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RESEARCH ARTICLE

Exploring drivers of within-field crop yield variation using a national precision yield network

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Abstract

1. While abiotic drivers of yields represent important limiting factors to crop productivity, the role of biotic drivers that could be directly managed by farmers (e.g. agri-environment schemes supporting key ecosystem services) remains poorly understood. Precision yield mapping provides an opportunity to understand the factors that limit agricultural yield through the interpretation of high-resolution cropping data. This has the potential to inform future precision agricultural management, such as the targeted application of agrochemicals, promoting increased sustainability in modern agricultural systems.
2. We used precision yield measurements from a network of 1174 fields in England (2006–2020) to identify drivers of within-field yield variation in winter wheat and oilseed rape. Potential drivers included climate, topography and landscape composition and configuration. We then explored relationships between in-field yield patterns and local landscape context, including the presence of features associated with ecosystem benefits.
3. Proximity to the field edge was associated with reduced yields in 85% of wheat and 87% of oilseed fields. This translating to an approximate reduction of 10% in wheat and 18% in oilseed yields lost due to field edge effects.
4. We found evidence that reduced yields at the field edges were associated with biotic features of the surrounding landscape, including the occurrence of semi-natural habitats. Specifically, agri-environment scheme (AES) presence increased the rate at which yields at field edges approach those of the field centres. This suggests that AES occurrence within a landscape (rather than field adjacent) may increase edge effects. However, these trends are unclear and suggest interactions between drivers and the spatial and temporal scale of investigation.
5. *Synthesis and applications*. While we found evidence of landscape context mitigating against field edge effects, these were counterintuitive. For example, AES at a landscape scale appeared to increase the severity of edge effects. This study highlights a lack of environmental data at sufficiently high spatiotemporal resolution to match that of precision agriculture data. This mismatch is hindering

the effective integration of precision agriculture data in an environmental policy and/or management context and potentially leading to unnecessarily poorly informed decisions related to AES deployment. This may limit environmental and economic benefits.

KEYWORDS
agri-environment schemes, crop yield, ecosystem services, field edge effect, pollinators, precision agriculture, semi-natural habitat

1 | INTRODUCTION

The current challenge for the agricultural industry is to meet the increasing future demands placed on the sector while minimising potential environmental impacts. Crop yields vary in response to multiple drivers which can interact over varying spatial and temporal extents (e.g. Deutsch et al., 2018). While some drivers, such as climate (e.g. precipitation and air temperature), may typically impact crop yields over large time-scales and areas (e.g. Zhao et al., 2017), others can drive variation at smaller scales, for example though changes in pest abundance in response to local landscape structure (Chaplin-Kramer et al., 2011 but see Savary et al., 2019).

While some drivers of crop yield are fixed and so not feasible to mitigate (e.g. slope and aspect of the growing area) at least partial mitigation is possible for others (e.g. soil compaction; Hefner et al., 2019). Many of the known drivers of crop yield cumulate at the field edge, which commonly results in the so-called 'field edge effect' (e.g. Raatz et al., 2019; Ward et al., 2021). For this reason, it is common to see a reduction in crop yields at the field edge compared to the field centre.

One aspect of the farmland landscape which farmers can, at least to some extent, manage is semi-natural habitat cover. Semi-natural habitats within the surrounding landscape have previously been shown to benefit crops through increased provisioning of ecosystem services (e.g. pollination and pest control). Redhead et al. (2020) showed that the relative cover of, and proximity to, semi-natural land cover is associated with increased yield stability and resilience metrics. On smaller scales, agri-environment schemes (AES) can provide similar benefits. Benefits afforded to crops by natural habitats, including AES, are often through ecosystem services, including the provisioning of beneficial species (e.g. pollinators and predators of pest species; Dainese et al., 2019). Due to the spillover effect whereby densities of some beneficial arthropods can be higher at field edges from where they disperse into the crop, such ecosystem benefits which may be higher at field edges potentially negating some yield edge effects associated with abiotic drivers (e.g. Woodcock et al., 2016).

AES creation established in association with fields represents a flexible and targetable management practice familiar to many farmers. As AES are typically small in size and designed to be compatible with production agriculture (e.g. flower-rich field margins), the required financial investment and practical limitations to their creation are much lower than the comparable creation of larger areas of semi-natural habitat (e.g. a nature reserve). While the value of AES has been questioned (e.g. Kleijn et al., 2006), research has shown that they have the potential to provide benefits to comparable areas of existing semi-natural habitat. For example, AES deployment has been shown to increase farmland biodiversity and the associated ecosystem services provided by pollinators (e.g. Ouvrard et al., 2018; Woodcock et al., 2016) and pest predators (e.g. Boetzl et al., 2019; Tschumi et al., 2016).

