0.064***	−0.012
Crop classifications	Beets (area ha)	−0.072	−0.046	−0.019	−0.013	0.002	−0.014
	Field Beans area ha)	−0.040**	−0.019	−0.039***	−0.012	−0.061***	−0.017
	Maize (area ha)	−0.043	−0.028	−0.027*	−0.015	−0.089***	−0.019
	Oil Seed Rape (area ha)	−0.032***	−0.012	−0.048***	−0.01	−0.054***	−0.011
	Potatoes (area ha)	0.027	−0.026	−0.032**	−0.014	0.014	−0.012
	Spring Barley (area ha)	−0.003	−0.013	−0.049***	−0.012	0.004	−0.01
	Spring Wheat (area ha)	−0.01	−0.013	−0.034***	−0.011	−0.006	−0.01
	Winter Barley (area ha)	−0.024*	−0.014	−0.040***	−0.012	−0.016	−0.012
	Winter Wheat (area ha)	−0.045***	−0.013	−0.052***	−0.01	−0.042***	−0.009
	Other crop type (area ha)	−0.033**	−0.013	−0.030***	−0.01	−0.020**	−0.01

(Continues)

TABLE A2 | (Continued)

Variables		Curlew model		Lapwing model		Oystercatcher model	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Additional explanatory variables	Pylons Density (Density of electricity pylons within the land parcel)	−0.445***	−0.116	−0.336***	−0.117	−0.375**	−0.155
	Tidal (distance of land parcel from nearest tidal boundary km)	0.015***	−0.003	0.013***	−0.004	−0.002	−0.003
	Watercourse (distance of land parcel from nearest tidal watercourse) (distance km)	−0.232**	−0.091	−0.409***	−0.085	−0.401***	−0.087
	Model year dummy: 0 = 2016, 1 = 2017	−0.02	−0.091	0.051	−0.101	0.013	−0.103
Constant		0.771	−1.053	4.350***	−0.902	1.644*	−0.853
Observations		3,626		3,620		3,610	
chi2		835.6		3.776		525.4	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Simpson et al. 2023.

TABLE A3 | Predicted species abundance across the case study region based on current land.

Bird species	Total predicted abundance across case study region (95% confidence intervals)	Total number of parcels with presence	Median count of birds in a single land parcel with presence (min—max)
Lapwing	9267 (8962– 9572)	4764	1.6 (0.1– 62.0)
Oystercatcher	4301 (3865– 4737)	4860	0.4 (0.1– 45.0)
Curlew	8986 (8697–9276)	4252	1.5 (0.1–40.3)

TABLE A4 | Predicted species abundance across the case study region based on current land and under a full offset scenario (the full offset scenario is based on all crop hectares being converted to improved grassland).

Bird species	Total predicted abundance across case study region (95% confidence intervals)	Total number of parcels with presence	Median count of birds in a single land parcel with presence (min—max)
Lapwing	12485 (12165– 12803)	4806	2.3 (0.1– 65.4)
Oystercatcher	5834 (5324– 6344)	5138	0.8 (0.1– 74.3)
Curlew	11149 (10883– 11416)	4762	2.0 (0.1– 40.4)