Despite the widespread uptake of AES and their promotion in multiple national and international policy frameworks (e.g. CAP), few studies have directly linked their associated ecosystem benefits to improved agricultural productivity. While the goal of AES is not solely to benefit agricultural production, such an added benefit demonstrable to farmers can encourage both engagement and the likely quality of individual interventions as farmers see the wider benefit of investing time into such management for their farm productivity. Such evidence is also important in justifying their expense both from a farmer and national policy perspective, as land is often removed from agricultural production, with resultant costs. Pywell et al. (2015) provided evidence that the removal of up to 8% of land from production was offset by increased yields in the remaining production area. Field et al. (2015) also showed that wildlife friendly farming practices could negate the productivity losses incurred by removing ~10% of land from production. While these studies make valuable use of yield data measured at a high spatial resolution, their scale was limited to single farms, making generalisations difficult. The scaling up of such studies is important as the benefits of AES are known to vary with respect to multiple factors, including features of the wider landscape (e.g. Boetzl et al., 2020).

Here we use precision yield data at high spatial and temporal resolutions, collected from a network of farms across the dominant agricultural regions of England. We focus on winter wheat and winter oilseed crops from 1171 fields from 2006 to 2020. We aimed to assess two key research questions:

1. Are in-field crop yield patterns affected by biotic and abiotic environmental drivers describing local environmental conditions?
2. Are there environmental drivers, including occurrence of semi-natural habitat, which could mitigate against edge effects and help to increase agricultural efficiency?

The latter question addresses the tendency for arable field edges to be lower yielding than their centres, an effect often anecdotally attributed to processes such as increased compaction or poor agrochemical delivery in these areas (e.g. Sklenicka et al., 2002). Identifying which factors reduce yields at crop edges provides an important mechanism for raising average field yields by reducing their yield heterogeneity. As precision agriculture technology aims to improve agricultural yields and reduce costs (Gebbers & Adamchuck, 2010) through the collection of data to inform management practices, it has the potential to facilitate beneficial ecosystem services provided by farmland biodiversity directly through reduced application of agri-chemicals (Frampton & Dorne, 2007). For example, the collection of large volumes of spatially and temporally explicit data facilitates the targeted application of agrochemicals (e.g. pesticides and synthetic fertilisers), reducing waste and the likelihood of non-target impacts. The widescale collection of precision field productivity data has the potential to provide valuable insights into the drivers of crop yield. Using this data, we have attempted to identify key patterns in within-field variation in crop yields and explore how these might be mitigated through management strategies that target agricultural landscapes, such as via AES.

2 | MATERIALS AND METHODS

2.1 | Precision yield data

Crop yield data were collected by combine harvesters, from 1171 fields (Figure S1), during crop harvesting using automated grain yield monitors. In addition to recording crop yields, yield monitoring systems also record a high accuracy RTK GPS position of the combine harvester, grain moisture content, a timestamp and machine operating metrics (e.g. speed).

Precision yield data are generally collected by commercial equipment and remain the property of the individual farmer. Additionally, precision yield data are collected by multiple proprietary systems, in various file formats. Therefore, collating data to analyse patterns in yield across large areas spanning different landscape and farm management contexts remains challenging. Yield data were supplied on a voluntary basis by farmers through manual data exports from farm management software, and downloads from the CLAAS Telematics cloud platform (http://www.claas-telematics.com/). We cleaned the raw data to remove potentially erroneous data points. Initial cleaning steps were the removal of data outside: (1) the reliable working conditions of the combine harvester, (2) known cropping areas and (3) the known biologically possible yield (Table S2). In addition, further cleaning procedures were applied, including the exclusion of yield measurements outside the field mean (±2 SD) and local mean, defined as the 10 adjacent data points (±2 SD; Muhammed et al., 2016). Yield data from two combine harvesters working the same field in the same year were standardised to the mean of both datasets and combined to account for potential calibration differences between the two machines. When more than two combine harvesters were working the same field in the same year, these data were removed. The yield recording rate varied between combine harvesters (1–15 s). To ensure consistency across all fields, we standardised data to a common recording frequency, through subsampling. This resulted in a median time and distance between points of 15 s and 20 m, respectively.

For all data points, we calculated the distance to and identity of the nearest field edge. We removed field edges and their associated yield records where the minimum distance to the nearest field edge was over 18 m (the 95% confidence interval). We also removed yield records where the difference between the distance to the nearest field edge and the second nearest edge was less than 20 m. This was to reduce the potential for the environmental impacts of other field edges, which are not the nearest, to significantly impact the analysed yields.

The rotation of crops is used extensively and is a longstanding and standard practice in agriculture, used to increase yields of subsequent crops by improving soil health, nutrient availability and limiting the establishment of pests (e.g. Conrad et al., 2021). Although exact identification of rotations is complex, generally our study fields were from agricultural systems where winter wheat was grown in rotation with other winter cereals (e.g. barley, oats), spring cereals (wheat, barley, oats) and combinable break crops such as oilseed rape and field beans. Other crops recorded in our fields (e.g. linseed, peas) were rare. Wheat crops are, on occasion, grown consecutively in the same field, the so called 'second cropping', but typically show lower yields (e.g. Knight et al., 2012). We identified instances of 'second cropping', where the same crop is grown in sequential years.

We also identified which field edges were used as vehicle turning headlands, used by farm machinery (Appendix S3). While inevitable in modern mechanised arable farming, turning headlands are known to impact crop growth through physical damage and soil compaction and are an important consideration when exploring within-field spatial patterns in crop yield.

2.2 | Field boundaries

We downloaded field boundaries from the CLAAS telematics cloud platform and supplemented these with polygons from the Ordinance Survey MasterMap Topography Layer® (www.ordnancesurvey.co.uk). Field boundaries were split into field edges based on the turning angle of the polygon vertices. Threshold angles defined for each field based on the number of field edges identified and the proportion of the total field perimeter covered by the field edges (Appendix S4). Field edges were restricted to a minimum length of 180 m to allow for approximately 10 data points (assuming the median spacing of 20 m).

2.3 | Environmental data

We used composite digital terrain and surface models derived from LiDAR data (Environment Agency, 2017a, 2017b) to calculate the topographic wetness, slope, aspect (measured as 'southness') and the relative shading for each yield data point (Table S5). Shading was obtained by calculating sun position (direction angle, zenith and azimuth) for each field centroid for the first day of each month in 2017, the mean harvest year, at three time points (1000, 1300 and 1600). We used slope, aspect and sun position information to calculate sunlight exposure, using the 'hillShade' function (Hijmans, 2020) which, when inverted, provides a metric of shading.

We used the UKCEH Land Cover Map 2015 (Rowland et al., 2017) to create three metrics of surrounding semi-natural land cover. We quantified the areas of: all non-cultivated habitats, semi-natural land cover and higher-quality semi-natural habitats within a 1 km radius of each field (Tables S5 and S6). We further generated Shannon evenness, Shannon diversity and relative patch richness indices as metrics of landscape structure surrounding each field.

We sampled AES agreement data (DEFRA & Natural England, 2020) of options known to benefit pollinating insects (Staley et al., 2021), within a 1 km radius of each field (Table S5). The exact position of AES options was not recorded, with most options being recorded at the level of field or farm centroid. To quantify the relative AES uptake in the local landscape, we calculated the area of AES options as a proportion of agricultural land within the same 1 km radius.

Lastly, we sampled HadUK 1 km mean annual daily precipitation and temperature data (Met Office et al., 2018) for each field and year combination (Table S5).

2.4 | Statistical analyses

All yield data preparation and statistical analyses were undertaken in R version 4.0.2 (R Core Team, 2020).

2.5 | Drivers of crop yield variation

To identify key within-field yield patterns, we ran independent linear mixed-effects models for wheat and oilseed crop yields (Bates et al., 2015). We modelled crop yield against distance from the field edge, slope, aspect and topographic wetness with all variables fitted as first and second order polynomial terms. We fitted models containing all combinations of the environmental variables (Table; Table S7). All candidate models contained the 'harvest year' term and a 'field edge ID' and 'field ID' nested random effect. All model terms were scaled and mean centred, except for aspect which was scaled only. Models for wheat crops also contained a 'second cropping' term. This term was not required in oilseed models as this practice does not occur. We used the MuMIn R package to fit and compare the models using their penalised Akaike information criterion (AICc) scores.

2.6 | Edge effect metrics

To quantify the field edge effect, we formulated linear models of crop yield against the environmental variables shown to be important in driving the within-field yield variation (Table 1) for each field, crop type and year. All explanatory covariates were scaled and mean centred, except for aspect which was scaled. As previous research has shown that the benefits of adjacent landscape features can be measured up to 50 m into the field (Woodcock et al., 2016), we tested for the presence of breakpoints (BPs) in the field edge effect over the first 50 m from the field edge into the field centre. We used the SEGMENTED R package (Vito & Muggeo, 2017) to identify potential BPs in the yield ~ distance from the field edge relationship, after accounting for the additional environmental variables (Figure S8). We conducted Davies tests (Davies, 2002) to find evidence to support these potential BPs. Where there was insufficient evidence of a BP for a particular field, year and crop combination or where that BP did not result in subsequent viable regression models (due to a BP at the boundary), these points were excluded.

We used the same environmental variables to calculate the regression slopes (β coefficients) between crop yield and distance from the field edge, after accounting for the additional environmental variables (Figure S8). We used data within 100 m of the field edge to quantify the yield drop off associated with the field edge. In keeping with previous studies (Collins et al., 2002; Raatz et al., 2019), we expected the relationship between crop yields and distance to the field edge to be positive, with yields increasing with increasing distance from the field edge. We excluded negative relationships, which we attributed to anomalous recording or unusual field shapes, from subsequent analyses (see Table S9 for a sensitivity analysis of this assumption).

We define BP values as the distances from the field edge towards the field centre over which the edge effect is identified as impacting yield. We therefore propose that higher BP values are detrimental to agricultural productivity. Similarly, we suggest that higher β coefficients are indicative of a greater field edge effect, as the yields differ to a larger degree between the field edge and the field centre. In the 'best case' scenario, BP distances would be minimal, suggesting that the field edge effect is affecting only a small area, and β coefficients would be zero, indicating that yields are consistent irrespective of proximity to the field edge. Our edge effect metrics do not necessarily relate to overall field productivity but instead reflect the magnitude of yield loss, due to the field edge effect, in relation to the average field yield at the field centre.

2.7 | Landscape and local context drivers of field edge effect

To explore how landscape and local context affected the severity of the edge effect, we applied a modified random effects meta-analytic approach (see Keogan et al., 2018) to fit linear mixed-effects models. Importantly, this modelling framework allowed us to account for the fact that our response variables are estimates themselves, by restricting their variance using their associated standard errors. We used INLA (Rue et al., 2009) to model the (1) the BP distance and (2) the β coefficients calculated previously. We fitted separate models for wheat

TABLE 1 Model coefficients for wheat and oilseed yields against features of the agricultural landscape over which land managers and policymakers have no reasonable control. The 'best-fit' model terms are shown with their associated model estimates and standard errors. Harvest year was treated as a categorical variable and 2012, a known poor yielding year, was treated as the reference year. Model selection was undertaken using orthogonal polynomials but raw polynomials are reported here for clarity

	Crop model	
Model term	Wheat	Oilseed
(Intercept)	8.978 (±0.258)	4.059 (±0.203)
Distance	0.351 (±0.002)	0.334 (±0.002)
Distance^2	−0.144 (±0.002)	−0.101 (±0.001)
Second cropping: Yes	−0.483 (±0.018)	
Slope	−0.026 (±0.005)	−0.052 (±0.005)
Slope^2	−0.015 (±0.002)	−0.010 (±0.002)
Aspect	0.057 (±0.006)	0.022 (±0.006)
Aspect^2	0.003 (±0.006)	0.020 (±0.005)
Topographic wetness	0.018 (±0.002)	0.003 (±0.002)
Topographic wetness^2	0.009 (±0.001)	0.005 (±0.001)
Shading	−0.014 (±0.007)	−0.003 (±0.006)
Shading^2	-4.36×10^{-04} ($\pm -3.10\times10^{-04}$)	−0.001 ($\pm 4.04\times10^{-04}$)
Turning headland: Yes	−0.059 (±0.004)	−0.059 (±0.004)
Slope × Aspect	0.048 (±0.006)	0.023 (±0.006)
Slope^2 × Aspect	−0.010 (±0.002)	−0.008 (±0.001)
Slope × Aspect^2	0.008 (±0.007)	0.008 (±0.007)
Slope^2 × Aspect^2	4.64×10^{-04} (±0.003)	−0.005 (±0.003)

and oilseed crops, and for the two edge effect metrics, against local and landscape metrics of the farmed environment that could plausibly be influenced by either farmer behaviour or wider agricultural policy. We modelled BPs and β coefficients against our three metrics of surrounding semi-natural land cover (all non-cultivated green space, semi-natural land cover and higher-quality semi-natural habitats), landscape composition (Shannon evenness, Shannon diversity and relative patch richness), and AES uptake in the surrounding environment. Our models also included two climatic terms, mean annual rainfall and temperature, in addition to a year term and a 'field ID' random effect. Wheat models also contained a 'second cropping' term.

Models were constructed sequentially, using Watanabe-Akaike information criterion (WAIC), introducing new model terms when found to improve the previous model. Interactions between terms were tested in the same way. Variation between years was tested by modelling harvest year as a categorical variable in addition to AR1 and RW1 processes, again using WAIC scores to determine any improved model fit. Due to being highly correlated, models did not contain either multiple semi-natural habitat or landscape composition metrics.

Ethical approval was not required for this study.

3 | RESULTS

3.1 | Drivers of crop yield variation

Model selection of the full set of candidate models resulted in one well-fitting candidate model (ΔAICc < 10) for wheat and two for oilseed (Table S7; Bolker et al., 2009). For both crops, the model with the greatest support was the maximal model (w_i = 0.999 and 0.969). The second oilseed model, for which there was some evidence, was the same as the maximal but did not contain a 'shading' term (ΔAICc = 6.910, w_i = 0.031).

Analysis of wheat and oilseed crops yielded qualitatively similar results (Table 1), with distance from the field edge being identified as a key determinant of crop yield. Specifically, crop yields increased as distance from the field edge increased (Figure 1). Yield declines, as measured as the difference in yield between the field edge and the highest predicted yield, are comparable between crops (0.9 t/ha for wheat and 0.8 t/ha for oilseed). However, when measured as a percentage of field centre yield, field edge declines are greater in oilseed fields (21%) than wheat (8.9%). For both crops, increased shading was associated with lower yields (Table 1) while an increase in topographic wetness was associated with higher yields (Table 1). Both crop models included a polynomial slope-aspect interaction term which indicated (1) that yields tend to decrease as fields became increasingly sloped and (2) this relationship varies with respect to the field's aspect, with the most severe and linear decreases in North facing fields (Figure 2). Lastly, fields which were growing wheat for a second consecutive year were associated with, on average, 5.6% lower yields.

3.2 | Edge effect metrics

Overall, 49% of wheat fields and 48% of oilseed fields showed evidence of field edge effect related BPs and 85% of wheat and 87% of oilseed fields showed positive β coefficients, evidence of yields increasing towards the field centre. BP distances and β coefficient estimates were similar between wheat and oilseed crops (mean BPs = 25.9 m [±11.1] and 26.2 m [±10.5], mean β

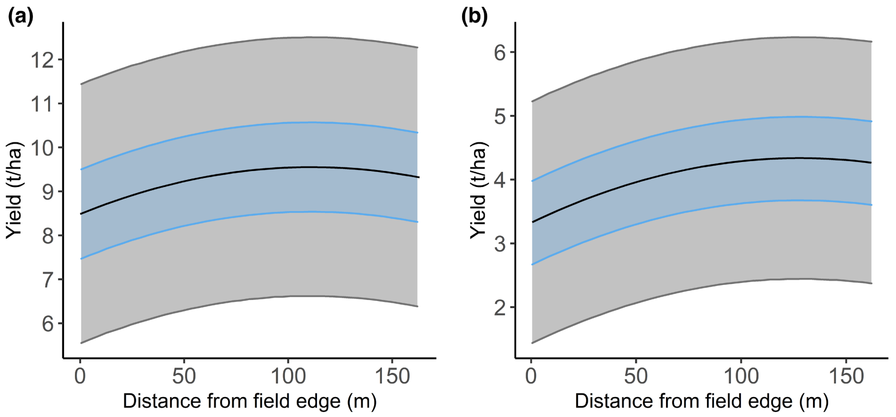

FIGURE 1 The predicted relationship between crop yield (tonnes per hectare) and distance from the field edge (m), using the best fitting models for wheat (a) and oilseed (b) crops. Model prediction (black) is shown with its 95% (grey) and 50% (blue) prediction intervals ($n = 999$).

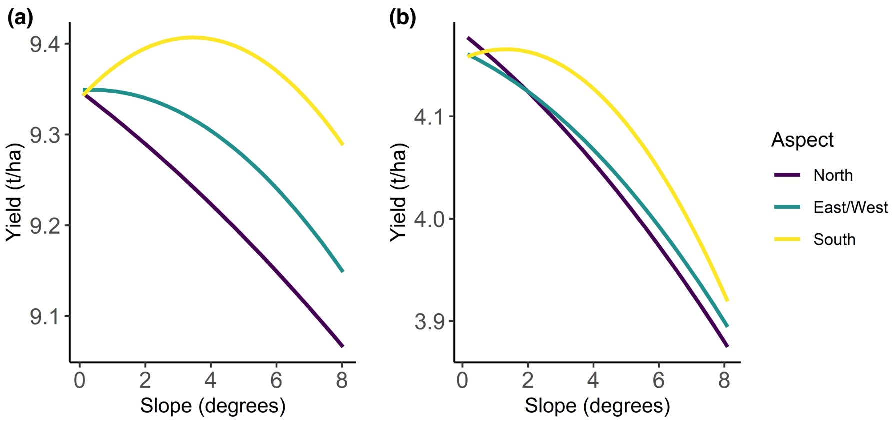

FIGURE 2 Interacting effects of slope and aspect (as measured as the degree of 'southness') on crop yield for (a) wheat and (b) oilseed. For both crops, increasingly sloped fields generally resulted in lower yields; however, this effect varied with the fields aspect. Yield declines with increasing field slope were the greatest in north facing fields, with south facing fields showing less extreme declines.

coefficients = 0.015 [±0.013] and 0.013 [±0.010]). Assuming average yields at the field centres and average field sizes, these β coefficient estimates would translate to approximately 10% of wheat and 18% of total potential oilseed yields lost due to the field edge effect.

3.3 | Landscape and local context drivers of field edge effect: BPs

Breakpoint models for both crops suggested the BP distances were associated largely with climatic variables (Table 2). Increasing rainfall was correlated with increasing BP distances in wheat crops (Figure 3). For oilseed crops, despite temperature being identified as an influential driver of BP distance, the effect of this was negligible. In contrast to wheat crops, increasing precipitation was associated with shorter BPs in oilseed fields. We found no evidence that variables describing features of the surrounding landscape or AES uptake were important in determining BP distances for either crop (Table 2).

3.4 | Landscape and local context drivers of field edge effect: β coefficients

Model selection provided evidence that β coefficients varied for both wheat and oilseed in response to climate, with rainfall and temperature interacting (Table 2). In wheat fields, the lowest β coefficients were predicted at average temperatures (~10°C) with estimates increasing at either temperature extremes. Increasing rainfall values were positively correlated with β coefficients. In oilseed crops, both temperature and rainfall were positively associated with increasing β coefficient predictions. These results highlight how climatic variables can interact into either an overall mitigating (e.g. high temperatures partially offsetting high rainfall via increased evapotranspiration) or exacerbating (e.g. high temperatures and low rainfall creating drought conditions) effect. Including AES cover improved the fit of both β coefficient models. These models suggested a general and moderate increase in β coefficients as AES uptake increases in the surrounding landscape (Table 2). This means that AES use is associated with increased yield loss at the field edge.

The degree to which the features of the surrounding landscape impact a field's β coefficient varied between the crop types. In wheat fields, the proportion of higher-quality semi-natural habitats interacts with our metrics of landscape diversity. However, our model only suggests a minor increase in a field's β coefficient in response to increasing landscape diversity (Table 2). In oilseed fields, we found evidence that the proportion of higher-quality semi-natural habitats was interacting with our metric of landscape evenness. Similarly to wheat fields, this interaction results in only minor changes to predicted β coefficients (Table 2). It is possible that evidence supporting the inclusion of this model term is driven primarily by the subset of fields containing an above average amount of higher quality semi-natural habitats in the nearby landscape. In this group, our model predicts in increase in β coefficients as the landscape evenness increases.

TABLE 2 Model coefficients and associated credible intervals for the BP and β coefficient analyses of wheat ($n = 418$ for BP and 1793 for β coefficient) and oilseed ($n = 210$ for BP and 913 for β coefficient) crops. Oilseed models did not contain second cropping variables as second cropping does not commonly occur in oilseed crops. The area of agri-environment (AES) schemes, known to beneficial to pollinators and whose recorded points are within 1 km of the field, were analysed as a categorical variable. Categories represent the area of AES as a proportion of agricultural area within 1 km of fields; 0% (the reference level), 0.001–3% ('AES: 0.001–3%'), 3–8% ('AES: 3–8%') and 8 +% ('AES: 8%+'). Similarly, the area of semi-natural habitats within the same 1 km buffer around fields was calculated for different habitat groups (see Table S5). '"Top" SNH cover' relates to semi-natural improved grassland and mountain, heath, bog categories of the UKCEH land cover map. Model selection was undertaken using orthogonal polynomials, raw polynomials are presented here for clarity

	Breakpoints							
	Wheat				Oilseed			
Model term	Mean	SD	2.5% CI	97.5% CI	Mean	SD	2.5% CI	97.5% CI
Intercept	39.819	12.511	15.221	64.354	70.652	90.389	−108.142	247.271
Rainfall	−0.043	0.033	−0.109	0.022	−0.017	0.103	−0.218	0.185
Rainfall^2	3.32×10^{-5}	2.16×10^{-5}	-9.23×10^{-6}	7.56×10^{-5}				
Temperature					−4.286	8.432	−20.768	12.364
Temperature^2								
AES: 0.001–3%								
AES: 3–8%								
AES: 8%+								
'Top' SNH cover								
Shannon diversity								
Shannon evenness								
Rainfall × Temperature					0.001	0.010	−0.018	0.020
Rainfall × Temperature^2								
Rainfall^2 × Temperature^2								
'Top' SNH cover × Shannon diversity								
'Top' SNH cover × Shannon evenness								

	Beta coefficients							
	Wheat				Oilseed			
Model term	Mean	SD	2.5% CI	97.5% CI	Mean	SD	2.5% CI	97.5% CI
Intercept	1.84×10^{-02}	1.91×10^{-02}	-1.91×10^{-02}	5.58×10^{-02}	6.97×10^{-02}	1.25×10^{-01}	-1.75×10^{-01}	3.16×10^{-01}
Rainfall	-2.66×10^{-05}	2.16×10^{-05}	-6.91×10^{-05}	1.58×10^{-05}	-2.83×10^{-05}	1.67×10^{-05}	-6.12×10^{-05}	4.56×10^{-06}
Rainfall^2					1.80×10^{-08}	1.69×10^{-08}	-1.50×10^{-08}	5.14×10^{-08}
Temperature					-1.20×10^{-02}	2.37×10^{-02}	-5.87×10^{-02}	3.44×10^{-02}
Temperature^2	-7.62×10^{-05}	1.66×10^{-04}	-4.01×10^{-04}	2.49×10^{-04}	6.88×10^{-04}	1.14×10^{-03}	-1.54×10^{-03}	2.92×10^{-03}
AES: 0.001–3%	1.57×10^{-03}	5.32×10^{-04}	5.25×10^{-04}	2.61×10^{-03}	8.34×10^{-04}	6.19×10^{-04}	-3.80×10^{-04}	2.05×10^{-03}
AES: 3–8%	1.30×1^{-03}	7.40×10^{-04}	−1.49 E-04	2.75×10^{-03}	-6.02×10^{-04}	7.86×10^{-04}	-2.15×10^{-03}	9.39×10^{-04}
AES: 8%+	4.07×10^{-03}	1.67×10^{-03}	7.94×10^{-04}	7.35×10^{-03}	2.03×10^{-03}	1.89×10^{-03}	-1.67×10^{-03}	5.73×10^{-03}
'Top' SNH cover	-2.89×10^{-04}	1.34×10^{-04}	-5.52×10^{-04}	-2.64×10^{-05}	-4.44×10^{-04}	1.78×10^{-04}	-7.93×10^{-04}	-9.45×10^{-05}
Shannon diversity	5.03×10^{-03}	$9.17\text{x } 1^{-04}$	3.24×10^{-03}	6.84×10^{-03}				
Shannon evenness					-3.23×10^{-04}	1.47×10^{-03}	-3.21×10^{-03}	2.56×10^{-03}
Rainfall × Temperature								
Rainfall × Temperature^2	2.74×10^{-07}	1.95×10^{-07}	-1.08×10^{-07}	6.56×10^{-07}				
Rainfall^2 × Temperature^2					3.34×10^{-11}	1.30×10^{-10}	-2.22×10^{-10}	2.87×10^{-10}
'Top' SNH cover × Shannon diversity	2.53×10^{-04}	1.53×10^{-04}	-4.84×10^{-05}	5.54×10^{-04}				
'Top' SNH cover × Shannon evenness					5.59×10^{-04}	3.24×10^{-04}	-7.74×10^{-05}	1.19×10^{-03}

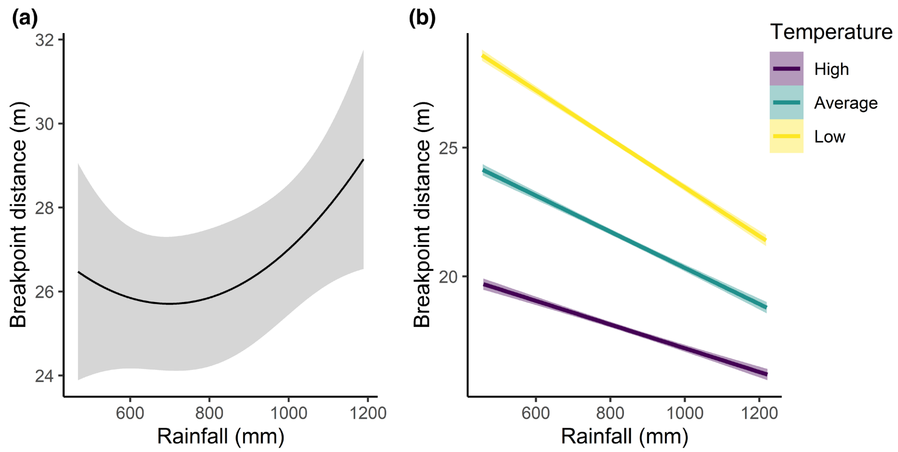

FIGURE 3 Effect of climatic variables on BP distances for wheat (a) and oilseed (b) crops. For wheat, increasing rainfall was positively associated with higher BP distances. This effect was most noticeable above 800 mm of annual rainfall. In oilseed crops, increasing rainfall was associated with decreased BP distances. Temperature was also important in determining the BP distance in oilseed fields, with higher temperatures associated with reduced BP distances. Temperature was analysed as a continuous variable but presented here as categories, to facilitate interpretation. High and low temperatures are defined as being over one standard deviation away from the mean temperature value.

4 | DISCUSSION

4.1 | Drivers of crop yield variation

Our results showed that a variety of factors have a strong and consistent influence on within-field patterns of crop yield, across a large sample of fields. Several of these variables are associated with topography (e.g. topographic wetness, slope and aspect) and, while they have a measurable impact on yields, options for mitigation are limited. For example, steep slopes can result in increased water runoff and associated soil damage; however, mitigation options are limited to minimising downslope tillage and practices to increase soil stability (e.g. direct drilling, cover cropping). Despite this long-term selection against topographic extremes, it is interesting to note that variation in yield remains evident over a relatively small range of slopes (0–25 degrees, 95% quantile = 6.6).

In addition to topographic related drivers, we also found evidence that the operation of agricultural machinery can impact crop yields. For example, turning headlands are associated with reduced yields, likely through changes in soil properties (Etana et al., 2020; Hefner et al., 2019), with this becoming an increasing problem in recent decades as the size and weight of agricultural machinery has grown. While complete mitigation of these effects is unlikely, practices such as controlled traffic systems (Bai et al., 2009) and the double drilling of headlands can minimise potential yield losses.

Landscape features therefore provide mitigation opportunities to increase agricultural productivity. Shading of cultivated areas by adjacent landscape features (e.g. woodland) is also associated with reduced yields. It is important to note that these same features (e.g. woodland) may also be associated with pests which can compound their apparent negative effect (Marshall et al., 2003) and/or interact with their potential crop benefits, for example, through buffering against climatic extremes (Kort, 1988; Raatz et al., 2019).

In addition to the aforementioned drivers of crop yield, we also found evidence of a consistent, strong effect of spatial context of the distance to the field edge. We found evidence that field edges had, on average, lower yields than field centres. We suggest that mitigating against effects of the field edge is a clear way in which the necessary increases in productivity might be achieved. By our estimates, such mitigation efforts could increase wheat yields by up to 10% and oilseed yields by up 18%. These estimates make distance from the field edge one of the greatest determinants of crop yield in our analyses and ultimately one of the most productive routes to increase yields in the future.

4.2 | Edge effect metrics

The effect on yield of proximity to the field edge is the compounded effect of multiple drivers. While many of these drivers are detrimental to crop yields [e.g. soil compaction (Sklenicka et al., 2002) and weed ingress (Marshall et al., 2003)], edges can also benefit nearby crops [e.g. sheltering from adverse climatic conditions (Kort, 1988; Raatz et al., 2019) and ingress of natural enemies of pests (Woodcock et al., 2016)]. While these interacting, and often opposing, underlying effects complicate identifying the specific driver of the field edge effect, our analyses have allowed us to marginalise known contributors to this combined effect to increase clarity of those sources of yield variation. Ultimately, our results suggest that, in the majority of cases under the typical English agricultural system, the detrimental physical effects associated with the field edge (e.g. soil compaction) outweigh any associated biological benefits (e.g. biological control).

In addition to the specific targeting of known components of the field edge effect (e.g. turning headlands), it should be possible to reduce the negative effects of the field edge effect through practices such as AES, which have been shown to improve crop yields and ultimately offset the areas of land removed from cultivation at the single farm scale (Pywell et al., 2015).

4.3 | Landscape and local context drivers of field edge effect

AES have received significant research attention and financial investment with the aim of mitigating environmental degradation in agricultural landscapes. Despite this, our current understanding of their benefits remains unclear due to the context specificity of their effects (Kleijn et al., 2001, 2011; Woodcock et al., 2010 but see Kleijn & Sutherland, 2003). We had hypothesised that AES may benefit crops through the provision of ecosystem benefits, which may be realised through increased yields or reduced edge effects. The spill over of advantageous invertebrate species being a potential mechanism for this (Woodcock et al., 2016). The provision of non-crop and semi-natural habitats (the restoration of which can be a target for AES) has also been demonstrated to be important in regulating yield via the same mechanisms (e.g. Martin et al., 2019).

However, our analyses suggested that, where an effect was detectable, AES and semi-natural habitat extent were generally slightly detrimental to crop yield, resulting in more extreme field edge effect metrics. It may be that the farm-scale beneficial effects detected by Pywell et al. (2015) and Field et al. (2015) are simply not present across the wider English agricultural system, due to insufficient, quantity, quality or spatial configuration of AES options. This would be in common with many studies demonstrating a lack of ability to translate demonstrable scale farm-scale AES benefits into larger scale impacts (e.g. Kleijn et al., 2006). An alternative (or additional) possibility is the mismatch between the resolution of our relevant spatial data (e.g. AES positions) and the resolution at which such benefits might be expected to occur (e.g. Woodcock et al., 2016). Specifically, our metrics of AES uptake were limited by the resolution of the data to aggregate farm level, making quantification of effects over small spatial scales difficult (e.g. adjacent crops). While precision agricultural technology now provides yield data at very fine spatiotemporal resolution, we lack data at the equivalent resolution on AES uptake, position and quality. It is likely that continued developments in remote sensing technology and machine learning techniques will be able to fill some of these current data gaps. However, there is an ongoing need to ensure that the advances in precision agricultural technology are matched by developments in environmental monitoring if we are to maximise the benefits of these datasets.

An additional explanation for our apparently counterintuitive results may also be that the relationships between the extent of habitats and yield are too complex to analyse across large samples of fields and are entirely dependent on local context. For example, the ability of a habitat to provide beneficial invertebrates to increase yield depends on interactions within the beneficial invertebrate and pest communities, and the extent to which pests and beneficials move into crops. Beneficial features of the landscape may well impact target and non-target species alike, for example, impacting pest and beneficial species to the same degree may result in no net change. Conversely, any effect of landscape features may interact with other variables of the growing environment, such as rainfall, which we have shown could impact wheat and oilseed crops differently, likely through a series of further complex interactions (e.g. rainfall may be interacting with common crop pests of the crops, which are likely different). It is because of these numerous and complex interactions that result in these relationships often being highly context dependant (Haan et al., 2020) with any benefits not always translating into changes in crop measurements (Martin et al., 2019; Smith et al., 2020). There is thus a great deal of scope for highly context-dependent effects, or effects which are only apparent under certain conditions. For example, Zamorano et al. (2020) provided evidence that while floral AES options increased pollinator abundance and diversity there were no measurable effects on crop yield. Similarly, Redhead et al. (2020) reported that landscape composition increased yield resilience, especially in reducing the impact of extreme weather events, but had no effect on average yields.

5 | CONCLUSIONS

We have provided evidence that the proximity to the field edge remains one of the primary determinants of crop yield in wheat and oilseed crops. We have shown how minimising yield loss at the field edge could be a way in which the ever-growing demands for agricultural outputs could be supported while meeting national and international environmental commitments. We had expected our use of precision yield data to, at least in part, elucidate some of the previous complexities surrounding the benefits provided by AES (e.g. Kleijn et al., 2006). However, despite our application of a large precision yield dataset, we were unable to show a measurable benefit of AES on crop yields, via metrics of the field edge effect. While it may be the case that AES are simply not providing these benefits across the wider agricultural system, our analyses also highlight the need for higher resolution data on AES positioning, to match that now available for agricultural data through precision agricultural systems. Mechanisms for achieving this could include new technologies in earth observation, but also future policy requirements to ensure the mapping and sharing of AES option data and the development of tools and protocols to support farmers in doing this. Ultimately, obtaining both environmental and agronomic data at common resolutions will be required to fully disentangle the complexities surrounding AES deployment and their associated benefits and ultimately justify their expense.

AUTHOR CONTRIBUTIONS

All authors contributed to the development of ideas and design of methodology. Data were collected by John Redhead, Richard Pywell and William Fincham. William Fincham led the data analysis and writing of the manuscript with contributions from all co-authors. All authors contributed critically to the drafts of the manuscript and gave final approval for publication.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Analysis code available via Zenodo https://zenodo.org/record/7220575#.Y06HckzMJhE(Fincham et al., 2022). Precision yield data remain the property of the individual land managers and are used in this manuscript, with permission, under non-disclosure agreements. We are therefore unable to share this data.

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SUPPORTING INFORMATION

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

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